Computational Agent-based Models of Offending:
Assessing the Generative Sufficiency of Opportunity-based Explanations of the Crime Event

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Abstract

This thesis demonstrates that agent-based modelling offers a viable compatriot to traditional experimental methodologies for criminology scholars, that can be applied to explore the divide between micro-level criminological theory and macro-level observations of crime; and in turn, aid in the assessment of those theories which aim to describe the crime event.

The following overarching research question is addressed:

Are the micro-level mechanisms of the opportunity theories generatively sufficient to explain macroscopic patterns commonly observed in the empirical study of crime?

Drawing on the approach of generative social science (Epstein, 1999), this thesis presents a systematic assessment of the generative sufficiency of three distinct mechanisms of offender movement, target selection and learning derived from the routine activity approach (Cohen & Felson, 1979), rational choice perspective (Clarke, 1980; Cornish & Clarke, 1986) and crime pattern theory (Brantingham & Brantingham, 1978, 1981). An agent-based model of offending is presented, in which an artificial landscape is inhabited by both potential victims and offenders who behave according to several of the key propositions of the routine activity approach, rational choice perspective and crime pattern theory. Following a computational laboratory-based approach, for each hypothetical mechanism studied, control and experimental behaviours are developed to represent the absence or presence of a proposed mechanism within the virtual population.

Using this model, a series of simulated experiments were performed, in which the crime patterns produced by virtual offenders operating under several distinct combinations of these mechanisms were examined and compared to three macroscopic regularities of crime derived from empirical study: spatial clustering, repeat victimisation, and the journey to crime curve. Each experiment was replicated 500 times, each replication exploring the same hypothetical decision calculus within a unique simulation environment inhabited by unique target and offender populations. Furthermore, two model variants were explored: the first simulating crimes against spatially static targets (e.g. residential burglary) and the second simulating crimes against spatially dynamic targets (e.g. street robbery).

In doing so the following focused research questions are addressed:

- *Are the mechanisms of the opportunity theories generatively sufficient to explain the spatial concentration of crime commonly observed in empirical study?*

- *Are the mechanisms of the opportunity theories generatively sufficient to explain patterns of repeat victimisation commonly observed in empirical study?*
- *Are the mechanisms of the opportunity theories generatively sufficient to explain the characteristic journey to crime curve commonly observed in empirical study?*
- *Do the mechanisms of the routine activity approach, rational choice perspective and crime pattern theory have differential impacts on commonly observed patterns of crime?*
- *Do these results differ by crimes that occur against static or dynamic targets?*

Results from this research demonstrate that the identified mechanisms of the opportunity theories provide a candidate *generative explanation* for why crime against both static and dynamic targets tends to be spatially clustered, experienced by a relatively small number of repeat victims, and why the aggregate journey to crime curve exhibits a characteristic distance decay. Furthermore, model findings suggest that the three mechanisms formalised are likely to have differential impacts on the regularities of crime studied. A number of ramifications of this study for theory, methodology and policy are discussed.

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Daniel Birks

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1 Introduction

Much of criminology has traditionally focused on explaining criminality, that is, how do those people who commit crime differ from those who do not. By contrast, environmental criminology and crime science focus on understanding the crime event itself, and in particular, the proximal circumstances which contribute to the emergence of criminal opportunities that are exploited by the motivated offender. A fundamental remit of these approaches is to identify, quantify and understand these patterns of criminal opportunity to facilitate the reduction and prevention of victimisation.

Current understanding within environmental criminology and crime science has been heavily influenced by three theoretical perspectives: the routine activity approach (Cohen & Felson, 1979), the rational choice perspective (Cornish & Clarke, 1986) and crime pattern theory (Brantingham & Brantingham, 1993a). These approaches, often described as the opportunity theories (Wortley & Mazerolle, 2008), concern themselves with how the spatio-temporal activities of individuals dictate where and when criminal opportunities arise, how the motivated offender reasons about those opportunities presented to them, and the role that the ever-changing environmental backcloth plays in situating them. Acknowledging the complexity of these interactions, environmental criminology and crime science are inherently multidisciplinary fields, drawing insight from psychology, geography, mathematics, urban planning, computer science, economics and a wealth of other disciplines.

The research presented in this thesis represents one such multidisciplinary effort, applying computational agent-based models (ABM[1]) to assess the explanatory power of several key micro-level mechanisms[2] described by the opportunity theories.

1.1 Research Rationale

Environmental criminology and the opportunity theories provide a number of hypothetical micro-level mechanisms considered significant to the crime event itself. These mechanisms describe the cognition and subsequent action of both potential victims and offenders, and, in turn, the influences that the local environment place upon them. As environmental criminologists we hypothesise that these mechanisms are operating, interacting, combining, exciting, inhibiting and subsuming one-another in complex and dynamic ways which influence the spatio-temporal distribution of criminal opportunities.

Unfortunately, several problems endemic throughout the social sciences dictate that we often struggle to directly observe how, and in what ways, such processes actually take place, and instead are left to observe only their output – the patterning of crime. As a result, theorists and practitioners can be forced to make a leap of faith in ascribing observed aggregate crime patterns to proposed individual-level behaviour, and visa versa. This divide between theory and observation dictates that the propositions of the opportunity theories can be difficult to empirically verify to the degree that would be desirable for both theory and policy development.

This thesis explores this divide between micro-theory and macro-observation by applying computational ABM of the crime event. It presents an explanatory ABM of crime in which a virtual landscape is constructed and inhabited by populations of potential victims and offenders whose behaviour is derived from several propositions of the opportunity theories. Using this model, the crime patterns produced by virtual offenders operating under a number of hypothetical decision calculi are examined and compared to several known

[1]For the sake of parsimony the acronym ABM will refer to both agent-based model and agent-based modelling.

[2]Here I appropriate Hedström's definition of a mechanism as "a constellation of entities and activities that are linked to one another in such a way that they regularly bring about a particular type of outcome" (Hedström, 2005, 11)

regularities of crime. In doing so, this thesis addresses the following overarching research question:

Are the micro-level mechanisms of the opportunity theories generatively sufficient to explain macroscopic patterns commonly observed in the empirical study of crime?

ABMs allow researchers to create artificial societies in which populations of virtual agents act and interact according to behaviours specified by the researcher. Operating from the *bottom-up*, the ABM then permits exploration of the divide between micro-level individual behaviour and the macro-level patterns that result from its interactions within society. By constructing these artificial societies researchers create the analogue to a petri-dish for the social scientist, in which the viability of theoretical proposition can be explored free from the ethical and logistical constraints of empirical experimentation.

Following the work of Schelling (1971, 1978) and Epstein and Axtell (1996) amongst others, the field of generative social science (Epstein, 1999) applies the ABM as its primary scientific instrument in identifying generative explanations of known phenomena. The statistical explanation, commonly employed within the social sciences, establishes an association between two or more observed characteristics – but without necessarily exposing a mechanism through which such characteristics are causally linked. By contrast, the generative explanation aims to identify those micro-level mechanisms which, when enacted by a population of virtual agents, are sufficient to generate macro-level patterns congruent with those observed in empirical study of the target system. If an individual level behaviour consistently produces aggregate outcomes similar to those observed in the real world it is deemed generatively sufficient, and as such, confidence in its validity is increased. Thus, the ABM allows researchers to identify candidate, generatively sufficient explanations of known phenomena, and in turn, provides a complimentary method to those commonly used in the study of social systems which can act as an additional point of triangulation when exploring the validity of theory.

Building on the observations and findings of several recent endeavours that have applied ABM in building explanatory models of the crime event(Birks, Donkin, & Wellsmith, 2008; Brantingham, Glasser, Jackson, Kinney, & Vajihollahi, 2008; Eck & Liu, 2004; Groff, 2007b, 2007a, 2008; Liu, Wang, Eck, & Liang, 2005; Wang, Liu, & Eck, 2008), this thesis provides a systematic study of the generative sufficiency of mechanisms described by the opportunity theories in explaining three independent macroscopic regularities of crime. Developing a generative ABM of offending, three key micro-level mechanisms of offender movement, decision-making and learning derived from the routine activity approach, rational choice perspective, and crime pattern theory are identified, formalised and explored. For each mechanism, a theoretical model is described, a conceptual model distilling the key propositions of this theoretical model set out; and a computational model formalising this conceptual model as a series of behavioural algorithms for inclusion within the ABM specified. Furthermore, applying a computational laboratory-based approach, control and experimental behaviours are developed for each mechanism, representing the absence or presence of a proposed mechanism within the virtual population; in turn, providing an appropriate counterfactual through which the impacts of specific mechanisms can be assessed.

Using this model, a series of controlled computational experiments are performed to explore the impacts of these micro-level mechanisms on simulated aggregate patterns of crime. The crime patterns generated during these experiments are then compared to three empirically derived macroscopic regularities of crime: spatial clustering, patterns of repeat victimisation and the journey to crime curve. Using a number of commonly applied analytical techniques, the generative sufficiency of each theoretical mechanism in explaining these known macro-regularities of crime is then assessed. Furthermore, two distinct model variants are explored: the first simulating offending against spatially static targets, such as personal residences targeted for residential burglary; and the second, spatially dynamic targets, such as pedestrians targeted in street robbery.

In doing so, this thesis explores the following focused research questions:

- Are the mechanisms of the opportunity theories generatively sufficient to explain the spatial concentration of crime commonly observed in empirical study?

- Are the mechanisms of the opportunity theories generatively sufficient to explain patterns of repeat victimisation commonly observed in empirical study?
- Are the mechanisms of the opportunity theories generatively sufficient to explain the characteristic journey to crime curve commonly observed in empirical study?
- Do the mechanisms of the routine activity approach, rational choice perspective and crime pattern theory have differential impacts on commonly observed patterns of crime?
- Do these results differ by crimes that occur against static or dynamic targets?

An overview of the research undertaken in this thesis, and the findings of Study 1 (see chapter 6) which concerns spatially static targets are presented in: *Birks, D., Townsley, M., & Stewart, A. (Forthcoming 2012). Generative Models of Crime: Using Simulation to Test Criminological Theory. Criminology, Wiley.*

1.2 Chapter Overview

The thesis is divided into seven chapters. This, the first chapter, provides an overview of the research presented in the thesis, outlines its underlying rationale, and states the overarching research questions it aims to answer.

The criminological theories that underpin the thesis are described in chapter two, which begins by identifying several key hypothetical micro-mechanisms proposed by the routine activity approach, rational choice perspective and crime pattern theory. The interdependence of these mechanisms is highlighted, suggesting that the depiction of crime they provide is best described as a complex dynamic system. Subsequently, a number of consistently observed macroscopic regularities of crime are discussed. In doing so, their salient macroscopic features are highlighted, and hypotheses suggested by the opportunity theories proposing how they might be generated from the decentralised interactions of society discussed. The gap that exists between the micro-level propositions provided by the opportunity theories and the scale at which crime is commonly observed is then discussed. In turn, it is argued that such a divide dictates that both academics and practitioners alike are often forced to make a leap of faith in ascribing observed crime pattern to proposed individual-level behaviour and visa versa; dictating that the propositions of the opportunity theories are difficult to empirically verify. The chapter concludes by arguing for the application of ABM to explore this divide, thus providing an additional point of triangulation in the the study of the opportunity theories.

Chapter three begins by providing readers with a brief primer for simulation within the social sciences. The rationale behind the simulation methodology is explained and its main scientific applications for theory testing and prediction are discussed. An overview of ABM is presented, its key components outlined, and a number of salient features that make it well suited for exploring the macro-level ramifications of micro-level mechanisms, such as those described by the opportunity theories, discussed. Subsequently, a discussion relating to the validity of simulation is provided, and a number of techniques through which simulation models can be assessed for validity identified. Next, an overview of several previous research efforts that have applied the agent-based methodology within the field of environmental criminology are discussed. Describing these existing endeavours, a number of strengths and weaknesses associated with each are highlighted. Drawing on these observations, several goals are set out for the development of an ABM of crime which aims to both extend and capitalise on the findings of previous models. Subsequently, an introduction to the emerging interdisciplinary field of generative social science is provided. The concept of the generative explanation is discussed and briefly compared to other forms of explanation. The chapter concludes by reiterating several micro-level hypotheses of the opportunity theories and discussing how they are well aligned to the development of a generative ABM of crime, which can then be used to assess the generative sufficiency of such mechanisms in explaining those macroscopic regularities of crime observed in empirical study.

Chapter four provides a summary of the previous chapters and sets out how the research proceeds through the development of a generative ABM of crime. The research questions are reiterated, and the methods through which they are addressed summarised.

Chapter five outlines the development of the ABM which forms the primary scientific instrument of the thesis. The choices made in its development are identified, the key mechanisms of theory it aims to formalise set out, and the methods through which these hypotheses are translated into a series of computational formalisms specified.

In chapter six the experimental method and findings are presented. The experimental design is defined, model configurations outlined, and the outcome measures used to analyse simulated crime data described. Subsequently, the results of these experiments are presented in two distinct studies, each exploring one of the two model variants which simulate offending against static and dynamic targets respectively.

Chapter seven provides a discussion of the findings presented in the previous chapter, summaries the research presented, and in turn, addresses each of the research questions of the thesis. Subsequently, the ramifications of these findings for theory, policy and practice are discussed. The chapter concludes by highlighting several general observations concerning the use of simulation models in the study of the crime event, describes a number of limitations of the research presented, and highlights potential paths for future enquiry.

2

Micro-specifications and Macro-structures of the Crime Event

This chapter provides an overview of the three theoretical frameworks that underpin this thesis. The key assertions of the routine activity approach, rational choice perspective and crime pattern theory are outlined, and a number of hypothesised micro-level mechanisms of crime provided by each are identified and described. Subsequently, several methodological critiques of these depictions of the crime event are presented. These critiques focus predominantly on the difficulties associated with observing the mechanisms of crime, and in turn, empirically verifying the propositions made by the opportunity theories. Subsequently, a number of commonly observed salient macroscopic regularities of crime are summarised. These regularities include the spatial and temporal concentration of crime, patterns of repeat victimisation, and the journey to crime curve. Drawing on Brantingham and Brantingham's (1993b) depiction of the crime event as a patterned activity that produces patterned outcomes, it is argued that such regularities represent some of the more predictable emergent outcomes of the mechanisms of crime operating *in-situ*[1].

Having identified both the hypothetical micro-level mechanisms put forward by the opportunity theories, and a number of observed macroscopic regularities of crime, a discussion of how we might attempt to link micro-theory to macro-observation, and in turn, provide assessments of the sufficiency

[1] Throughout this thesis real world mechanisms are referred to as occuring *in-situ*, and those that occur in a silicon-based computer simulation as *in-silico*.

of theory is presented. In summarising methods through which such links are commonly made, it is argued that two fundamental problems limit our ability to make generalizable causal inferences about the proximal mechanisms of the crime event, and in turn, their causal links to those patterns of crime we commonly observe. These are (1) a relative scarcity of reliable and representative micro-level data concerning the offence process and (2) a number of fundamental difficulties associated with undertaking controlled experimentation in the study of crime.

As a result of these problems, it is argued that a gap still exists between the level at which crime is commonly observed, and the level at which inferences concerning its underlying mechanisms must be made. This divide requires researcher, and practitioner alike to make a 'leap of faith' in ascribing observed crime pattern to proposed offending behaviour (and visa versa). Consequently, dictating that rigorous empirical validation of the propositions of the routine activity approach, rational choice perspective and crime pattern theory is difficult to undertake – a task that offers considerable utility to those who aim to implement opportunity-based crime prevention interventions. Additionally, it is argued that the interconnectedness of these theories further confounds problems of verification. In turn, highlighting the need for diverse analytical techniques aimed at exploring the complex and dynamic interactions from which the crime event emerges.

The chapter concludes by proposing the development of a simulation model that aims to explore this micro-macro divide, and in doing so provide a distinct but complimentary approach to those existing methods of study discussed previously.

2.1 Micro-specifications of the Opportunity Theories

Environmental criminology proposes that macro-level patterns of crime are best described as the aggregation of numerous micro-level interactions between potential offenders, victims, crime controllers, and the environment they inhabit. Contemporary understanding in this field has been heavily influenced by three theoretical perspectives: the routine activity approach

(Cohen & Felson, 1979), the rational choice perspective (Clarke, 1980; Cornish & Clarke, 1986) and crime pattern theory (Brantingham & Brantingham, 1978, 1981, 1993a). These three approaches, commonly referred to as the opportunity theories (Wortley & Mazerolle, 2008) provide proximal descriptions of the criminal event that are tangible, intuitive and mutually supportive (Clarke & Felson, 1993) and in application have demonstrated considerable utility in reducing crime through the application of situational crime prevention (SCP) (Clarke, 1997), problem oriented policing (POP) (Goldstein, 1990) and crime prevention through environmental design (CPTED) (Jeffrey & Zahm, 1993).

Unlike many traditional criminological theories, the opportunity theories focus on the criminal event, not the offender and their associated criminality. In doing so, each approach operates under the premise that the crime event is the result of a specific criminal opportunity. Focusing predominantly on developing an understanding of the crime event that fosters practical utility for crime prevention, each approach aims to identify suitable 'handles' through which crime can be reduced by altering the criminal opportunity. In identifying such handles and understanding how they might be manipulated, each approach provides a number of key propositions which it considers significant to explaining why crime opportunities are situated when and where they are, and in turn, why some are exploited by potential offenders. As such, the opportunity theories concern themselves with the proximal causes for crime rather than the potential myriad of distal causes for criminality. In doing so, proponents assert that while concepts such as criminal propensity are difficult to measure, predict and tackle, the criminal event itself can be more easily, and justifiably, identified and manipulated to remove the crime opportunity (Clarke, 1983).

Considering the overall scope of these three perspectives, the routine activity approach describes the crime event as a spatio-temporal convergence of three essential elements: a motivated offender, a suitable target and the absence of capable crime controllers, each in turn influenced by the spatial and temporal constraints of everyday activity. Crime pattern theory concentrates on where and when these convergences take place and, in particular, the role that the dynamic backcloth of criminal and non-criminal activities plays in influencing their occurrence. When such convergences do occur, the rational choice perspective provides a framework for thinking about the decision calculus employed by the offender and the proximal cues drawn upon to assess the suitability of a given criminal opportunity.

In approaching the study of crime, each perspective then focuses on a different element that contributes to the criminal event in some way: society, the local environment and the individual (Rossmo, 2000). These elements, however, are intrinsically interconnected at a multitude of scales, each impacting upon the other. The crime event as described by the opportunity theories is the result of numerous spatial and temporal interactions of a vast number of interconnected heterogeneous entities whose actions are both dynamic and interdependent.

This observation dictates that the crime event can be viewed as the output of a complex system. This is certainly not the first time this observation has been made of social systems in general (see for example (Sawyer, 2005)), or more specifically in describing the crime event (see for example (Brantingham et al., 2008; Brantingham & Brantingham, 1993a, 1993b; Eck, Clarke, & Guerette, 2007; Ekblom, 2008; Wang et al., 2008)). It is however, a point that will remain of significant importance throughout this thesis and is the premise that underlies the research presented throughout.

Complex systems theory aims to describe and understand the nature of complex systems. While there is no definitive consensus on what makes up a complex system, Cilliers (2000) succinctly summarises a number of salient features commonly exhibited by complex systems, all of which to varying degrees apply to the crime event as depicted by the opportunity theories. A summary of these follows (Cilliers, 2000, 24):

1. Complex systems contain large numbers of entities that may, in themselves, be simple;
2. The entities of complex systems interact dynamically and in rich non-linear ways;
3. Complex systems also contain direct and indirect feedback loops; as such, the actions of some system entities are interdependent on the actions of others;
4. Complex systems are open systems – the interactions that take place

between entities do so within some environment and cannot be described by static equilibria;

5. Complex systems exhibit collective memory, previous states of the system impact on new states of the system;
6. The behaviour of a complex system is derived from the interactions of entities within it – not by properties of the constituent entities. As such, system behaviour cannot be predicted by simple examination of the entities;
7. Complex systems are adaptive.

The aim of this thesis is to explore the complex system of the crime event through use of the simulation methodology, and permit the systematic study of likely macro-level ramifications of a number of the micro-level mechanisms proposed by the opportunity theories.

In the following sections a description of each of the three theoretical perspectives provided by the opportunity theories is presented. As discussed, these approaches are commonly described as acting at different levels of description: micro – the rational choice perspective, meso – crime pattern theory, and macro – the routine activity approach (Clarke & Felson, 1993). This distinction is however dictated by the proposed ramifications of assertions associated with each approach, which, for the most part, describe the micro-level actions and interactions of individual actors involved in the crime event.

For each of the three perspectives a key micro-level mechanism of interest is identified. These mechanisms are: the spatio-temporal activities of individuals described by the routine activity approach; the offender expected utility calculus outlined by the rational choice perspective; and the offender awareness space learning mechanic proposed by crime pattern theory. These three mechanisms of movement, decision making and learning then form the underlying assumptions from which entities within the simulation model developed in this thesis derive their behaviour. Thus, permitting the systematic exploration of the macro-level ramifications of these micro-level hypotheses, and in turn, a further assessment of their viability as crime event explanations.

In focusing on these mechanisms it is acknowledged that each approach offers a considerably richer account of the crime event than is covered here. The interested reader is directed to a thorough and insightful treatment of the opportunity based explanations of crime provided in Wortley and Mazerolle (2008).

2.1.1 The Routine Activity Approach

Drawing heavily from theories of human ecology (see (Hawley, 1950)) the routine activity approach describes the influence that day-to-day spatial and temporal constraints have on legal and illegal activities, and in turn, how the former provides opportunities for the latter. Cohen and Felson (1979) propose that where and when offenders and potential victims interact as they go about their day-to-day routines dictates their relative risks of victimization.

Thus, the routine activity approach aims to understand how the spatial and temporal patterns of societal routine activities influence the occurrence of crime. This approach relies on the premise that the crime event is the exploitation of a criminal opportunity that is generated by the convergence of particular circumstances. The routine activity approach states that direct contact offending[2] requires the spatio-temporal convergence of three essential elements: a motivated offender, a suitable target and the absence of a capable guardian (Cohen & Felson, 1979). A motivated, or likely, offender is considered anyone inclined to commit a crime. A suitable target is something considered both vulnerable and rewarding by the likely offender (Felson, 1983). Guardianship then refers to the presence or proximity of some individual or implement that in some way dissuades or disrupts the likely offender (Felson, 2002). Guardians are considered capable if they are in some way able to protect the target or, more specifically, are perceived by the motivated offender as capable of doing so. However, guardians are not commonly police officers or security guards catching an offender red-handed. Instead, they are more likely to be security devices or ordinary citizens going about their daily routine, such as a neighbour or bystander (Felson, 2002). To illustrate, those who stay home on a Friday night will have much lower

[2] Any crime that is perpetrated physically and intentionally against person or property.

rates of personal victimization than those who frequent bars or nightclubs where the likelihood of offender/victim convergence is much greater. Similarly, the homes of college students that are commonly left unoccupied until the early hours of the morning are likely to suffer greater levels of victimization than those occupied throughout the day by young families – who in turn provide guardianship.

The routine activity approach describes routine activities specifically as "any recurrent and prevalent activities which provide for basic population and individual needs, ... including formalized work, leisure, social interaction, ... which occur (1) at home, (2) in jobs away from home, and (3) in other activities away from home" (Cohen & Felson, 1979, 593). Most people travel between work and home on a regular basis, at regular times and via familiar routes. Similarly, a discrete number of other locations are also visited regularly. These routine activity nodes, as they are commonly referred to (Brantingham & Brantingham, 1981), might include the homes of friends and family, shopping malls and entertainment districts. Such activity nodes are often also temporally specific, in that they are visited at particular times. For instance, entertainment locations are frequented on weekend evenings and work locations during daylight hours Monday through Friday.

Therefore, it is the routine activities of all individuals - potential victims, offenders and guardians that bring together the essential components of the theory and dictate when and where an individual may commit, become the victim of, or provide guardianship against crime. It is these routine activities that lead to the intersection of large groups of potential victims and offenders at sporting venues on game day; crowds and pickpockets in city squares on public holidays; and unoccupied homes and burglars who are travelling home from the local shopping mall.

In describing this confluence of essential elements and their impact on crime Cohen and Felson (1979, 589) state that "structural changes in routine activity patterns can influence crime rates by affecting the convergence in space and time of the three minimal elements of direct-contact predatory violations". Considering this assertion, it is important to note that while the routine activity approach is commonly described as a macro-level theory of crime (Clarke & Felson, 1993), its fundamental propositions are derived from actions that wholly take place at the micro-level: that is the activities an individual takes part in. The routine activity approach is then, in reality, a micro-level theory that is often described in terms of its macro-level ramifications (Eck, 1995). Given that the approach describes how the spatial and temporal activities of individuals influence the occurrence of crime, this assertion is the first that the simulation model developed in this thesis aims to explore the ramifications of, that is:

What are the likely crime impacts of individual routine activities?

Given its ultimate aim to permit reductions in crime, the routine activity approach argues that crime is prevented through the removal of any one of the offender, target or lack of guardian from the aforementioned convergence. Initially the routine activity approach considered only one actor capable of crime control – the guardian. Subsequent revisions however identified two further crime controllers – the handler and manager. Embracing concepts from control theory (Hirschi, 1969), handlers are persons with whom the offender has some effective tie and whose presence is sufficient to dissuade offending (Felson, 1986). Examples of handlers might include teachers, spouses, relatives, and peers. Eck (1994) then proposed a further crime controller, this time focused on the place rather than the target or offender – the manager. Place managers prevent crime by preventing offender access to a location, or undermining offender's abilities to offend within it. Such place managers might include shopkeepers, cinema ushers, bar owners or landlords. In incorporating these additional dimensions Felson (2008, 74) states that "[a] crime occurs when the offender escapes handlers, finds targets free from guardians in settings not watched by managers". This interaction of offender, victim and place, and the associated crime control agents that may in turn act upon them is often depicted by the crime triangle (Figure 2.1).

In applying this approach to the study of observed crime patterns, routine activities have been used to explain a range of crime characteristics from wide scale changes in crime trends observed over time, to the formation of particular crime patterns. In asserting that crime rates need not necessarily be dependant on the absolute numbers of potential offenders, Cohen and Felson attribute changes in national crime trends to changes in widespread societal activities that put people and places at greater risk of victimisation. Increases in residential burglaries, for instance, resulting from the reduced

Figure 2.1: The Crime Triangle (Clarke & Eck, 2005)

guardianship of homes during daylight hours as more women entered the workforce post World War II (Cohen & Felson, 1979).

The dynamics of routine activities also provide explanations of micro- and meso-level crime patterns and have been applied to explain the concentration of crime in particular places (Sherman, Gartin, & Buerger, 1989). Concentrations of crime in particular hot spots can be described as the aggregation of numerous individual routine activities. In other words, hot spot areas are those locations that give host to a high number of offender-target-lack of guardian/handler/manager convergences, whilst cool areas do not. In application the routine activity approach has been used to understand a wide range of criminal activities including both property (Cohen & Cantor, 1980, 1981; Mustaine & Tewksbury, 1998; Rengert & Wasilchick, 1985) and interpersonal crime (Caywood, 1998; Clarke, Ekblom, Hough, & Mayhew, 1985; Cohen, Cantor, & Kluegel, 1981; Lynch, 1987; Mustaine & Tewksbury, 1999).

Whilst the routine activity approach is widely accepted amongst criminologists, a number of critiques have been levelled against it. Perhaps the most significant of these concerns the difficulties associated with direct measurement of the individual components it describes – that is, the routine activities of individuals and the suitability and capability of targets and controllers. In acknowledging the limitations of the original data used to describe the key elements of theory, Cohen and Felson (1979, 600) state that "annual time series data do not allow construction of direct measures of changes in hourly activity patterns". Thus, in the absence of reliable data concerning these characteristics, aggregate demographic data are employed as proxy measures of activity. Cohen and Felson utilise indicators including marital and employment status to estimate likely routine activity characteristics. Similarly, other studies employing the approach have used measurements of television viewing, number of nights spent away from home per week and VCR ownership to infer the likely lifestyles of individuals (Clarke et al., 1985; Gottfredson, 1984; Messner & Blau, 1987; Sampson & Wooldredge, 1987).

The ramification of this limitation is substantial. As has been discussed, the hypothesised mechanisms described by the routine activity approach specify the actions and interactions of individuals, that is – where people go, when they go there, and who/what do they encounter/interact with as they do. Data concerning these activities are difficult not only to collect, but also to appropriately quantify in a systematic fashion. Unfortunately, a reliance on aggregate data to describe such activities obfuscates much of the underlying complexity, which, to those who aim to verify the propositions of the routine activity, is of great use. Furthermore, by applying aggregate indicators to infer individual characteristics, such methods are vulnerable to the ecological fallacy (Durkheim, 1897; Robinson, 1950).

In discussing the implications of this weakness Eck (1995) highlights that a reliance on macro-level data precludes rigorous testing of the micro-level propositions outlined by the routine activity approach. Furthermore, considering how these weaknesses have impacted the application of the approach in general Pease (1997) notes that studies applying the routine activity approach are invariably post-hoc and descriptive in nature, thus limiting their ability to test the underlying propositions of the approach, and in turn restricting its predictive capacity.

Additionally, and of considerable relevance to this study, Jeffrey (1993, 492) states that the routine activities approach provides a "description of [crime] events and not an explanation". This thesis will contest this assertion, and in doing so follow the approach laid out by generative social science (Epstein, 1999) - proposing that a systematic micro-level description of crime events does constitute an explanation – *a generative explanation* (see section 3.8).

2.1.2 The Rational Choice Perspective

When victim and offender do converge, the potential offender must make the decision to exploit the opportunity presented. The rational choice perspective deals with how offenders make such decisions (Clarke, 1983). Providing an ideal compliment to the routine activity approach, the rational choice perspective provides a hypothetical offender calculus operating at the convergence of potential target and motivated offender.

The rational choice perspective portrays the offender as a rational decision-maker who applies some level of preparation and foresight to their criminal activity. This notion of offender rationality implies a form of cost-benefit analysis undertaken by the offender (consciously or unconsciously) with regard to criminal opportunities presented to them. Potential offenders, it is suggested, weigh up the risks, rewards, and required effort associated with engaging in criminal activity. However, such rationality is not absolute and instead must draw upon restricted and localised information relating to both proximal cues and previous experience, and as such can be described as bounded (Simon, 1990). The assertion of the rational choice perspective then is that offenders are capable of adapting their behaviours to unforeseen or altering external influences in an attempt to minimise both risk and effort while maximising reward – that is, the optimisation of expected utility.

This approach to understanding the crime event is underpinned by several important premises outlined by Cornish and Clarke (1986). First, offenders are self-interested parties who are in some way out to profit from their criminal endeavours, be it through money, status or excitement. Second, the choices associated with one type of offence are distinct from the choices associated with another. Thus, a crime-specific focus is required if one is to adequately explain criminal choices. Finally, the rational choice perspective calls for the development of distinct decision-making models for the criminal involvement process and that of the criminal event. In this regard, both Cornish and Clarke (1986) and Gottfredson and Hirschi (1990) point out that decisions about criminal involvement are determined by multiple choices made over considerable periods of time. Event decisions, on the other hand, which dictate specifically when and where criminal opportunities are encountered and assessed for viability, are often based on restricted information, which usually relates to the immediate situation an offender finds themselves in. It is these pre-crime situations that determine the variable perceptions of risk, reward and effort associated with a given criminal opportunity (Cusson, 2002). Suggested factors that contribute to crime-attractive situations are: with respect to victims - negligence, provocation, vulnerability; targets - interesting objects, CRAVED – Concealable, Removable, Available, Valuable, Enjoyable, Disposable (Clarke, 1999); facilitators - weapons, alcohol, drugs, vehicles; and the physical environment - obscurity (Cusson, 2002).

Given this proposed criminal event calculus operated by offenders, a fundamental tenet of the rational choice perspective is that some opportunities for offending are deemed more attractive to offenders than others, and it is these opportunities that are most likely to be targeted. Here it is hypothesised that those targets deemed most suitable by this expected utility function are those proximal, known opportunities that are deemed to offer the greatest rewards while minimising risk and effort. This proposition is the second explored in this thesis:

What are the likely crime impacts of an expected utility calculus employed by offenders?

While the rational choice perspective initially implied an expected utility calculus utilised by all offenders prior to committing an offence, more recent research has suggested that offenders do not always assess risks and rewards associated with committing an offence, and may instead be influenced directly by specific localised situational factors (Wortley, 2002). These *situational precipitators* provide cues that in turn may prompt individuals to offend, put pressure on individuals to offend, permit individuals to offend or provoke individuals into offending (Wortley, 2002). In response, recent revisions to the rational choice perspective suggest a typology that categorises offenders by their readiness to offend (Cornish & Clarke, 2003). This typology proposes three classes of offender: the 'anti social predator', who is ready to offend and may actively seek out viable opportunities to do so; the 'mundane offender', who will only offend if presented with a viable opportunity; and the 'provoked offender', who reacts to those situational precipitators previously described.

A considerable breadth of research is consistent with the proposition that offenders employ some form of rationality in their offending strategies (Clarke, 1997). For example, burglars favour unoccupied homes (Bernasco & Nieuwbeerta, 2005), and further, those which are not overlooked by neighbours (Wiesel, 2002); violent offenders avoid victims who may be armed (Wright, Rossi, & Daly, 1983); and sex offenders undertake actions that aim to reduce their risk of detection (Beauregard, Rossmo, & Proulx, 2007). In addition, reductions in offending are observed given the introduction of effort/risk increasing and reward reducing interventions provided by SCP (Clarke, 1997). Thus, providing further support for the underlying assertion that offenders are rational in their criminal endeavours.

The rational choice perspective has always situated its efforts in providing a pragmatic tool for crime prevention underpinned by what it describes as 'good-enough theory' (Cornish & Clarke, 2008). As such, it does not aim to offer a holistic explanation of criminal behaviour. However, an important critique of the approach lies in the difficulties associated with empirically verifying the mechanisms it does suggest are operating at the individual level, that is, the expected utility calculus. While Fattah (1993) proposes that the simple observation that target selection is not random suggests that some form of rationality is employed by offenders, Jeffrey and Zahm (1993, 339) contend that such choices are "neither observable nor empirical", suggesting that it is only possible to infer choice when some external action takes place. Notwithstanding this criticism, numerous studies remain consistent with the assertions of the rational choice perspective, and SCP has been demonstrated to be effective in a wide variety of contexts. However, it is generally acknowledged that data at the appropriate resolution to permit rigorous testing of the rational choice perspective is difficult to obtain.

2.1.3 Crime Pattern Theory

Whilst focusing on the offender decision-making process, the rational choice perspective also draws significantly on event and environmental information. It is this that informs much of the offender's perceptions concerning the relative risk, reward, and effort associated with a given criminal opportunity, and in turn their previous experience of criminal opportunities within an environment. Furthermore, the routine activity approach describes the convergence of victim and offender constrained by patterns of activity that are both influenced by, and exert influence on, the environment. Consequently, in any analysis of the crime event the significance of the environment should not be overlooked.

Rudimentarily, Brantingham and Brantingham's (1993a) pattern theory of crime[3] focuses on the mechanics of how offenders find suitable targets and crime places within their environment. By concentrating on when and where convergences between victim and offender take place, crime pattern theory includes the environment in opportunity-based explanations of crime; thus providing the backcloth for both offender movement and the supply of criminal opportunities which help to explain target selection (Hearnden & Magill, 2004).

Drawing on Jeffrey's initial work on CPTED (Jeffrey, 1976, 1977), Brantingham and Brantingham's early theoretical endeavours proposed a hypothetical model of crime site selection, setting out a number of propositions concerning the person-environment interaction and its influence on crime commission (Brantingham & Brantingham, 1978). The geometry of crime theory which subsequently followed extended these efforts by exploring the likely ramifications of such selection strategies on the spatial patterning of crime (Brantingham & Brantingham, 1981). In doing so, the authors present a series of hypothetical offender-target-environment configurations which begin at the most abstract (single offender, uniform distribution of targets, single activity node) and move towards the more realistic (multiple offenders, non-uniform distribution of targets, multiple activity nodes), in turn examining the likely offender search strategies and crime patterns that will result given these varying initial conditions. These scenarios are of particular relevance here as the simulation model presented in this thesis offers a formalised tool through which the likely ramifications of such hypothetical offender-target-environment configurations can be systematically explored.

Brantingham and Brantingham's (1993a) pattern theory of crime provides a meta-theory for environmental criminology (Andresen, 2010). Uniting several analogous and complementary propositions from both their own research

[3]Or crime pattern theory as it has become commonly known

(Brantingham & Brantingham, 1978, 1981, 1982, 1984) and a range of others including the routine activity approach (Cornish & Clarke, 1986), rational choice perspective (Cohen & Felson, 1979), strategic analysis (Cusson, 1983) and lifestyle theory (Hindelang, Gottfredson, & Garafalo, 1978), crime pattern theory operates under a number of common interconnected propositions concerning the crime event. Crime is the output event of a multi-staged sequence of conscious or unconscious decisions. These decisions which bring offender to crime opportunity and, in turn, affect its assessment are "neither random nor unpredictable" (Brantingham & Brantingham, 1993a, 261). Such decision sequences are rational, crime specific (Brantingham & Brantingham, 1978) and involve an offender who is sufficiently motivated. The potential sources of such motivation are diverse, but understandable. Offenders going about their day-to-day activities, or through purposeful searches in and around such activity spaces (Brantingham & Brantingham, 1984) encounter opportunities for crime. The suitability of a given opportunity is a function of both the target itself and its proximal environment. Offenders develop cognitive maps, or awareness spaces (Brantingham & Brantingham, 1984) in and around their activity spaces. These awareness spaces are influenced by a multitude of cues that the physical, social and cultural environment provide to the offender about the suitability of potential crime targets at specific times, locations and under specific circumstances. Over time, offenders learn which of these cues differentiate good and bad targets, and in turn develop templates for successful offending which are applied and reinforced (Brantingham & Brantingham, 1984; Cornish, 1994). As a result, the distributions of motivated offenders, suitable crime opportunities and ultimately victimisation are influenced by the activity patterns of both offenders and victims, the dynamic environmental backcloth upon which they take place, and the multidimensional interactions that occur between them.

Importantly, the interconnectedness of the above axioms dictates that crime is complex. However, Brantingham and Brantingham (1993a) suggest that such complexity does yield patterned trace effects that allow for the understanding of the criminal event as a complex patterned system. In discussing this patterning of crime Brantingham and Brantingham state that "[c]rimes are patterned; decisions to commit crime are patterned; and the process of committing a crime is patterned" (Brantingham & Brantingham, 1993a, 264). This concept is of considerable importance to this study, as it is this complex system that the simulation developed in this thesis aims to explore, and in turn, such emergent patterns which its application aims to identify candidate explanations for.

A fundamental tenet of both the crime pattern and geometry of crime theories is that potential offenders are most likely to target crime opportunities that are deemed suitable and are encountered within their own personal awareness spaces (Brantingham & Brantingham, 1993b; Clarke & Eck, 2003) (see Figure 2.2). These awareness spaces reflect the knowledge of a given locality built up over time as an offender becomes more familiar with locations that are frequented on a regular basis. As such, awareness spaces are likely formed around the common activity nodes of an individual and the paths between them (Brantingham & Brantingham, 1984; Eck et al., 2007). As previously described, such routine activity nodes are likely to be related to non-criminal activity such as the home, workplace and entertainment areas. As an individual spends more time in these areas, both their awareness of, and ability to exploit, opportunities for crime that exist within them increase.

It is this micro-level assertion that is the last of the three to be explored in this thesis:

What are the likely crime impacts of offender awareness spaces?

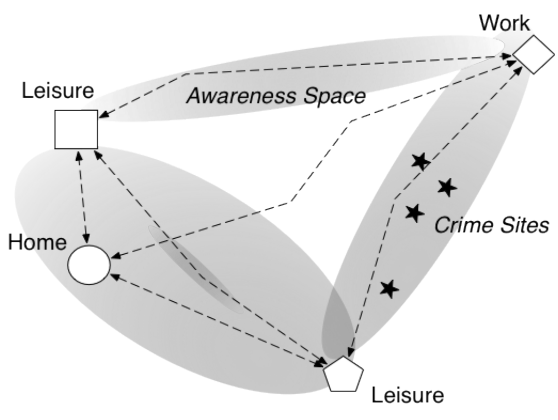

Figure 2.2: The Geometry of Crime (adapted from Brantingham & Brantingham, (1981))

Crime pattern theory also provides a number of specific hypotheses concerning the underlying mechanisms that generate observed distributions of crime: crime attractors, crime generators, and crime enablers. Each of these hypotheses describe the spatio-temporal interaction of offenders, victims, controllers and their environment and how these interactions lead to the development of locations which are subject to disproportionate levels of offending (Brantingham & Brantingham, 1995; Clarke & Eck, 2003).

Crime *generators* are locations that attract large numbers of individuals for non-criminal reasons, such as shopping malls, transportation hubs, downtown intersections, theme parks, and hospitals. These locations bring together large numbers of potential victims and offenders, in turn increasing the number of victim-offender convergences that take place, and as a result, increasing the likelihood of offending occurring within them.

Crime *attractors* describe locations that are known to offenders due to the wealth of criminal opportunities they offer. Given their potential rewards, these locations attract offenders. At first, offenders might travel to these locations to commit crime, however, over time offenders may relocate closer to them in order to more readily take advantage of the opportunities they provide. Examples of crime attractors might be locations used for open drug markets or street prostitution.

Crime *enablers* describe locations which lack adequate place management and in turn both guardianship and handling. These locations 'permit' more offences to occur, as targets within them are not as well protected and the behaviour of potential offenders is less well regulated. Examples of crime enablers might include unsecured and unattended car parks or poorly managed bars or nightclubs.

While these three hypotheses specify different mechanisms that may cause the emergence of disproportionate levels of offending, they need not be mutually exclusive. Instead, locations may be described as both crime attractors and generators or enablers, or alternatively, locations may evolve from one type to another. To illustrate, Clark and Eck (2003) describe a new shopping mall that may initially begin as a crime generator attracting large numbers of shoppers, and, in doing so bring together large numbers of potential victims and offenders. As offenders become aware of this concentration of potential criminal opportunities they may be attracted to the location in greater numbers, leading to the development of a crime attractor. Over time, greater concentrations of offending may lead to a decline in shoppers visiting the location, which in turn may influence shops and other facilities to relocate to other areas. This withdrawal of both potential guardians and place managers may then lead to further increases in offending and the development of the location as a crime enabler. Alternatively, some locations may function as a crime generator during daylight hours but convert to an attractor at night. Thus, all or some of the underlying mechanisms described may influence one another and the distribution of crime occurring in an area over time. Such processes through which specific facilities or locations can facilitate a multitude of crime related interactions further highlights the complexity of the crime event as described by crime pattern theory.

Much like the routine activity approach and rational choice perspective, a key criticism of crime pattern theory focuses on the difficulties associated with establishing its empirical validity in a rigorous fashion. To illustrate, consider the concept of the awareness space. Understandably, our ability to empirically verify the presence of a cognitive map that aids in offending is limited. Such a structure may well not be apparent to the offender as an identifiable entity, never mind anyone external who aims to ascertain its existence and significance in relation to offending. Indeed, the only way one might aim to explore the notion of such a cognitive map which aids in offending is through asking offenders, yet such discussions are unlikely to reveal its actual characteristics. Such a map is likely unconsciously represented as a complex interplay of memories and experience. Therefore, quantifying individual offenders awareness spaces at the level that would be desirable to rigorously test their impacts on the occurrence of crime is a difficult endeavour. Thus, again a lack of reliable micro-level data concerning the proposed mechanisms limit our abilities to rigorously explore their validity and likely impacts on crime.

2.1.4 Summary

The routine activity approach, rational choice perspective and crime pattern theory are compatible and mutually supportive (Clarke & Felson, 1993), each describing a different component of the crime commission process. The rational choice perspective focusing on the decision-making process of the offender; the routine activity approach providing the framework from which hangs the backcloth of choices; and crime pattern theory concentrating on where and when such choices take place, and hence, where and when both offenders and opportunities for offending are distributed.

In discussing these approaches it was noted that while each of the three theories are commonly depicted as operating at different levels of explanation (see Figure 2.3) this distinction is predominantly framed around the level at which the ramifications of the mechanisms they describe are discussed. The mechanisms of environmental criminology operate at the micro-level – that is, they describe actions and interactions of individuals and their internal cognitive processes.

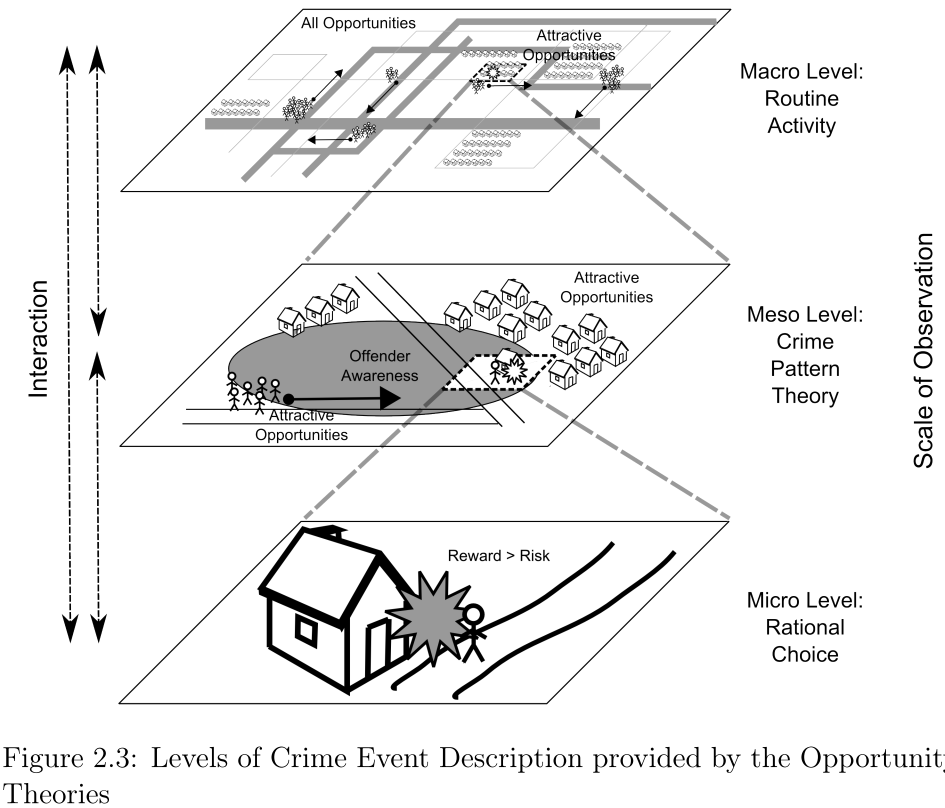

Figure 2.3: Levels of Crime Event Description provided by the Opportunity Theories

In focusing on these micro-level hypotheses provided by the opportunity theories – three micro-level mechanisms of interest were then identified.

1. The spatial and temporal activity patterns outlined by the routine

activity approach;

2. The expected target utility calculus described by the rational choice perspective;

3. The awareness space spatial learning mechanic suggested by crime pattern theory.

Figure 2.4 depicts these micro-mechanisms of movement (routine activities), learning (awareness spaces), and decision-making (rational choice). In considering these three hypothesised mechanisms, a number of critiques associated with their empirical verification were then outlined. These critiques focused on the difficulties associated with observing the crime event at an appropriate resolution in order to empirically verify the existence of such mechanisms. Given these problems associated with observing and measuring the micro-level mechanisms of the crime event, the following section now describes some of the more salient findings from the study of those characteristics of crime that we can, and do, commonly observe. And which the opportunity theories propose are the emergent outcomes of the micro-level hypotheses they provide – that is, the macro-structures of crime.

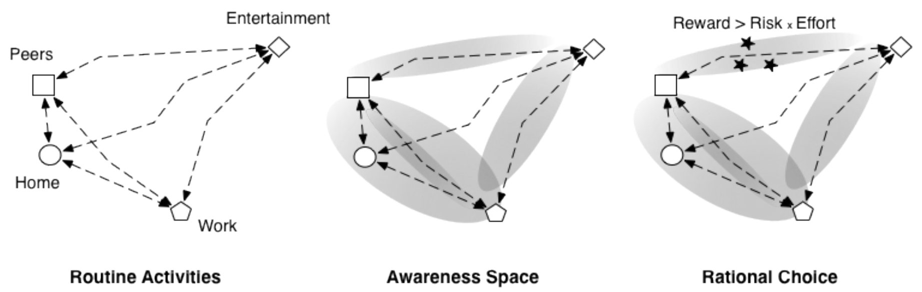

Figure 2.4: Micro-Mechanisms of the Opportunity Theories (adapted from Brantingham & Brantingham, (1981))

2.2 Macro-structures of Crime

Having described several micro-level crime event mechanisms suggested by the routine activity approach, rational choice perspective and crime pattern theory, this section highlights a number of salient macroscopic regularities of crime that are commonly observed in its empirical study. These macroscopic regularities of crime are observed across a wide variety of offence types, localities and contexts and include the non-uniform spatial and temporal distribution of crime, patterns of repeat victimisation and the journey to crime curve. Through induction, hypotheses proposing these regularities as the observable trace-effects of the mechanisms of the opportunity theories can be generated. A number of these regularities and several associated hypotheses provided by the opportunity theories that relate to their formation are now described. Subsequently, it will be argued that through the use of simulation these hypotheses can be tested, assessing if the micro-mechanisms of the opportunity theories described previously are indeed sufficient to produce such macroscopic regularities of crime.

2.2.1 Non-Uniform Spatial & Temporal Distributions of Crime

Spatial Clustering

Crime is not uniformly distributed across the landscape. Instead, the spatial patterning of crime conforms to a Pareto law of concentration, with the majority of crime concentrating in a minority of geographic areas often referred to as crime hot spots or hot places (Block & Block, 1995; Braga, 2005; Brantingham & Brantingham, 1982; Eck, Chainey, Cameron, Leitner, & Wilson, 2005; Sherman, 1995; Sherman et al., 1989; Weisburd, Maher, & Sherman, 1992).

Crime hot spots are best thought of as a method for conceptualising the distributions of crime across space. It is important to note that there is no definitive quantity of crime required within an area for it to be considered hot. Rather, hot spots are delineated as such when examined relative to their surroundings; hence, a hot spot within a low crime area may have less crime than a cool spot within a high crime area. What is significant is that within some area of study some locations experience disproportionate levels of victimisation relative to others. Hot spots can be identified at varying scales of aggregation (Brantingham, Brantingham, Vajihollahi, & Wuschke, 2009; Rengert & Lockwood, 2009; Weisburd, Bruinsma, & Bernasco, 2009) (see Figure 2.5). Thus, the term 'crime hot-spot' can be used to describe a wide variety of geographical units of analysis, from individual hot locations or addresses, streets, blocks or intersections to hot neighbourhoods, towns or cities.

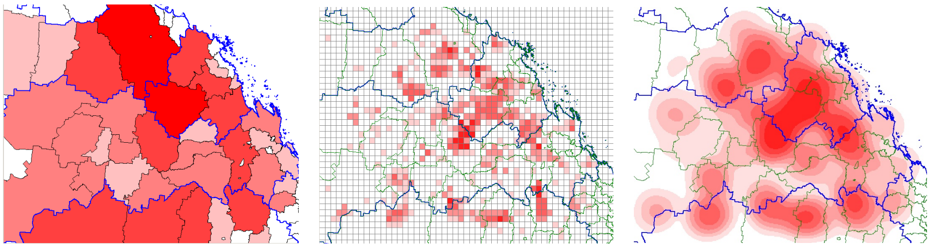

Figure 2.5: Crime Hotspots at Varying Scales of Aggregation

A number of different mechanisms proposed by the opportunity theories offer potential explanations for these observed distributions of crime. Routine activity theory suggests that specific hot addresses experiencing disproportionate levels of crime are those which lack adequate guardianship, or more specifically, place managers, whose aim it is to regulate behaviour within them. This assertion is derived from the analysis and comparison of crime and non-crime locations (Eck & Weisburd, 1995; Homel & Clark, 1995).

Crime pattern theory and the routine activity approach also suggest that the distribution of criminal events is a function of the intersections of potential offender, victim and guardian routine activities (Brantingham & Brantingham, 1993b) (see for instance the depictions of crime generator, attractors, and enablers discussed in section 2.1.3). Thoroughfares bring together high numbers of people, including potential victims and offenders. Thus, block and street or intersection concentrations of crime can be described as locations where comparatively large numbers of offender activity and awareness spaces intersect with locations which contain desirable, vulnerable and/or rewarding targets or victims. For example, consider pick-pocketing in inner city locations where large numbers of potential victims congregate whilst going about their daily routines and offenders are offered reasonable levels of anonymity. Similarly, hot neighbourhoods can be explained by examining the intersection of aggregate offender and victim routines at a neighbourhood level.

Temporal Clustering

Much in the same way that crime is not uniformly distributed in space, neither is it over time. Very few locations experience constant levels of victimisation. Instead, crime hot-times where the level of victimisation is disproportionate relative to other times are often observed (Brantingham & Brantingham, 1981; Bromley & Nelson, 2002; Nelson, Bromley, & Thomas, 2001; Ratcliffe, 2002, 2006; Townsley, Homel, & Chaseling, 2000). Similar to spatial hot spots, this temporal clustering of crime is observed at several levels of granularity. At the lowest level, crime concentrations vary by hour throughout a single day. The assertion of the opportunity theories is that such clustering is intrinsically linked to the temporal nature of both available criminal opportunities and the routine activities of potential offenders, victims and controllers. For example, more residential burglaries occur throughout the day when people are working and guardianship of the home is reduced (Felson, 2002). Similarly, criminal damage committed by youth offenders clusters not only around the paths between potential offenders' homes and schools, but also at the times students travel to and from school. In considering these patterns, Ratcliffe (2006) proposes a temporal constraint theory that describes how the targeting strategies of potential offenders are restricted by temporal requirements of their everyday non-crime activities.

In addition to hourly trends, crime also clusters in daily patterns dictated by the changes in routine activities that occur over the course of a week. For instance, alcohol-related disorders are more likely to occur on Friday and Saturday nights when more people frequent bars and nightclubs, thus bringing together more potential victims and offenders. Crime is also subject to seasonal trends, where a disproportionate number of offences occur within certain months of a year. In examining such seasonal variations, Hird and Ruparel (2007) demonstrated that 25 of 29 crime types examined experienced some kind of seasonal trend. Such seasonal trends can be attributed to wide scale changes in the routine activities that occur throughout the year. For example, reduced daylight hours during winter dictating that more people travel home at night, or increased numbers of young people in public places during semester breaks.

Thus, it is the assertion of the opportunity theories that the observed non-uniformity of both spatial and temporal concentrations of crime are a function of the spatial and temporal characteristics of offender, victim, and controller activities, and their subsequent interactions.

2.2.2 Patterns of Victimisation

Repeat Victimisation

Following the same Pareto distribution described previously, crime not only concentrates spatially and temporally, but also with respect to a small number of individuals. These individuals commonly referred to as 'repeat victims' experience disproportionate levels of victimisation (Farrell, 1995; Farrell & Pease, 2001; Hindelang et al., 1978; Pease, 1998) as depicted in Figure 2.6. More generally, the term repeat victimisation describes any person, place, or target that is subject to repeated criminal victimisation.

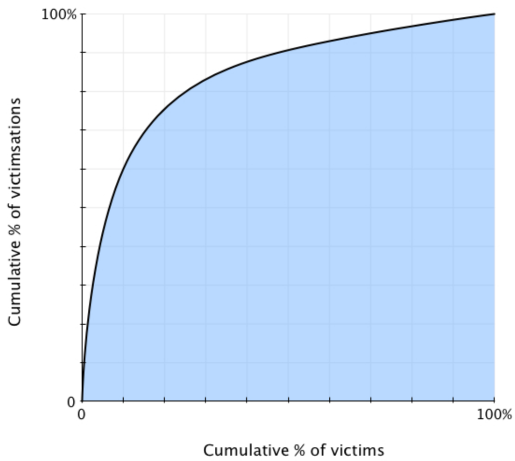

Figure 2.6: The distribution of victimisation

This observed concentration of victimisation might imply that there is a level of consistency in what makes a target attractive to offenders, be it the most rewarding, least risky, most easily exploited or any combination of the above. Consequently, suggesting a consistency in the mechanisms used by offenders to evaluate potential targets. However, in studying the risk of residential burglary re-victimisation, Johnson, Bowers, and Hirschfield (1997) empirically demonstrate that while the risk of victimisation for previous victims is greatly increased directly after an initial victimisation, this risk decays over time, implying that the temporal diffusion of crime risks is dynamic.

Existing theory provides two potential and compatible explanations for this diffusion of crime risk; event dependence: often referred to as the *boost* hypothesis, and event heterogeneity: the *flag* hypothesis (Pease, 1998; Tseloni & Pease, 2003). Briefly, the boost hypothesis suggests that by successfully victimising a property, the offender learns about the suitability of the selected target. This increase in an offender's awareness of a particular target permits minimisation of both the effort and risk associated with any consequent victimisation. In addition, offenders returning to a target have more complete information about the rewarding goods it offers, and are also aware that those they originally targeted are likely to have been replaced by insurance (Farrell & Pease, 1993). Hence, previous victimisation boosts the likelihood of subsequent victimisation. On the other hand, the flag hypothesis proposes that victimisation flags the enduring risk of a victimised target, be it an inherent weakness that makes victimisation easy or less risky, or alternatively, some aspect that makes the rewards a target offers especially desirable. Therefore, while repeat victimisation of a target may not imply the return of a previously successful offender, other offenders may identify the same characteristics that made the target desirable and victimise it themselves.

Near Repeat Victimisation

By extension of the boost and flag explanations of repeat victimisation, recent research concentrating on the occurrence of residential burglary has demonstrated that when victimisation occurs at a property, it is not only the initially victimised property that is at a heightened risk of victimisation for a finite amount of time, but also those within close proximity (Johnson & Bowers, 2004; Townsley, Homel, & Chaseling, 2003). Using methodologies developed within the field of epidemiology, a number of international studies have demonstrated that the risk of residential burglary victimisation clusters both spatially and temporally (Johnson et al., 2007). Likening this spatial and temporal spread to that of a communicable disease, offences that occur within close spatial and temporal proximity of an initial victimisation have been termed *near-repeats*.

This research theorises that such patterns of victimisation are the trace effects of the way in which offenders search for potential targets. In keeping with crime pattern theory, it is suggested that offenders become familiar with certain areas that overlap their existing routine activity spaces and offer suitable criminal opportunities. Over time, offenders develop templates for successful offending which allow them to generalise to targets with similar characteristics to those initially victimised. The law of spatial dependence states that things which are spatially proximate are likely characteristically similar (Tobler, 1970), thus implying that properties within close proximity to the initially victimised one will have similar layouts, weaknesses, residents, target goods and so on. Thus, targeting other properties in close proximity to some initial victimisation minimises effort – providing offenders with opportunities that are perceived as a known quantity with respect to potential risks and rewards.

2.2.3 The Journey to Crime Curve

Journey to crime research concerns itself with the spatial distribution of offenders and the offences they commit. By examining the distances and directions over which offenders travel to commit offences, journey to crime studies attempt to increase understanding of offender mobility. The general observation of a significant number of studies within this area is that offenders do not commonly travel long distances to commit crime. As such, numerous studies examining crime trips have demonstrated the presence of a distance decay function where the majority of crime trips, after some initial buffer zone (Rossmo, 2000), lie within a short distance of offenders' homes as depicted in Figure 2.7. Such observations have been made across a range of different crime types including residential burglary (Barker, 2000; Costello & Wiles, 2001; Rengert, Piquero, & Jones, 1999; Rengert & Wasilchick, 1985; Reppetto, 1974; Snook, 2004), robbery (Nichols, 1980; Pettiway, 1982; Reppetto, 1976) and rape (Amir, 1971; Canter & Larkin, 1993; LeBeau, 1987; Rossmo, 2004).

It is often suggested that the presence of this distance decay function reflects the use of some form of cost-benefit calculus on behalf of the offender

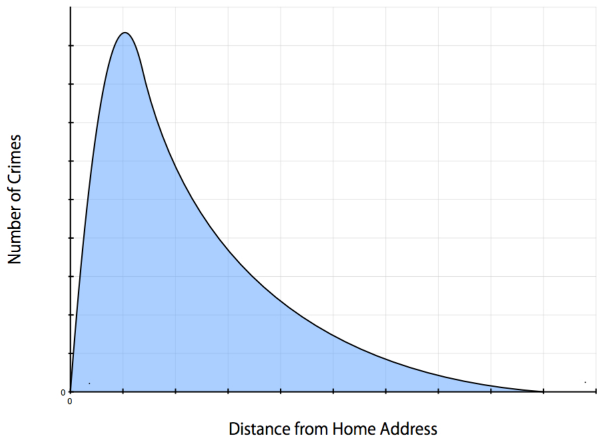

Figure 2.7: The Characteristic Journey to Crime Curve

(Rossmo, 2000). Briefly, offenders are looking for viable and rewarding targets, yet as distance and travel time from the home increases, so does the effort required in, and cost associated with reaching these targets. Therefore, if offenders attempt to minimise effort, viable targets close to the home are more likely to be selected than those further away. This observation provides further support for the rational choice approach to crime occurrence. Further, it is also suggested that the observed 'buffer zone' of few very short crime trips can be explained by offenders' reluctance to commit offences within the direct vicinity of their own homes where they are more likely to be recognised and thus are at a heightened risk of detection (Rossmo, 2000).

Recent research however has suggested that the ubiquity of these observations may only extend to aggregate journey to crime curves, where multiple offenders' crime trips are collated and analysed. While this approach may often be necessitated by the relatively low numbers of identified crime trips, a recent large-scale empirical study has highlighted the dangers of committing the ecological fallacy by ascribing the typical distance decay curve to individual offender activities (Townsley & Sidebottom, 2010). Studying just over twenty thousand journeys to burglary the authors demonstrate extensive variation in distances travelled by individual offenders; and furthermore, that the characteristic distance decay curve is most commonly observed in only a small proportion of the offending population, and typically by those who are most prolific.

2.3 Linking Micro-theory and Macro-observation

The first sections of this chapter outlined a number of micro-level propositions concerning the crime event provided by the routine activity approach, rational choice perspective and crime pattern theory. These three theories were shown to be compatible and mutually supportive, providing a holistic view of the offence process that can be applied to many types of crime (Felson & Clarke, 1998). They are well established and a substantial amount of empirical evidence appears consistent with the environmental and opportunity-based explanations for crime they provide (Clarke, 1997). Furthermore, in application, the 'handles' identified by the opportunity theories have provided significant reductions in offending through crime prevention approaches such as SCP, POP and CPTED.

For these reasons, much place and event-focused research tends to take a unified approach to the three theories, each describing a different component of the crime commission process. The rational choice perspective focusing on the decision-making process of the offender; the routine activity approach providing the framework from which hangs the backcloth of choices; and crime pattern theory concentrating on where and when such choices take place, and hence, where and when both offenders and opportunities for offending are distributed.

Many of these concepts draw upon, and are influenced by one another. As a result it can often be difficult to delineate between where one theory should end and another begin. Indeed, several key concepts of each of the theories discussed are analogous. To illustrate, the rational choice perspective discusses the search process undertaken by offenders in choosing a suitable crime opportunity. While such a process is not explicitly spatial, both spatial and temporal characteristics of potential criminal opportunities can be seen to impact on both the availability and suitability of offending choices. Similarly, while Cohen & Felson's routine activity approach predominantly discusses the macro level ramifications of changes to societal activity patterns, such activity patterns are inherently occurring at the individual level and it these patterns of activity (and their subsequent interaction with the environmental backcloth) that are discussed throughout Brantingham & Brantingham's theoretical endeavours (1981, 1993a, 1993b). This overlap amongst theoretical approaches is in fact an appropriate reflection of the interconnected nature of the phenomena being studied. Crime is the result of a complex dynamical system. Crime patterns such as those discussed in section 2.2 are the direct result of numerous micro-level spatio-temporal interactions of multiple heterogeneous actors who are connected at multiple scales, and whose actions are interdependent.

While direct observation of these mechanisms and their interactions is rare (see the critiques of the opportunity theories discussed in section 2.1), their outputs are routinely observed – crime. The last 25 years have seen significant advances in both the quantity and quality of data collected concerning the crime event. In analysing these data a number of salient macro-level crime patterns have been consistently observed (see section 2.2). For example, crime concentrates in specific places at specific times; a few victims experience a lot of victimisation; property crimes cluster in both space and time; and the journey to crime curve follows a characteristic distance decay.

Following the assertions of crime pattern theory that depict the crime event as a patterned activity that produces patterned outcomes, these regularities can be thought of as some of the more predictable emergent outcomes of those complex interactions operating in-situ. It is a fundamental remit of environmental criminology to identify, describe and understand such patterns ((Wortley & Mazerolle, 2008), so that methods for addressing them can be devised and in turn, crime reduced. Indeed, the opportunity theories have proposed a number of mechanism-based explanations for these regularities, many of which have demonstrated considerable utility in reducing crime through the targeted application of crime prevention intervention.

Given this reliance on understanding these mechanisms – there is obvious utility in ascertaining the sufficiency of our descriptions of them, which in turn should facilitate the incremental refinement of theory. Hence, if we are to develop hypotheses about how the interactions of society generate patterns of offending, so that they might be subverted, we must also employ techniques for assessing the validity of theory. Unfortunately this endeavour is difficult to undertake. Ascertaining the validity of such hypotheses often requires that we bridge the divide between those micro-level hypotheses proposed by theory and the macro-level descriptions of crime commonly used in its analysis – overcoming this gap is difficult for a number of reasons.

While intuitive in isolation, the mechanisms proposed by the opportunity theories quickly become intractable to traditional analytic methods as they interact with one another. For instance, considering only those three micro-level mechanisms of interest identified in section 2.1 – that is, the spatio-temporal activity of victims and offenders described by the routine activity approach; the expected utility calculus outlined by the rational choice perspective; and the awareness space cognitive map proposed by crime pattern theory, problems quickly arise when attempting to quantify how these mechanisms might combine and give rise to observed patterns.

Most importantly, the routine activity approach describes the crime event as an inherently nonlinear process (Eck, 1995). The prerequisites for crime described by the approach are dictated by the dynamic spatial and temporal activities of numerous interdependent actors. Capitalising on the routine activity approach's depiction of the crime event requires quantification of where and when these elements converge and where and when they do not. This is not a simple task. For one, all of the actors described by the routine activity approach are different, and there are lots of them. The routine activities of victims, offenders, guardians, handlers and managers are each specific to an individual's lifestyle, which in turn is impacted by numerous factors including employment status, social connectivity, personal preferences, and in turn the spatial and temporal constraints these individual characteristics impose on behaviour. Furthermore, such routine activities are not only influenced by the nature and form of the environment – they also exact influence upon that environment. In the attempt to quantify such complexity, traditional analytical techniques such as logistic regression are likely to be of limited use in estimating the nonlinear relations of all these potential correlates.

By extension, the two remaining mechanisms of decision-making and learning proposed by the rational choice perspective and crime pattern theory must also necessarily operate within the nonlinear system of routine activities. Offenders make choices about targets they converge with throughout such activities, and their accumulated awareness and experience of the local environment and criminal choices is dictated by previous activity. Thus, in considering the validity of the mechanisms described by the routine activity approach, rational choice perspective and crime pattern theory, another problem arises. That is, these mechanisms do not purport to act in isolation, and instead are embedded within, or alongside one another in a complex system. This interconnectedness dictates that even with substantial insight into the offence process it would likely be difficult to estimate the impacts of individual theoretical processes, and, by extension, interrogate hypotheses that link individual-level behaviour to observed macro-level crime pattern (and visa versa). One important ramification of such interconnectedness is that if one of the hypothesised mechanisms is erroneous it is almost impossible to eliminate as a potential explanation without adequately quantifying the interactions that are occurring in-situ. Hence, even if the crime event is observed in all of its complexity, and indeed these three mechanisms are significant, it is still difficult to disentangle the respective effects of each. Put another way, there is no appropriate method to "turn off" offender learning and rationality and observe simply the impact of routine activity, or any combination of the above.

The following section briefly discusses a number of methods through which the validity of theory may be explored, and a number of associated weaknesses which encumber empirical investigation of the micro-level properties of the crime event.

2.3.1 Evaluation as a Test of Theory

In the natural sciences, experiments are utilised to assess the impact of specific mechanisms – experimental conditions are manipulated in a controlled fashion, the resulting outputs observed and inferences made. Hence, the ultimate test of the opportunity theories may well lie in the design and implementation of interventions which aim to manipulate purported mechanisms. For those interested in the underlying mechanisms of crime, the evaluation of intervention can provide a sufficient but sub-optimal analogue to the scientific experiment. In an ideal world, if an intervention aimed at deterring offending produces desired outcomes, some inference can be made about the causal link between the mechanism manipulated by intervention (the independent variable), and crime occurrence (the dependant variable). If interventions are designed to manipulate one or more of the purported mechanisms of the opportunity theories (for example, the expected utility calculus suggested by the rational choice perspective), they rely not only on the presence of these mechanisms, but also a sufficient understanding of them to facilitate their manipulation. For this reason, intervention evaluation provides valuable feedback that can be used to correct and refine not only policy and practice, but also theory (Tilley, 2002). Unfortunately, the process by which theoretical insight might be gained through the evaluation of intervention is fraught with potential problems endemic throughout the social sciences. A number of these problems are now discussed.

2.3.2 Units of Analysis and Inference

A number of problems stem from the resolutions at which data concerning the crime event are commonly collected and subsequently used. Where the hard sciences have developed considerable tools in the observation of specific phenomena (thermometers, Geiger counters, telescopes, particle accelerators etc.), social scientists have invested heavily into the development of theory, and as a result possess toolkits that by comparison are sub-optimal at best. To illustrate, evaluations of individual level interventions (i.e. those which aim to affect individual decisions) such as those provided by SCP often rely on aggregate or small sample data. Studies of prolific offenders and criminal careers remain at the individual level and are rarely linked to area-level patterns (see Townsley and Pease (2001) for a notable exception). Conversely, area-based evaluations that dominate much enforcement-led crime analysis concentrate on retrospective descriptions of small-scale crime patterns. These evaluations often utilise aggregate geo-demographic data sets and consequently may be vulnerable to the ecological fallacy. Most importantly, such analysis fails to focus on the individual level decisions that wholly contribute to aggregate patterns observed (Brantingham & Brantingham, 2004; Liu et al., 2005) and are the very mechanisms intervention attempts to manipulate. As a result, evaluations of individual level interventions are usually inherently defined at the area level, data about which are unsuitable for testing the micro-level mechanisms proposed by theory (Eck, 1995).

2.3.3 The Frailties of Crime Data

Data commonly collected concerning crime are inherently error prone. Considering first those data that describe the output of the complex system – crime, the reliability of recorded crime data is uncertain. Behaviours considered criminal can become non-criminal, and conversely, previously legal activities may be criminalised. Similarly, the crime categories in which certain types of behaviour are placed can change over time (Maguire, 2007). Series of incidents may initially be recorded separately but then combined into a single more serious offence (Maguire, 2007). Furthermore, only some offences are reported to the police, and subsequently only some of these are recorded (Biderman & Reiss, 1967). In addition, such recording is not always accurate (Maguire, 2007). To further confound these problems, disparities in recording and reporting are also unsystematic and can vary according to a range of factors including crime type (Nicholas, Kershaw, & Walker, 2007), seriousness (Gove, Hughes, & Geerken, 1985), and location (Maguire, 2002).

Similarly, where offender self report methods are employed to establish what micro-level mechanisms might be operating and in turn provide contributory or contradictory evidence for those proposed by theory, a host of potential problems become apparent. Speaking generally, individuals may not be conscious of the decision-making strategies they utilise in certain situations (Schelling, 1978). Offenders in particular may also perceive a vested interested in not portraying their behaviours accurately to investigators, or may portray their ability, knowledge, reasoning or opinions in a positive light (Cook & Campbell, 1979). In addition, hypothetical scenarios, in which offenders are asked to describe how they might act in particular circumstances can lack a richness of overt and covert cues which may otherwise greatly influence behaviour in real pre-crime situations (Cornish & Clarke, 1986). Similarly, a lack of real consequences for actions may lead offenders to suggest their behaviours to be more casual than those they would employ in reality (Cornish & Clarke, 1986).

Furthermore, when surveys are used to assess decision-making processes, potential problems relating to item representativeness or specificity can also arise. Surveys may emphasise particular decision-making preferences over others or not provide adequate options for response. Conversely, in research projects where subjects are interviewed about their decision-making processes, researcher interpretation may be highly subjective. In addition surveys and interviews often struggle to capture data relating to the interactions of individuals (Hedström, 2005), which are of key importance when exploring the validity of theoretical perspectives such as the routine activity approach. Finally and perhaps most importantly, the threat of sampling bias in methods of subject selection must also be considered when attempting to study representative groups of offenders from which generalisations about offending behaviour in general are to be made.

In summary, while numerous sources of data are available to those who wish to better understand both the decision-making strategies of those involved in crime, or characteristics of the crime event itself, a series of acknowledged problems dictate that the 'signal-to-noise ratio' within such data is often less than desirable.

2.3.4 The Weaknesses of Statistical Explanation

Once data have been collected the process of ascribing cause to effect is also exceedingly difficult. In the social sciences, inferences about the association of two or more characteristics are typically supported by inferential statistics, which are used to quantify the goodness of fit between the hypothesised independent variable (the IV) and the target dependant variable (the DV). While these methods quantify the extent to which variance in one characteristic is associated with variance in another, they in no way reveal a process through which this relationship may manifest, i.e. the mechanism (Hedström, 2005). Yet within criminology, the mechanism should be of most interest to scholars who in turn wish to manipulate it with the aim of reducing crime.

Furthermore, a fundamental problem of causal inference within the social sciences is that of confounders – that is, establishing that A did indeed cause B and not that some other unmeasured construct C in fact causes both A and B. The world in which criminological experiments take place is not simple and potential confounders abound. Crime prevention interventions are implemented in a complex and dynamic context (Pawson & Tilley, 1997), and a multiplicity of interactions beyond those which are apparent upon surface observation are constantly influencing the ebb and flow of all activities, criminal or otherwise.

In discussing the problems faced by those who aim to make generalised causal inferences within the social sciences Shadish, Cook, and Campbell (2002) highlight a number of issues relating to the methodological quality of experiments. These include statistical conclusion validity (the extent to which presumed cause and effect are related); internal validity (the ability to accurately ascribe changes in the observed DVs to experimental manipulations of the IV); construct validity (the extent to which measurement of both intervention and outcome are representative of the characteristics they aim to capture); and external validity (the extent to which an observed causal relationship holds across different configurations of units, treatments, outcomes and settings).

Thus, in order to maximise the utility of their findings, experiments require effective design. Current doctrine provides three overarching types of experiments utilised within the social sciences: experimental, quasi-experimental and non-experimental designs. Experimental designs are characterised by pre and post intervention measurements of statistically equivalent treatment and control groups. Equivalence of groups is obtained through the random assignment of units to treatment or control conditions. Randomised experiments rely on the assumption that the sample used to produce both treatment and control groups is sufficiently large in order to be representative of the population about which generalisations aim to be made, and that the allocation of units to each group is sufficiently random. If these two conditions are met both treatment and control groups are considered sufficiently equivalent to ascribe any differences in outcome measure to the treatment administered. Thus, minimising potential confounding effects, and in turn, maximising internal validity and the reliability of any causal inferences generated.

Despite being viewed as the 'gold standard of evidence', within the field of criminology randomised experiments have been performed rather sparingly (Farrington & Welsh, 2005). This is due to a number of problems associated with their implementation. Many consider that considerable ethical issues are associated with the assignment of treatment (often perceived as advantage) through chance (Weisburd, 2003). Practically speaking, the method through which one can randomly allocate treatment to areas rather than people, as is often the focus of crime prevention, is also a point of considerable contention (Farrington, 2003). Further, the requirement of a sufficiently large sample of experimental units often does not fit well within problem-oriented crime prevention approaches, which aim to identify relatively small numbers of high-crime areas / individuals. Hence, establishing a valid counterfactual can be difficult. In addition, when assessing the effectiveness of intervention, control groups rarely receive no treatment, instead receiving the original treatment that was present pre-intervention (Pawson & Tilley, 1997).

Due to these issues, quasi-experimental designs are often more popular within criminology. Quasi-experimental designs utilise pre and post test measurements for both treatment and control groups, but lack the random assignment of experimental units to treatment and control groups. Instead, control and treatment groups are commonly selected on the basis of statistical similarity. Such experiments are easier to implement both practically and ethically; but also produce less robust evaluations of cause and effect and, in turn, are less generalizable.

Finally, non-experimental designs refer to experiments that take the form of simple pre and post intervention measurement without the use of a control group. Such experiments offer the least in terms of their ability to generate causal inferences and as such can offer little insight into the validity of theory.

2.3.5 The Control of Experimental Conditions

Further confounding these problems, the control of experimental conditions within the social sciences is an exceedingly difficult enterprise. The laboratory conditions in which experiments are performed within the natural sciences afford considerable experimental control. Within the social sciences however such control is simply unobtainable, be it for logistical, ethical or monetary reasons. While hypotheses may propose that some characteristic influences the occurrence of crime, it is often logistically or ethically impossible to directly manipulate. For example, many of the propositions of environmental criminology relate to the impact that the environment might have on the crime event. For instance, consider the spatial distribution of mass transit nodes or entertainment districts, or the morphology of the transport network itself – all of which one might hypothesise influence the occurrence of crime – and all of which it would be difficult to systematically manipulate. Similarly, the ethical implications of administering intervention to some individuals / areas and not others are questionable – yet such allocation is likely required if one is to attempt to assess the efficacy of treatment, and moreover gain insight into the validity of theory. While such issues raise interesting questions their ramifications are still that such endeavours have commonly been difficult to undertake (see Ratcliffe, Taniguchi, Groff, & Wood, (Forthcoming) as a recent exception). Finally, monetary expenditure associated with intervention can be considerable. Longitudinal designs, measurement of pre and post intervention and control areas, all require high levels of interagency cooperation and considerable resources. Furthermore when considering the application of evaluation for theory refinement, evaluation scope, comprehensiveness and robustness are, at least in part, proportionate to financial expenditure.

2.3.6 Replication

While the results of a single evaluation study may quantify the impact of a given intervention, the level of certainty one can have in any causal inference made about the underlying mechanisms it aims to manipulate is extremely limited. Thus, even when experiments are robust they must be replicated. A key component of the scientific method is reproducibility (Popper, 1959) – for the findings of an experiment to be considered valid, its results must be reproducible through replication. By comparing the results of replications to those presented by the original investigator, scientists attempt to rule out any hidden factors that may have been specific to a previous experiment, establishing whether the originally observed outputs were an exceptional case or indeed representative of the phenomena being studied. It is in this way that hypotheses move from the realm of educated proposition to verified and accepted 'fact', and moreover, how science in general proceeds. Further, varying the context in which interventions are implemented aids in determining the extent to which observed causal relationships hold in different settings, allowing causal inferences to move from the specific to the general

(Cronbach, 1982).

When interventions are associated with reductions in offending it is not hard to understand why others often wish to adopt similar strategies. Thus, while often unsystematic in nature, replications of crime prevention interventions are relatively common. However, when they do occur, substantially different effects are often observed even given seemingly similar implementations (Pawson & Tilley, 1997). Such variability in outcome only serves to highlight the complexity of the system in which crime prevention interventions must operate. Differences in context and outcome may be considerable and while their presence may lead to the generation of novel hypotheses concerning the occurrence of crime, they limit the confidence with which one can make inferences about the purported mechanisms an intervention aims to manipulate. Where differences in impact are observed, what might they be caused by? A different mechanism influencing offending; the different setting in which the intervention was employed; differences in experimental units; differences in implementation or evaluation practices; or a combination of all or some of the above?

2.3.7 Realistic Evaluation

In response to some of these problems, Pawson and Tilley (1997) suggest an approach of 'Realistic Evaluation' where the focus of evaluation is shifted from simply 'what works' to 'what works for whom in what circumstances', given that the former may assume a consistency in mechanism manipulation rarely observed in real world experimentation. Given this focus on mechanism context, realistic evaluation concerns itself with specific problem analysis, in order to first define the context in which interventions are implemented. As such, it is well placed to compliment SCP and POP methodologies that focus on highly specific crime problems. Advocates suggest that realistic evaluation may provide substantial advances to the evidence base of interventions by characterising their applicability at a finer level of granularity than other evaluation methodologies. However, this specificity can limit the generalised causal inferences that can be drawn from such evaluations about the presence and influence of specific mechanisms.

2.3.8 Summary

When evaluating the effectiveness of intervention, crime prevention practitioners are, for good reason, often most interested in the relative direction of outcome, i.e. a reduction or increase in crime. For those interested in theory however, an understanding of the mechanisms through which the observed outcomes come about is most appealing. It is this knowledge that allows theory to be refined and in turn, intervention efficiency increased. Establishing how offending declined, moved to a new location or took on a new target consists of identifying the causal mechanisms which influence the occurrence of crime. However, in the pursuit of such knowledge researchers must go to great lengths if they aim to gain insight into the validity of theory through the evaluation of intervention. In order to be effective at increasing the understanding of the underlying mechanisms of crime, interventions rely on the constellation of a number of factors. These include well-specified theory, its effective translation into intervention and high competence of intervention implementation and evaluation design (Ekblom & Pease, 1995). The debate over how evaluations should be conducted in order to maximise their utility is on going, both in terms of its ability to aid intervention and subsequently theory. Sherman (1998) describes high rates of variability in methodological quality observed amongst crime prevention evaluation studies. Similarly, in discussing the quality of evaluation in crime prevention initiatives, Ekblom and Pease (1995) suggest that standards are generally low. The most common types of evaluation being measures of crime pre and post intervention or interrupted time series, in some cases with the use of a control area to account for confounding effects.

In summary, two key weaknesses endemic within the social sciences encumber the investigation of the crime event and moreover adequate assessments of the validity of theories describing it. These are (1) a relative scarcity of reliable and representative micro-level data concerning the offence process, and (2) a number of fundamental difficulties associated with undertaking controlled experiments in the study of crime.

As a result of these two problems a 'leap of faith' is often required in ascribing observed crime patterns to proposed individual-level behaviour. This gap between theorised micro-level mechanism and observed macro-level crime phenomena confounds the observation and verification of proposed mechanisms, and as a result, dictates that it is often difficult to accurately test theory to the extent that would be desirable for both theory and policy development. Furthermore, the complexity of mechanism interaction dictates that the identification of salient macro-level patterns or significant micro-level processes does not necessarily reveal the interactions through which one is causally linked to the other. Yet, it is the interplay of mechanisms leading to the commission of an offence that are of most interest to those who aim to refine theory, and in turn, develop more effective intervention strategies aimed at manipulating such mechanisms.

Figure 2.8 depicts this divide. The left most image outlines how the mechanisms of the opportunity theories portray the behaviour of a single offender – undertaking a number of routine activities, developing an awareness of the nodes and paths commonly visited, and in doing so victimising those known targets which offer sufficient utility. The centre image then depicts the hypothesised reality of numerous individuals operating under some or all of these mechanisms. The rightmost image then represents what we commonly observe as an output of whatever mechanisms are operating. As such, in order to explore the validity of micro-level theory, environmental criminologists are often required study the crime event from the right hand side and work back via a process of induction.

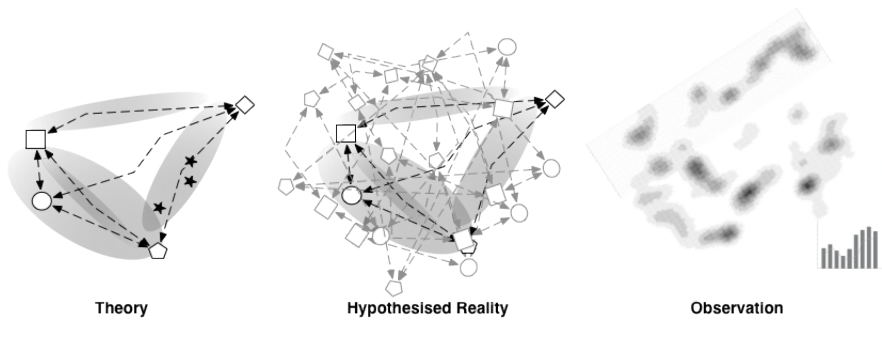

Figure 2.8: The Divide between Theory and Observation

2.3.9 Simulation for Triangulation

In considering how such complexity might be best understood, Brantingham and Brantingham (1993a) highlight that a wide variety of analytical methodologies from both within and outside criminology are likely required (and have applied a number themselves). To this end, advances in the quantitative analysis of crime data demonstrate considerable promise, techniques such as geographic information systems, multi-level and discrete choice modelling and time series analysis offer tools to those interested in the spatial and temporal distribution of crime and moreover, the inferences that can be made from its analysis.

Recently a number of authors have also highlighted the potential utility of creating artificial worlds and inhabiting them with virtual populations who act according to criminological theory (Birks et al., 2008; Bosse, Elffers, & Gerritsen, 2010; Brantingham & Tita, 2008; Brantingham & Brantingham, 2004; Brantingham et al., 2008; Brantingham, Glasser, Kinney, Singh, & Vajihollahi, 2005a, 2005b; Eck & Liu, 2004; Groff, 2007b, 2007a, 2008; Groff & Birks, 2008; Johnson, 2008; Liang, 2001; Liu et al., 2005; Malleson & Brantingham, 2009; Malleson, Evans, & Jenkins, 2009; Malleson, Heppenstall, & See, 2010; Malleson, See, Evans, & Heppenstall, 2010; Van Baal, 2004; Wang et al., 2008). In applying these computational models, the field of computational criminology (Brantingham et al., 2008) aims to gain insight into the potential interactions and ramifications of proposed individual level behaviour. Such explanatory simulation models differ significantly from the existing inductive approaches discussed previously, in that they trade predominantly in theory and aim to explore its ramifications. Thus, while they are unlikely to be able to predict where the next burglary or robbery will occur they may provide insight into the validity of micro-level hypotheses by assessing their sufficiency in generating plausible crime patterns. One particular type of simulation – the agent-based model (ABM) provides considerable utility here. ABM allow researchers to study the decentralised spatio-temporal interactions of autonomous heterogeneous actors without the need to transform non-linearity or suppress unit heterogeneity (Epstein & Axtell, 1996). While such models need not purport to mimic any particular locality, they empower the social scientist with an analogue to the petri dish in which controlled experiments aimed at exploring novel and interesting questions can be performed without the need for ethical approval or significant logistical or monetary investment (Birks et al., 2008; Brantingham & Brantingham, 2004; Groff, 2007b; Liu et al., 2005; Van Baal, 2004). By imbuing a virtual population with behaviours developed to mirror those micro-mechanisms suggested by theory the macro-ramifications of such hypotheses can be systematically explored. Moreover, through the systematic application of controlled simulation experimentation it is possible to explore the likely contributions of different mechanisms, thus allowing the propositions of theory to be untangled in a way that is almost impossible with the use of traditional experimentation. As such, the simulation model provides a significantly different but viable compatriot to existing methods of enquiry. And, in doing so, furnishes the environmental criminologist with a further point of triangulation in studying the crime event and its underlying dynamics.

This thesis builds on those efforts of previous authors that have explored the use of ABM in furthering our understanding of the crime event, and in doing so provides a systematic test of the sufficiency of the three micro-mechanisms derived from the opportunity theories outlined in section 2.1. In undertaking this research an ABM of offending as described by the opportunity theories is developed. Capitalising on a number of strengths of the simulation approach in systematic control, observation, and replication the model is then used to perform a series of computational experiments. Applying the approach of generative social science (Epstein, 1999) (see section 3.8), these experiments assess if the key assertions of the opportunity theories identified in section 2.1 are indeed sufficient to generate the macroscopic regularities of crime outlined in section 2.2. Thus, providing a systematic test of the viability of the opportunity theories as an explanation for the crime patterns commonly observed in empirical study.

In the next chapter an outline of the simulation methodology and in particular the ABM approach undertaken in this thesis is provided. An overview of several existing studies that have applied ABM within environmental criminology is then presented, and the differences between such previous endeavours and the one discussed here outlined. Subsequently, the approach of generative social science undertaken in this thesis is described.

3

Computational Modelling & Simulation

This chapter provides an overview of the simulation methodology applied in this thesis. Focusing primarily on the application of simulation within the social sciences, the rationale behind simulation is specified, and its application in building explanatory models of complex systems discussed. Subsequently, the simulation methodology applied in this thesis – the agent-based model (ABM) is described. The key components of ABMs are specified, and a number of features that make them ideally suited to the study of complex social systems outlined. In addition, a discussion relating to the validity of simulation models and their findings is provided.

These initial sections provide a brief primer in the simulation methodology and ABM in general. Readers familiar with these techniques may wish to skip directly to section 3.5 (p 67) where the strengths of the ABM approach are directly aligned to the features of the crime event as described by the opportunity theories. Thus, highlighting the utility of ABM in furthering understanding of the crime event by providing a means through which the micro-propositions of the opportunity theories can be systematically explored.

Subsequently, a review of several previous endeavours that have employed explanatory ABMs in the study of crime is provided. In doing so a number of existing ABMs of crime are discussed and their strengths and weaknesses identified. Drawing on several discussions relating to the different uses of simulation within environmental criminology the approach of generative social science as set out by Epstein (1999) is then described. The notion of the generative explanation discussed, and the premises under which ABMs can permit the identification of generatively sufficient explanations of known phenomena outlined.

The chapter concludes by proposing the development of a generative ABM of crime. Thus, providing a platform to systematically test the generative sufficiency of mechanisms described by the routine activity approach, rational choice perspective and crime pattern theory in explaining several known regularities of crime. In turn, linking the micro and macro divide previously highlighted, and addressing the overarching research questions of the thesis.

3.1 Building Models

The concept of building models of complex systems has been around since the advent of modern science. Through the process of modelling we hope to increase our understanding of the things we model. A model is an abstraction of some entity or system, often referred to as the target (Edmonds, 2005; Gilbert & Troitzsch, 2005). The underlying aim of modelling is to capture the key attributes of the target system at a manageable level of complexity, thus providing an appropriate analogue to the object of interest, which is easier to both manipulate and study than the target system itself.

Models can take a number of forms. Within most disciplines, verbal models are commonplace. Verbal models distil some process into a coherent description or discussion of how a system works (see for instance the opportunity theories depiction of crime as discussed in section 2.1). It is typical for verbal models to be translated into written models and included in journal articles or books. While verbal and written models can be exceedingly useful, they lack formalisation, can be difficult to empirically verify, and may be more open to interpretation by the reader than more formal models. Furthermore, depending upon the complexity of the target, the ramifications of the concepts they discuss can be difficult to adequately envisage at higher orders than those initially described.

Mathematical and statistical models are popular in a number of fields such as physics, chemistry and economics. Both mathematical and statistical models employ equation-based descriptions of the target phenomena. When compared to verbal or written models, such models allow for more formalised and explicit descriptions of the target system. However, when dealing with complex systems, equation-based models can be forced to implement undesirable levels of abstraction in order to provide mathematical equivalencies for what are often intricate dynamic processes. Depending upon the intended use of the model, this in turn may reduce the utility of model outputs.

3.2 Computational Models

One specific type of mathematical model aimed at modelling complex systems is the use of computer programs as models, or more specifically, computational models and simulations. Drawing from a number of fields including mathematics, computer science, artificial intelligence, cognitive science, and complexity theory, computational models attempt to capture the dynamics of the target system by formalising it as a series of algorithms and data objects. The use of computer simulation has become popular in a wide range of disciplines including both the natural and human sciences and a number of engineering fields. In this capacity simulation models are now used to examine a wide breadth of complex phenomena including protein folding (Levitt & Warshel, 1975), consumer behaviour (Schenk, Löffler, & Rauh, 2007), traffic flow (Cremer & Ludwig, 1986) and urban sprawl (Shoufan, Gertner, & Anderson, 2005).

This increase in the popularity of computational modelling is primarily the result of two distinct implications of Moore's law[1] (Moore, 1965). These are (1) a rapid increase in the computational capacity available to researchers to create and run simulation models, and (2) the relative ease with which vast quantities of data describing a system of interest can be both collected and stored, and in turn used to calibrate and validate models of that system.

The logic of the simulation method as proposed by Gilbert & Troitzsch (2005) is outlined in Figure 3.1. The approach begins with some target system that

[1]Moore's law states that every two years the number of transistors that can be fit onto an integrated circuit doubles – thus capturing the increasing rate at which computational capacity becomes readily available.

the simulation aims to emulate. A model of that system is built through a process of abstraction, and then 'run'. When a simulation is run it proceeds through a number of simulated time steps. At each time step, entities within the simulation process data and perform actions that aim to mirror those observed in the target system. By repeatedly applying these steps in an iterative fashion, simulations predict longitudinal patterns of system behaviour. Simulation output data describing the modelled system behaviour is then referred to as simulated data. Once a simulation has been run, the simulated data it produces is compared to collected data about the target system. Similarities between simulated and collected data can suggest that the simulation model may be sufficient to describe the target system. However, such similarities can mean a number of different things that are dependant on the underlying approach taken in the development of the model and its aims (be they explanatory or predictive). Correctly interpreting these similarities is of key importance and a number of different approaches to this process are discussed later in this chapter.

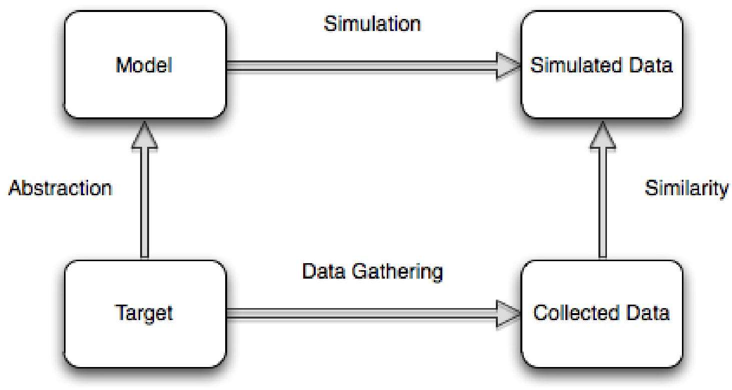

Figure 3.1: The Logic of Simulation as a Method (Gilbert & Troitzsch, 2005)

In the study of complex systems, the application of computer simulation as described above offers a number of distinct advantages over other model types. An overview of these strengths follows:

- *Managing Complexity:* While equation-based models are well suited to modelling in certain scenarios, when examining complex systems that contain large numbers of entities that interact in nonlinear and nondeterministic ways, mathematical equivalencies of some target processes can be very difficult to derive (Axelrod, 2006). Thus, equation-based models may require levels of abstraction that limit utility in specific applications (Epstein & Axtell, 1996). Conversely, the programming languages used to construct computer simulations are commonly less abstract and more expressive than their mathematical counterparts, and as such allow complex system elements to be decomposed into manageable sub-processes which are represented through algorithms and data objects. Additionally, computational models can be parameterised with empirical data (Hedström, 2005), deal well with nonlinearity (Bonabeau, 2002), and allow researchers to perform vast numbers of simulations (Epstein, 2006), thus providing estimations of the extent to which certain relationships may hold within nondeterministic systems.

- *Hierarchical Decomposition:* Computational models allow for the exploration of target systems at multiple levels of abstraction. Computational models may initially be built from high orders of abstraction only to subsequently explore further complexity at a later date. This is especially useful in the study of complex systems, as capturing all elements of a system at fine levels of granularity may initially be overwhelming (Gilbert & Troitzsch, 2005). Once an initial model has been built, lower orders of abstraction can be incrementally added to replace those initially devised higher order concepts, thus allowing effective management of model complexity (Jennings, 2001). This process is often referred to as hierarchical decomposition.

- *Modelling Dynamics:* Equation-based models are often best suited to describing the current state of a given system. However, questions that often interest researchers concern *what if?* scenarios, that is, the modelling of change. Another strength of the simulation approach lies in its ability to develop dynamic models in which endogenous processes can be examined (Bonabeau, 2002; Epstein, 1999). Thus, simulations can be used to explore scenarios where both influential factors, and as a result system behaviour, change over time.

3.3 Explanation vs. Prediction: Types of Simulation Models

Simulations models can be applied to address a wide variety of different goals, providing those who utilise them with entertainment, education, scientific insight, or the capacity to predict target outcomes. Within the scientific discipline, simulation models can be rudimentarily divided into two distinct categories – explanatory models, which aim to increase our understanding of how a particular system might function, and predictive models that aim to predict the likely outcome of a particular system given some initial conditions. These approaches to modelling play critical but distinct roles in advancing scientific knowledge, a brief description of both follows.

3.3.1 Explanatory Simulation Models

Explanatory models are commonly exploratory in nature, acting as formalised thought experiments. They explore what types of mechanisms might be viable explanations of observed outcomes, or under what circumstances certain outcomes might arise. In such models, parsimonious definitions of theory are often formalised as simulation constructs and the ramifications of these theories on the system as a whole explored. The process of building an explanatory model can itself be of great benefit to the development of theory. Building a simulation and formalising theoretical concepts for inclusion forces the researcher to be explicit about their theories and the concepts, entities and relationships that they propose exist between them. Thus, the construction of explanatory models can often highlight potential ambiguity, inconsistencies and problems in the underlying theories being examined (Gilbert & Troitzsch, 2005). This process is commonly referred to as theory formalisation.

Using explanatory models theories can be interrogated by comparing the output of computational models to observed real world phenomena. If the output of a simulation model bares no resemblance to the phenomena observed in the real world, the validity of theory is called into question. If, on the other hand, simulation output shares characteristics with real world observation, theoretical hypotheses are strengthened. Similarly, if several rival theories exist which purport to explain a particular phenomenon; several competing formalisms can be evaluated alongside one another in simulation. Thus, allowing researchers to eliminate explanations which are not sufficient to produce results observed in real world experimentation (this use of computational models for interrogating theory has recently been promoted within the social sciences by Joshua Epstein and peers under the banner of generative social science (Epstein, 1999, 2005, 2006; Hedström, 2005) and is discussed in more detail in section 3.8).

3.3.2 Predictive Simulation Models

In addition to furthering our understanding of particular systems, computational models can also be used for prediction. It is in this capacity that computational models are often most commonly known(Gilbert & Troitzsch, 2005). Predictive models aim to accurately forecast future characteristics of the target system given some initial conditions. For example, given data describing current air temperatures, pressure distributions and wind speeds, simulations can be built to forecast likely future weather conditions. While such models do not necessarily provide absolute predictions, they have been shown to produce sufficiently reliable results for use within a wide variety of applications (Gilbert & Troitzsch, 2005).

While the research presented in this thesis concentrates on the application of simulation for explanatory purposes, an important point to note concerning the relationship between explanatory and predictive models is that one is not necessary for the other (Epstein, 2006). Predictive models may produce empirically valid predictions, but may do so in a black-box manner, that is, where it is impossible to infer how some input data is mapped to an output prediction – correct or otherwise. Alternatively, predictive models may also transparently produce accurate predictions, but do so using vastly different mechanisms to those that are observed operating in the real world. While such models may provide considerable predictive capacity, they do little for increasing understanding of the target systems mechanisms.

Similarly, explanatory models may offer little in terms of prediction. For example, Epstein (2006) highlights that while electrostatic models can adequately explain the formation and occurrence of lightning, they cannot predict when and where it will strike. Instead, they help us to understand under what circumstances certain processes take place and the sufficient conditions for their formation.

The following section discusses one particular type of simulation applied in this thesis – the ABM, and highlights a number of strengths it offers in developing explanatory models of complex systems, such as the crime event described by the opportunity theories.

3.4 Agent-based Modelling

In section 2.1 several mechanisms of the crime event proposed by environmental criminology were presented. A key assertion of the concluding discussion was that, while conceptually simple, the theoretical descriptions of these mechanisms give rise to a number of complex and not easily quantified interactions between victims, offenders, controllers and the environment they inhabit.

Such complexity is not unique to criminological theory. By definition, the social sciences deal with the functions and interactions of human society; thus, complexity is inherent in almost all phenomena they aim to study. In relation to this issue, Herbert Simon called for the so-called 'soft' social sciences to be relabelled the hard sciences, due to a range of issues that encumbered investigation (Simon, 1987). Simon asserted that the laboratory conditions used by those who deal with the natural sciences permit a much clearer observation of cause and effect than is ever possible within the social sciences. In a similar vein, Epstein and Axtell (1996, 1-2) discuss a number of methodological difficulties that have limited the productivity of traditional equation-based models applied within the social sciences for the purposes of theory testing. A summary of these observations follows:

- Social systems are rarely characterised by discrete, easily decomposable sub-processes, instead most social phenomena encompass mechanisms which are spatial, cultural, economic, demographic and so on;
- Controlled experiments that aim to test hypotheses within the social sciences are often very difficult to perform due to a number of ethical and logistical constraints;

- Traditional social science models often assume that entities are perfect rational actors who have access to perfect information;
- In order to manage computational requirements, typical social science models suppress unit heterogeneity through the use of 'representative agent' methods which dictate that all actors within a system are assumed to be homogenous;
- Heterogeneity is inherent in social systems; however, within the social sciences "there has been no natural methodology for systematically studying highly heterogeneous populations" [p2];
- Models within the social sciences often assume social systems can be characterised as static equilibria, and as such ignore the importance of temporal dynamics.

In the attempt to overcome some of these problems, research within the social sciences over the last two decades has begun to embrace the application of computational modelling techniques drawn from a number of disciplines. The ABM is one particular technique that offers considerable promise to those who aim to build explanatory models of complex social systems. ABM is a well-established method of computer simulation with many real and promising applications across a range of disciplines. Although technically straightforward, its concept is considered profound (Bonabeau, 2002).

Rudimentarily, ABMs simulate the interactions that occur between multiple autonomous entities with the aim of analysing how the decentralised behaviour of constituent units impact on the behaviour of the system as a whole. ABM have been applied in a vast range of applications that include the design and development of mobile robot control paradigms (Matarić, 1997), investigating the dynamics of pedestrian flow in emergency situations (Helbing, Farkas, & Vicsek, 2000), exploring youth subcultures (Holme & Grönlund, 2005), the study of financial markets (Gou, 2006), and understanding consumer purchasing behaviour (North et al., 2009; Zhang & Zhang, 2007). While a thorough treatment of the ABM literature is well beyond the scope of this thesis, the following discussion concentrates on a number of strengths ABMs offer to better understand the interactions of society; subsequently highlighting the utility of these features in providing a method to explore the interactions proposed by the opportunity theories depiction of crime. The interested reader is directed to the many books and papers that have described the agent-based methodology in greater detail than space permits here (see, for example Bonabeau (2002), Jennings and Wooldridge (1998), and Weiss (1999)).

Within the social sciences, ABM allows researchers to create virtual societies and inhabit them with simulated populations of heterogeneous autonomous actors. Using these models, the societal level impacts of differing individual-level behaviours can be examined (Epstein & Axtell, 1996). In this way, ABMs provide a platform to explore how the decisions people make on a day-to-day basis translate into observable phenomena. Advocates of the approach suggest that it is this ability to capture the links between micro-action and macro-outcome that place ABM as a 'natural' methodology for the study of human systems (Axelrod, 1997b; Bonabeau, 2002; Epstein, 1999; Hedström, 2005). The observed behaviour of complex societal systems often arises from the interactions of relatively simple micro-level behaviours (Schelling, 1978), and it is in exploring this micro-macro divide amongst complex social systems that ABM offer considerable promise. By manipulating the initial conditions of the ABM and scrutinising data collected about virtual populations researchers gain insight into the likely dynamics of certain societal configurations. Within the social sciences ABM have demonstrated considerable promise in a variety of research areas including demography, economics, geography, anthropology and sociology (see Billari, Fent, Prskawetz, and Scheffran (2006); Epstein (2006); Gilbert and Troitzsch (2005); Trajkovski and Collins, (2009) for a range of applications).

Fundamentally, ABMs are made up of two key components: a population of agents and a simulated environment in which they are situated. A description of these key model elements follows.

3.4.1 Simulation Agents

In an ABM each member of the population is represented by an autonomous decision making entity, commonly referred to as an agent. Just like the members of a real population, agents exhibit individual characteristics, preferences and behaviours; for example each agent might have an age, home location and preferred social group etc. Within an ABM agents execute a variety of behaviours that govern how they perceive, reason and act in a given situation. These behaviours define how agents interact with one another, how they observe and analyse their surroundings, and how they might alter that environment or their internal state by performing certain actions. Such agent behaviour is commonly defined by a series of condition-action rules outlining how agents act in certain circumstances. In the case of explanatory ABM this decision calculus is often inspired by the formalisation of theory, such that rules, algorithms and heuristics are developed to reflect the mechanisms theory suggest are operating at the individual level. By exploring the macro-level ramifications of particular individual level theoretical constructs and comparing them to known output characteristics of the real world system, social scientists can use ABM to interrogate the validity of social science theories.

3.4.2 Simulation Environment

The environment in which agents are situated may take on a wide variety of forms depending upon the purpose of the model being built. A model environment may represent some form of abstract physical or social space, where proximity relates to the convergence of entities in space, or their ideals, opinions and connectivity, respectively. Conversely, model environments may be developed to closely mirror real environments, be they individual floor plans, neighbourhoods or cities. The significant notion is that agents are situated in an explicit space, abstract or otherwise, thus allowing the concept of localised interaction to be appropriately modelled (see below for further detail). The level of realism suitable for particular simulation environments, and moreover ABM in general, is subject to much debate (Edmonds & Moss, 2005). What is a necessary requirement however is that it is sufficiently detailed to encapsulate any features that are drawn upon by agents which reside within it. For instance, if an ABM of flower pollination dictates that the behaviour of a simulated worker bee relies on flower colour for selection purposes, the environment model must provide not only the location of flowers but also their colour. In considering model complexity in general Gilbert (2004, 9) states that "[t]he art of modelling is to simplify as much as possible, but not to oversimplify to the point where the interesting characteristics of the phenomenon are lost.".

3.4.3 Agent-Based Interactions

Given these two key components a number of interactions may be modelled within an ABM. *Agent-agent* interactions are those where agents receive information or resources from one another, develop social links with other agents, or compete for some entity within the simulation, be it territory, resources or status. *Agent-environment* interactions are those where agents draw information or resources from the world in which they are situated. *Environment-agent* interactions characterise those situations where the environment influences an agent, perhaps by constraining movement or defining the locations in which certain activities can and cannot take place. *Environment-environment* interactions may also occur, for instance, a resource within some environment may spread over time from its initial location to those adjacent. In reality, the types and ways in which elements of ABMs may interact are almost limitless and it is this level expressiveness that allows ABMs to be used to represent an unprecedented number of systems, processes and mechanisms.

3.4.4 The Temporal Dynamics of ABM

Another important feature of the ABM is its inherent ability to capture the temporal dynamics of a system. ABMs simulate the progression of time via discrete increments, often referred to as cycles. During each cycle agents within the environment perceive, reason and act based upon their specified behaviours that in turn draw on an agent's local circumstances and individual characteristics. Many thousands of these cycles may occur as a simulation progresses. Thus, ABM is performed in a recursive fashion, permitting the longitudinal examination of time dependant phenomena and the formation, interaction and separation of system elements over time. Such temporal dynamics are especially important for the modelling of phenomena such as tipping points, where the accumulation of individual action over time can lead to rapid and significant diversions in system behaviour (Grodzins, 1958).

3.4.5 Common Characteristics of ABM

Demonstrating the utility of ABM within the social sciences, Epstein and Axtell (1996) and Epstein (1999) succinctly highlight a number of key characteristics that, while not requisite, are often exhibited by ABMs. These characteristics, they suggest, make ABM ideal tools for the study of complex social systems, and provide a number of strengths that overcome some of the weaknesses associated with more traditional attempts to understand complex dynamic social systems. A summary of these characteristics follows.

- *Autonomy:* ABMs are devoid of overarching top-down control mechanisms. Rather, each agent within the simulation perceives, reasons and acts individually. While exchanges of information between agents may occur directly or indirectly through the environment, no centralised controller regulates behaviour. Thus, micro, meso and macro-level patterns emerge and coexist within any ABM – it is only in the eye of the beholder that these are examined as distinct phenomena.

- *Heterogeneity:* ABMs often simulate large numbers of entities as agents, which may differ both within and between groups. For instance, agents may operate using different decision-making strategies; for instance, probabilistic vs. deterministic reasoning. Agents may also differ by characteristics, with all agents utilising the same decision calculus but drawing on different internal characteristics. This ability to capture unit heterogeneity is of great importance, especially when attempting to investigate real world phenomena where unit homogeneity is rare.

- *Explicit Space:* ABMs represent entities embodied in some abstract or realistic space, allowing the concept of localised interactions to be well formed.

- *Local Interactions:* Equation-based models often assume system entities possess complete knowledge of both the world they inhabit and the other entities within it. This is often an unrealistic assumption. ABMs, on the other hand, predominantly deal with localised interactions occurring between entities that are spatially or socially proximate within the simulation environment.

- *Bounded Rationality:* The concept of bounded rationality relates directly to that of local interactions. While agents are often bestowed with rational decision-making behaviours, these behaviours can be developed to draw only from localised, limited information. Thus, rationality is limited by the information available at the time a decision is made. In addition, agent behaviours can be designed to utilise limited processing power - *bounded computation* - and therefore do not exhaustively search all possible actions in order to determine an optimal solution. Such representations of rationality are much closer to those employed by human actors in the real world.

- *Non-Equilibrium Systems:* ABMs concern themselves with phase transitions, tipping points and generally, how macroscopic phenomena are generated from numerous local decentralised micro-level interactions between multiple heterogeneous agents. Thus, they deal equally well with equilibrium and non-equilibrium systems, and where equilibrium does exist, the importance of its formation through non-equilibrium dynamics is often of most interest to agent-based modellers.

3.4.6 Epistemological Benefits of ABM

In addition to these inherent strengths in modelling social systems, the application of ABM within the social sciences also confers a number of distinct epistemological benefits when compared to other approaches.

- *Accessibility:* Agent-based approaches are often very effective at demonstrating complex concepts to both researchers and a wider audience. They offer a parsimonious, minimal, elegant and intuitive method to examine complex systems (Epstein, 2006). ABM elements are most commonly specified at the individual level – that is as the decision-making strategies of individuals. Specifying model concepts at this level means that model assumptions and propositions can be much more easily understood than models which require complex mathematical abstractions (Bonabeau, 2002). For instance, if an ABM aims to model consumer behaviour, the rules employed by consumer agents can reflect human decision-making strategies (e.g. if y is more expensive than x, purchase x), and need not be expressed as complex price differentials and cross-elasticity coefficients that lack transparency to all but the most seasoned of economists. This dictates that the ABM audience need not be highly skilled in the field of ABM in order to both inform and interpret simulations. As a result, simulations can often be interrogated by domain experts who may well ask more pertinent questions of models than those whose interests lie predominantly in their development (Gilbert & Troitzsch, 2005).

- *Aiding Scientific Discourse:* Further to the previous point, ABM's intuitive depiction of complex phenomena dictates that they can often better scientific debate concerning the target system they examine. As discussed previously the process of theory formalisation forces researchers to be explicit about their theories. Furthermore, the results of ABM can lead to the development of new questions and the generation of novel hypotheses, some of which may have seemed counterintuitive prior to the observation of ABM.

- *Simulation Experimentation:* ABMs allow for experiments to be performed that would otherwise be impossible due to ethical or logistical constraints (Gilbert & Troitzsch, 2005). Furthermore, simulation experiments can be performed en-masse easily and quickly. Once a model is built minor adjustments are simple to perform (Gilbert & Troitzsch, 2005; Townsley & Birks, 2008). In essence, the number of experiments that can be performed is only limited by the computing power and the time available to researchers. This assertion links directly to the remaining characteristics of simulation outlined below.

- *Absolute Control:* ABM offers an analogue to controlled experiments for examining social phenomena. Researchers can manipulate any number of influencing factors otherwise outside their control in traditional experimentation (Eck & Liu, 2008). Thus allowing the exploration of dose-response relationships in endless configurations (Townsley & Birks, 2008; Townsley & Johnson, 2008). Furthermore, simulation experiments can manipulate single characteristics of a model while holding all other characteristics static.

- *Absolute Observation:* ABMs provide synthesis of real-world systems in which perfect observation and measurement can occur (Townsley

& Birks, 2008). Data sets can be collected to describe every action undertaken by all agents. Furthermore the internal calculus employed by every agent in every action can be systematically recorded. Thus, it is possible to not only observe when some decision-making calculus lead to the commission of a certain action, but also when it did not.

- *In-situ and In-silico experimentation:* ABM research often identifies potential new lines of empirical enquiry. In turn, this external experimentation may lead to the development of better simulations. This iterative interaction of in-situ and in-silico experimentation can offer substantial advances in the way phenomena are investigated.

3.4.7 An Example Explanatory ABM – Schelling's Segregation Model

To illustrate a number of these features and strengths of ABM, one of the first and perhaps most famous applications of the approach undertaken within the social sciences is now outlined. In 1971 Thomas Schelling employed the agent-based methodology to explore how racial segregation might occur within urban environments (Schelling, 1971). While Schelling did not use a computer to create his model (due to the computational limitations of computers available at the time), the experiments he performed wholly embody the concepts of ABM, examining the macro-level patterns that could emerge from numerous micro-level interactions between autonomous agents.

Schelling's thought experiment envisioned a world inhabited by two types of households. Representing this environment as a two dimensional grid, households were initially positioned at random, leaving 10% of cells unoccupied. At each cycle of the model, a household was selected at random; if that household had two or more neighbours of the same type in its eight immediately adjacent cells, it was considered content and performed no action. If alternatively, it had fewer than two like neighbours, it was said to be unhappy and moved to a randomly selected unoccupied cell. Following these simple rules the experiment was run over numerous cycles and the output macro-patterns of household distribution observed. Over a relatively short number of cycles the model demonstrated that high degrees of segregation could emerge from this simple and seemingly conservative desire for neighbourhood integration (see Figure 3.2). These results are indicative of the nonlinear interdependency of household actions, which, as discussed previously, are difficult to capture using traditional analytic methods. In summary, when one household becomes unhappy with their surroundings and moves to a new location this action impacts on both the neighbourhood of origin and destination, these patterns of decisions can then lead to a domino-like effect where one household's movement, leads to another and so on.

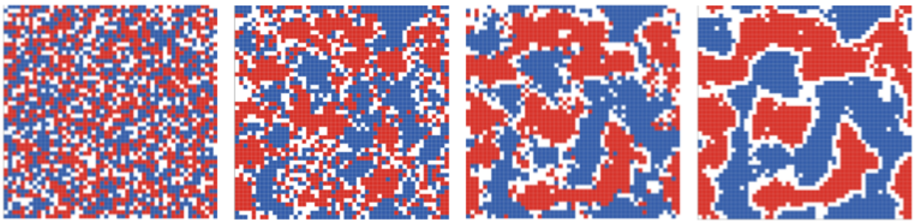

Figure 3.2: The Emergence of a Segregated Society

The results of Schelling's models encouraged people to think differently about what factors might influence the emergence of segregated neighbourhoods. Challenging the assumption that segregation was the by-product of high levels of discrimination, and demonstrating that the segregation phenomenon could persist even when households preferred predominantly integrated neighbourhoods.

Having highlighted the utility of explanatory ABM in studying complex social systems, the following section identifies how the strengths of the approach align well with the propositions of the opportunity theories described in section 2.1. And, in turn, demonstrates how ABM may provide a method through which the divide between micro-level crime theory and macro-level crime pattern might be more thoroughly explored.

3.5 Agent-based Models of the Crime Event

The previous sections of this chapter have provided an overview of the simulation methodology. The logic underpinning the use of simulation within the social sciences was outlined, and two key applications of simulation – to predict and explain were discussed. Subsequently one particular type of simulation, the ABM was described. The key components and characteristics of ABM were outlined and the strengths of the approach in exploring the dynamics of complex social systems were discussed. This section reiterates a number of these key attributes of ABM and aligns them with the theoretical hypotheses of the opportunity theories. Thus highlighting how they are well suited to the study of the crime event as depicted by environmental criminology.

As discussed, ABM are made up of two key elements, a population agents and a simulation environment in which they operate. Considering an ABM of crime occurrence, agents are an ideal fit to represent each of the individual actors portrayed by the opportunity theories. Agents can be used to represent victims, offenders, guardians, handlers and managers, and in turn the individual characteristics and behaviours exhibited by each. Such actors are all intrinsically autonomous entities – while the actions of some may draw upon or influence other actors, directly or through the environment, no overarching entity controls all human behaviour.[2]

Furthermore, the actors portrayed by the opportunity theories are inherently heterogeneous. Individuals undertake unique routine activities dictated by the spatial and temporal constraints of their unique day-to-day existence. Furthermore, individual characteristics such as motivation, capability, suitability and awareness are likely to change over time, space and context. Furthermore, the rational choice perspective views offender decision making as bounded – offenders rely on imperfect, localised knowledge of their environment – a process that could be captured through the study of local agent interactions. As such, ABM's ability to capture boundedly rational, heterogeneous, autonomous entities is well positioned to represent the key actors portrayed by the opportunity theories depiction of crime.

In considering a suitable simulation environment, direct contact predatory offences described by the routine activity approach take place within an explicit spatially referenced environment – the real world. A simulation environment could be developed within which these interactions play out on a virtual landscape that aims to mimic the environmental backcloth described by crime pattern theory. Such an environment might contain a representation

[2]This precludes both God and aliens, neither of which I have been able to find sufficient empirical support for.

of the transport network around which agents must navigate, key routine activity nodes representing locations commonly visited by individuals, and potential targets for crime such as homes, shops and vehicles.

Mirroring the distinct types of interactions ABMs are capable of modelling (see section 3.4.3) the opportunity theories describe a multitude of interactions that occur between potential offenders, victims, crime controllers and their environment. These individual level interactions, which traditional methods of enquiry often struggle to adequately capture, can be formalised relatively easily within an ABM. Crime event interactions might include the spatial and temporal constraints on actors provided by routine activity patterns; the victim, offender, lack of guardian convergences prerequisite in the commission of crime; the constraints imposed on actor movement by the environmental backcloth; the development of a localised knowledge as suggested by crime pattern theory; and the assessment of potential targets encountered within the environment as described by the rational choice perspective. Furthermore, when considering the direct contact predatory offences described by the routine activity approach, these interactions occur within an explicit space and are almost exclusively dependant on the proximity of actors and the particular local features of an environment.

Finally, in considering the epistemological benefits of building ABM (as discussed in section 3.4.6) the utility of building explanatory ABMs of crime is also considerable. The routine activity approach, rational choice perspective and crime pattern theory all outline a number of individual level mechanisms which can be used to define agent behaviour in an ABM of crime. These mechanisms are intuitively defined at the individual level – in that they describe the actions undertaken by individual offender, victims and crime controllers. Thus, agent behaviours can be derived to mirror these hypothesised mechanisms of crime, and in turn, explore their ramifications.

Furthermore, ABM permit controlled experiments to be performed that would otherwise be logistically or ethically impossible in real world settings. For instance, using ABM the transport network, target and offender distributions, or even the decision calculus employed by offenders can be systematically manipulated and the resulting impact on simulated crime observed. By doing so the potential impact of particular individual or environmental configurations can be explored in a systematic and rigorous fashion. In addition, given absolute observation provided by simulation models, all crimes that are committed by a virtual population can be recorded with complete accuracy. Furthermore, it is possible to scrutinise the internal structure of offender agents and identify for instance, how an individual offender's awareness space develops over time or when and where the expected utility calculus described by the rational choice perspective is employed. Such experiments aid scientific discourse within the field of environmental criminology by allowing systematic examination of the likely macro-level impacts of proposed individual level behaviours, and further by highlighting interesting patterns or observations which may in turn lead to development of new hypotheses concerning the proximal causes of both the crime event and particular crime patterns.

In summary, the features of ABM provide a number of distinct strengths over more traditional forms of modelling in examining the individual level interactions between those actors considered significant to the crime event and the environment they inhabit. By building models of these interactions and undertaking controlled simulation experiments the underlying dynamics of theoretical processes can be examined and the theories from which they are derived explored.

The previous sections of this chapter have provided a description of the simulation method and in particular the explanatory ABM. A number of distinct advantages the ABM approach offers over other methodologies in examining complex systems such as those often studied by the social scientist have been outlined. It is important however to consider the validity of simulation – that is, to establish what can and cannot be reliably inferred from the results of what are, in essence, wholly artificial experiments. Given the recent groundswell in simulation approaches within the social sciences a number of prominent authors within the field have considered the validity of simulation approaches in the study of social systems. The following section now outlines several key issues.

3.6 The Validity of Simulation

Like any other scientific instrument, simulation models must be appropriately validated in order for their findings to be of use. This section provides a discussion of simulation validity and outlines a stratified approach through which simulation models and their outcomes may be validated with respect to several criteria.

Explanatory simulation models offer a unique means of theorising about the formation of observed phenomena. With a new method however, comes new problems, and in turn, new approaches which aim to minimise their impact on the integrity of experimental findings. Once a model has been developed it should be validated. This process frames the interpretation of simulation results so that the investigator can make appropriate inferences within the scope of a model's intended use. The requirements for the validation of simulation models are, for the most part, defined by its intended application. As discussed above, simulation models intended for predictive purposes need only be capable of producing empirically accurate predictions of the target system's output for them to be considered valid. Thus, an accurate depiction of the underlying elements of the target is not required.

Conversely, the validation of simulation models used for explanatory purposes (like the one presented in this thesis) predominantly relates to a simulation's ability to adequately reflect the theory being examined through simulation. Thus, to assess the validity of an explanatory model, the investigator must evaluate whether the theoretical model has been appropriately translated into conceptual and computational models. This mapping of theoretical model to conceptual and computational constructs can be seen as simulation construct validity (Townsley & Johnson, 2008).

When assessing the construct validity of an explanatory simulation model, the translation from theoretical to computational mechanism is verified and validated. In contrast to predictive models, validation of the output of explanatory models is then utilised to assess the ability of theoretical mechanisms to describe the target phenomena. As such, if the theories being studied are translated into validated and verified computational constructs, the output of a simulation model is used to make inferences about theory.

This idea is further expanded upon in section 3.8 where the concept of generative sufficiency (Epstein, 1999) is described. Briefly, generative social science suggests that given an appropriately validated and verified model of theory, the output of explanatory models can be compared to empirical data to assess whether theoretical constructs are sufficient to generate observed regularities of the target system, thus providing a method through which theory can be tested in terms of its viability, and in some cases falsified (Epstein, 1999).

While there seems no definitive consensus regarding the validation and verification of simulation models, here the work of Schlesinger (1980) is adapted, presenting a three-tiered approach to the process. This approach offers considerable utility by providing measures of model validity at a number of stages throughout the model development process; appropriately stratifying verification and validation to the different stages of the simulation method, from theoretical model to conceptual model and then to computational model. Figure 3.3 depicts this process of model qualification, verification and validation.

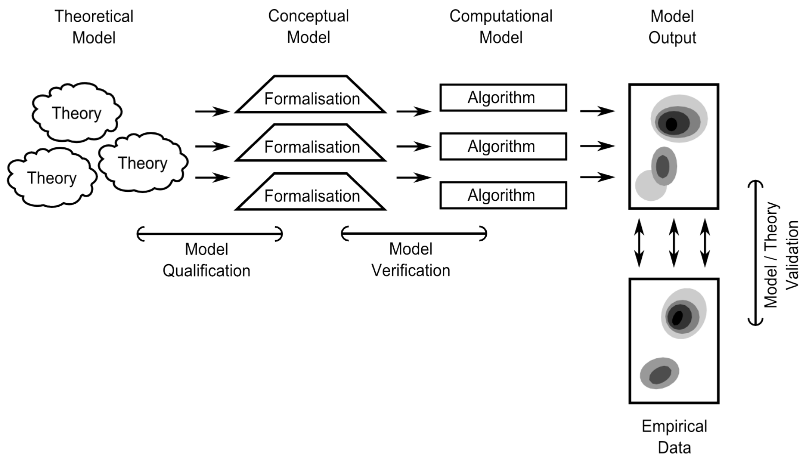

Figure 3.3: Verification and Validation of Simulation (adapted from Schlesinger (1980)

First, a theoretical model of some phenomenon is selected. From this theory, a number of formalisations are derived, together forming a conceptual model of the simulation to be developed. Such formalisms encompass the key propositions of a given theoretical model, and in essence provide a formalised verbal model of some theory. This conceptual model is validated in terms of its ability to provide an adequate representation of the original, and often 'fuzzy' theoretical model – this process is known as model qualification. Model qualification poses the question: do these conceptual formalisations and the proposed interactions amongst them adequately capture the theories they aim to simulate and subsequently examine? Model qualification occurs through observation. Where discrepancies between the theoretical and conceptual models are identified, conceptual formalisations are refined to reflect more accurately the theoretical constructs of interest. If ambiguity exists in the existing theoretical model, a number of candidate formalisations may be produced, each to be tested through simulation.

Once the investigator is satisfied that the conceptual model has been adequately qualified, a series of computational algorithms representing that conceptual model are implemented. Model verification assesses whether these algorithms sufficiently represent the conceptual model upon which they are based. This process often takes place by examining the output of specific algorithms in relation to particular scenarios. For instance, if theoretical and conceptual models suggest individuals are attracted to some characteristic of their environment, the observation of simulation test scenarios should demonstrate entities gravitating to locations that present this characteristic.

While the emergent properties of simulation are often beyond the scope of model verification (as they are often inherently unexpected), these techniques of model qualification and verification allow simulation components to be examined individually with respect to the results expected by theory. This is of considerable use as the verification of interacting simulation components can be much more difficult. Given a sufficient number of test cases where model outputs are consistent with the results expected by both theoretical and conceptual models, the computational model may be considered appropriately verified.

After both conceptual and computational models have been assessed, model validation aims to assess a model's ability to adequately capture the output behaviour of the target system as a whole. This is done by comparing the output of simulation models (i.e. simulated data) to empirical data. Con-

Table 3.1: Levels of Equivalence between simulated and empirical data (Source: Axtell & Epstein, 1994)

Level of Equivalence	Description
Level 0	The model is a caricature of reality, as established through the use of simple graphical devices (e.g., allowing visualisation of agent motion);
Level 1	The model is in qualitative agreement with empirical macro-structures, as established by plotting, say, distributional properties of the agent population;
Level 2	The model produces quantitative agreement with empirical macro-structures, as established through on-board statistical estimation routines; and finally,
Level 3	The model exhibits quantitative agreement with empirical micro-structures, as determined from cross-sectional and longitudinal analysis of the agent population.

sidering how such comparisons should take place it is obvious that various levels of equivalence between simulated and empirical data can be observed. Speaking specifically about how the output of ABM of social systems can be compared to empirical data known of the target system, Axtell and Epstein (1994) propose four cumulative levels of in-situ and in-silico system equivalence (see Table 3.1).

Obviously, models offering the greatest equivalence are the most desirable, but that is not to say that those which only provide lower levels of equivalence are not of use. In discussing this issue Axtell and Epstein consider that what is currently known about the target system – that is, the state of the field in which models are to be used, is perhaps the most significant factor in determining at what level model-empirical equivalence should highlight interest from fellow scholars. In essence, the better understood the target system is, the greater the level of equivalence required to provide novel insight. To illustrate, they suggest that economic models will likely require quantitative micro- and macro-equivalence, as much is already known about both the micro- and macro-characteristics of many economic systems.

Relating this to the study of crime through simulation, as applied in this thesis, what might we infer about suitable levels of equivalence in simulations of crime? Here I believe it is fair to say that, due to those previously highlighted problems of observation and experimentation, relatively little is definitively known about the underlying dynamics of the crime event. Thus, it would seem that with respect to crime simulation, a relatively underdeveloped area of research, equivalence at any of the levels would be of interest to criminological scholars.

Epstein and Axtell suggest that in developing models researchers should consider the level of equivalence they aim to achieve, as this will influence the data collection and analytical procedures that are devised to analyse simulation output. Furthermore, model complexity may also dictate the likely attainable levels of equivalence. Highly abstract models for instance are unlikely to attain quantitative equivalence, but instead may demonstrate qualitative equivalence with a broader range of target regularities. Drawing on the observations of Eck and Liu (2008), who suggest that quantitative equivalence between simulated and empirical crime patterns may be difficult to determine given the inherently error prone nature of crime data, the model presented in this thesis aims to achieve qualitative equivalence with multiple macroscopic regularities of interest.

Having discussed issues relating directly to the validity of simulation models as analytical tools, the following section describes how the outputs of a sufficiently validated model should be scrutinised to maximise the confidence one can have in the insights gained from it.

3.6.1 Assessing Model Outcomes

Given a sufficiently qualified, verified and validated simulation model, a number of methods may be employed in assessing the overall validity of the results it produces. These tests aim to ensure that the inferences drawn from a model are reliable and truly indicative of the computational mechanisms under study, and in turn, maximise insight into those hypotheses from which they are derived.

Simulation Replication

Simulations, like all experimental methods, require that their findings be reproducible for them to be considered valid (Axelrod, 1997a; Edmonds &

Hales, 2003). In the same way as they are used in traditional experimentation, replications of simulation aim to highlight implementation-specific factors which may have influenced the observed results. In fact, simulation models may be more susceptible to these implementation-specific factors due to their relative complexity and the skill set required in examining them (Axelrod, 2005; Galán et al., 2009). Therefore, without systematic and rigorous methods for scrutinising simulation, factors unbeknownst to onlookers, and in some cases even the investigator, may influence simulation outcomes and hence, the inferences being drawn from them. For example, in discussing their attempts to replicate a published simulation model, Edmonds and Hales (2003) highlighted that seemingly subtle differences in the temporal order in which simulation entities performed actions lead to substantially different outcomes from those observed in the original study.

Given the potential impact of these problems, replication of simulation experimentation is of considerable importance (Edmonds & Hales, 2005; Townsley & Birks, 2008; Townsley & Johnson, 2008). Simulation replications can be rudimentarily divided into two categories: *within-* and *between-* model replication. *Within-model* replication describes a process where the outputs of simulation experiments are averaged over numerous 'runs' using the same simulation model and configuration. As simulations often contain stochastic elements the results of one simulation run may differ from the next (Axelrod, 1997a). Within-model replication is an important method through which the range and consistency of possible simulation outputs can be explored, assessing simulation statistical-conclusion validity (Townsley & Johnson, 2008). Thankfully, the nature of development environments used in simulation development dictates that within-model replication is relatively easy to perform, requiring little investment other than time and computing power.

Between-model replication, on the other hand, refers to the replication of original simulation experiments using different simulation models. Between-model replications take the theoretical and conceptual models of an original model and attempt to transfer them into another model in order to assess whether similar results are observed. This process may highlight weaknesses in simulation construct validity. In order to facilitate between-model replication, simulations should strive to provide transparency in their documentation. Usefully, the process of formalisation required in the development of simulation necessitates explicit definitions that can be utilised by those who aim to perform subsequent between-model replication. For example, conceptual algorithms can be included in research documentation, critical parameters identified, and the range of values used for each simulation experiment specified. Thus, while the process of between-model replication can be time consuming, such explicit definitions make replication easier to perform and increase the likelihood that subsequent replications are equivalent to the original experiment.

Model Robustness

When simulation models are developed it is commonplace for a number of significant model parameters to be specified. These parameters often dictate the initial conditions of the simulation model and the entities that reside within it. With respect to ABM, such parameters might describe the size and form of the simulation environment, agent populations, or the specific thresholds at which agents within the model undertake certain actions. While the results of a particular simulation are of interest, the mapping between input parameters and output behaviour should also be scrutinised (Axelrod, 1997a; Gilbert & Troitzsch, 2005). Model robustness tests seek to examine the influence that these initial model parameters have on outcome patterns. The aim of this process is to ensure that the results observed are not unique to a specific set of selected parameters. Robustness tests commonly involve selecting a number of significant model parameters (ideally reflecting both model initial conditions and behavioural parameters (Fung & Vemuri, 2003)), manipulating each in isolation, performing a number of within-model replications, and examining changes in model outcomes. In this way robustness tests are akin to sensitivity analysis performed in a number of statistical models.

However, given the dynamic, nonlinear, and nondeterministic nature of the systems simulation models commonly aim to emulate it is unlikely that results from such robustness tests will not differ somewhat given parameter manipulation. Indeed, a lack of impact may indicate that model parameters do not act as they are intended. When variations in outcomes are observed the evaluation of robustness testing often looks for distributional equivalence. That is, do the same types of macro-patterns remain given changes in initial parameters?, is the magnitude of effect from specific mechanisms similar? etc. Such tests ensure that the model's plausibility does not completely break down when seemingly innocuous changes in input parameters are performed (Fung & Vemuri, 2003).

Similarly, if the results of parameter manipulation are highly implausible further investigation into the underlying model structure is required. For instance, if an expanding population leads to a lower density of individuals throughout the environment; or a decrease in agent income levels leads to an increase in model-wide wealth. In these cases the underlying structures of the model should be scrutinised (returning to the methods of qualification and verification described previously), ensuring that the observed results are indeed indicative of unforeseen but plausible interactions, rather than an indication of underlying errors in the model formalisation, or the presentation of the data it produces. While it is often impractical to sweep an entire range of possible input parameters, it is reasonable to explore a number of key model parameters within the computational constraints of a proposed study.

In addition to testing the robustness of model results to differing initial parameters, models that incorporate stochastic elements should also be subjected to robustness testing with respect to selected random number seeds[3] (Axelrod, 1997a). In such tests the random number seed used in generating all random numbers are systematically manipulated to ensure that observed results are not unique to a particular seed. Such tests are undertaken by running numerous within-model replications of a model under the same initial parameters but each using a different random number seed.

In summary, the answers to questions such as 'is your model valid?' are likely best met in terms of probabilities (Axtell & Epstein, 1994) – there are however a number of techniques which can minimise potential threats to the validity of both models themselves and, in turn, the inferences derived from their outcomes. Furthermore, it is worth noting that the uncertainty of validity in this analytical technique is, in broad terms, no different from the

[3]Random number seeds are a programming construct used to initialise pseudorandom number generation.

uncertainty associated with other widely used methods that are forced to make assumptions in order to aid our understanding of complex real world processes.

The following section describes a number of previous endeavours that have applied ABM within the field of environmental criminology. Subsequently, the differences between these previous approaches and the one presented in this thesis are outlined, and the approach of generative social science undertaken here discussed.

3.7 Criminology & Simulation: Existing Research

The notion of building ABMs of the crime event is not novel. While currently in its infancy, research relating to the use of ABM within criminology has recently gained considerable momentum. Recent publications edited by Liu and Eck (2008) and Groff and Mazerolle (2008) present considerable evidence of the growing interest in computational modelling within the field of criminology. The research presented in these volumes cover a wide variety of topics relating to both the implementation of simulation techniques within criminology and criminal justice, their ramifications for both theoretical and policy development, as well as a number of issues associated with their use in general.

While acknowledging the wide range of applications for computational modelling within environmental criminology, this section focuses on the most relevant existing studies that have applied explanatory ABM specifically with the aim of exploring the mechanisms proposed by environmental criminology. In addition, a number of significant foundational issues with respect to the use of crime simulations are discussed. It is through this body of existing work, and discussions with several of its authors that the work in this thesis has drawn insight and inspiration. In concluding this section, the important differences between these previous endeavours and the research presented in this thesis, which aims to extend efforts within this burgeoning field, are then highlighted.

In considering the general suitability of computational modelling within environmental criminology, Brantingham and Brantingham (2004) make a call for the use of ABM in understanding the crime event, suggesting that its application could be well used to aid in the validation of crime patterns and theories. The authors propose a framework for developing such ABM primarily focusing on the routine activity approach but also drawing from the rational choice perspective and crime pattern theory. The culmination of these discussions has led to the development of the Mastermind simulation model, an interdisciplinary modelling platform which aims to provide a tool for criminologists, policing agencies and city planners interested in the spatial and temporal characteristics of crime in urban areas (Brantingham, Brantingham, & Glasser, 2005; Brantingham et al., 2008; Brantingham, Glasser, et al., 2005a, 2005b). Employing a mathematical framework known as abstract state machines, which permit the "mathematical modelling of discrete dynamic systems" ((Brantingham et al., 2008, 255), Mastermind provides distributed asynchronous ABM of the key actors and entities involved in the crime event. Brantingham et al. (2008) present an example application of the Mastermind modelling platform, focusing specifically on motor vehicle theft and exploring the impacts that individual awareness spaces might have on target selection, and in turn, the distribution of crime. In performing a series of experiments using the model, Brantingham et al. present results of a sample simulation of two offenders situated within an environment drawn from real road network data of Vancouver, British Columbia. In this example offenders differ only by their navigational preferences. The model itself is run through ten within-model replications and results describing the activity patterns and target selection of each agent scrutinised. Analysis of this data demonstrates the impact that differing activity and awareness spaces can have on the occurrence of offending, and moreover the clear utility of using ABM in considering the complex interactions which occur between offender, target, environment and their individual characteristics. In discussing the utility of the approach, Brantingham et al. state that the specific outputs of the model are less important than the underlying 'trace' that generates them. However, they do suggest that model validity can be assessed by comparing outputs with those expected by theory, and by the model's ability to produce crime patterns that are characteristically similar to those observed in empirical research.

In one of the most sophisticated approaches to date, Groff (2007a, 2007b, 2008) presents an explanatory ABM of street robbery. Groff's model aims primarily to explore a core assertion of the routine activity approach – as time spent away from home increases, so does the likelihood of victimisation (Cohen & Felson, 1979). Groff (2007a) presents an initial model in which agents representing both police and potential offenders, victims and guardians move randomly between intersections in an environment derived from GIS data describing the road network of Seattle, Washington. Using this model a number of experiments are performed where the time agents spend away from home is systematically manipulated and the resulting levels of street robbery observed. Results of these experiments are congruent with those predicted by theory – as time spent away from home increases significant increases in street robberies are observed, and furthermore the spatial patterns of street robberies change. Results of a series of robustness tests demonstrate also that the observed relationship between time spent away from home and risk of victimisation are robust to both changes in initial parameters and changes in random number seeds.

Extending this work, Groff (2007b) presents a modified version of the original model in which the spatial activities of agents are more developed. In this variant the impact of differing conceptualisations of agent activity spaces are examined. Firstly, a directed movement behaviour is compared to the initial random movement presented in (2007a). Agents operating under the 'street directed' movement behaviour are allocated a number of routine activity nodes and a series of intersection paths that connect them via predetermined shortest routes. In addition, a further model variant is presented in which agents again utilise the random movement behaviour but do so in an abstract environment in which the Seattle street network is replaced by a uniform grid of intersections. In comparing these three model variants, time spent away from home is held static and resulting crime trends are observed under each of the three conceptualisations of activity spaces (grid random, street random, street directed). Results of these experiments demonstrate that the presence of the real street network versus the abstract grid impacts on the incidence and concentration of offending. In the grid model lower numbers of victim-offender convergences and actual crimes are observed and crime is generally more dispersed compared to the real street network. Groff suggests this is likely "due to the funneling effect of the street network on human activity; it increases the number of times people converge" (2007b, 522). In comparing the street directed to the street random model (as presented in Groff (2007a)) further differences are observed. Under the street directed model variant an overall reduction in offending is observed but an increase in both convergences and spatial concentration of offending is apparent. Each scenario is run through five within-model replications, each time utilising a different random number seed.

Groff (2008) then presents a further model extension which incorporates temporal constraints into the routine activities of agents. The study provides a comparison of three further conceptualisations of activity spaces - simple, temporal, and spatio-temporal. In the simple condition, agents move randomly throughout the street network for some proportion of each day and stay at home for the remainder; in the temporal variant, movement remains random but time away from home is specified by a series of temporal constraints; finally in the spatio-temporal variant offenders are allocated routine activity nodes, specified paths to those nodes, and a schedule of when such activities should take place. As in the initial study, a series of experiments are then performed where the average time spent away from home is manipulated and the resulting crime examined across all three model configurations. By comparing the simple model to the temporal and spatio-temporal variants an appropriate counterfactual is established permitting the examination of the effects of each type of hypothesised activity space as compared to the null model. Results demonstrate that temporal and spatial constraints have differential effects on both the overall amount and spatial distribution of robbery events within the model. In considering the limitations of the study the author states that the model should be extended to explore further environments with the hope of increasing the generalizability of its findings.

Using a similar approach, Wang, Liu and Eck (2008) presents the latest endeavour of an interdisciplinary research program undertaken by scholars from the departments of geography and criminal justice at the University of Cincinnati (Liang, 2001; Liu et al., 2005). The authors present a simulation model of street robbery underpinned by the routine activity approach and crime pattern theory. The model utilises a hybrid of ABM and cellular automata and situates agents within a realistic environment drawn from a subsection of the Cincinnati street network. Agents within the model represent three key entities involved in the criminal event: offenders, targets and places. Offender agents operate under a number of key behaviours that allow them to navigate their environment, choose suitable targets and learn from past experience about good crime places. Similarly, target agents are capable of traversing the simulation environment and adapting their behaviour to avoid locations where previous victimisation has occurred. Place agents then represent the locations at which crimes can occur and are represented as cells on the street network modelled. Each place agent is associated with a place manager designed to represent the crime controller initially described by Eck (1994). The management effectiveness of a place is then reflected in a measure of a place's ability to control crime within it. Drawing on the routine activity approach, when offender and target agents converge at a given place, offenders then assess their current motivation, the desirability of a target, the capability of any present guardians and the management effectiveness of the current place in their decision to offend.

Having established that the routine activity mechanism formalised produces results congruent with those expected by theory, two key scenarios are presented. The first demonstrates that providing agents with temporally constrained routine activities leads to hourly patterns of offending much like those observed in the empirical study of crime. The second explores the impact of providing both offender and target agents with the ability to adapt to what is known about 'good' crime places (to either gravitate towards, or away, from them respectively). Results of these experiments demonstrate that activating the adaptation mechanism leads to greater levels of repeat victimisation, and the presence of a power curve in describing high crime places much like that observed in empirical study (Spelman, 1995).

The research presented by these authors again demonstrates the utility of ABM in exploring the macro-ramifications of micro-level propositions outlined by theory. Demonstrating that ABM are well suited to explore the dynamic nature of individual level interactions that are difficult to capture through traditional analytical techniques. Furthermore, the application of controlled experimentation within a simulation laboratory, and, in particular, Groff's use of a null model against which competing activity space conceptualisations can be compared shows considerable promise, highlighting the strength of simulation in performing experiments that would otherwise be impossible in-situ.

Finally, Birks (2006, 2005); Birks, Johnson and Bowers (2005); and Birks, Donkin and Wellsmith (2008) outline the initial efforts of the author in developing ABM of crime. Birks, Donkin and Wellsmith (2008) presents two illustrative ABMs of crime - an initial abstract model of crime against the person, and a second more complex model of residential burglary, incorporating mechanisms of the routine activity approach, rational choice perspective and crime pattern theory. Agents within this second model are again situated on a real road network drawn from GIS data describing a suburb in the United Kingdom. While the analysis of simulated crime patterns is only illustrative, initial findings demonstrate that agents operating under the formalised mechanisms of the opportunity theories produce patterns of burglary victimisation that are spatially and temporally clustered in a similar way to those observed in empirical study. This work served as a learning exercise in dealing with the practicalities of developing ABM of crime, and formed the initial inspiration for this thesis.

Having described the key models that have provided insight for the model presented in this thesis, the following discussion now highlights a number of foundational issues discussed within the crime simulation literature that have also informed a number of decisions made in the development of the model presented here.

Capitalising on previous research efforts within the field of crime simulation (Van Baal, 2004), Elffers and Van Baal (2008) provide a significant discourse concerning the current movement towards incorporation of realistic environmental data in simulation models (see for example (Birks et al., 2008; Groff, 2007b; Wang et al., 2008)). Elffers and Van Baal express concerns that rather than increasing the utility of ABM, such endeavours may instead obfuscate the fundamental dynamics of the crime event that simulation is so well positioned to examine. Suggesting that the causal effects of the mechanisms of interest may be difficult to unpick from the impacts of environmental conditions specific to the location being simulated. In considering this issue the authors remind us that "real world correspondence is not the kernel of a simulation model" (Elffers & Van Baal, 2008, 22). Instead proposing that the utility of simulations is derived by the systematic examination of model mechanisms and parameter changes on output. Thus, increasing understanding of the ramifications of the underlying mechanisms formalised within the model, and in turn the theories from which they are derived.

Similarly, in presenting an abstract model of offender movement, Brantingham and Tita (2008) demonstrate that simplistic reductionist models of offending are capable of generating plausible spatial concentrations of crime. Utilising only a random walk behaviour that derives trip distance from a levy probability distribution, Brantingham and Tita's model of offender movement produces hot spots that bear a striking resemblance to those observed in empirical study. Much like Elffers and Van Baal (2008), in advocating their reductionist approach, Brantingham and Tita express overarching concerns regarding the use of overly complex models, suggesting that simple models provide "a degree of analytical and quantitative tractability that are not available in more "holistic" approaches" (Brantingham & Tita, 2008, 204).

The observations of both these studies have influenced the author's conceptualisations of ABM environments (given previous endeavours presented in Birks (2006) and Birks et al. (2008)), and have resulted in a shift in direction from the realistic – to the more synthetic environmental representations that are utilised in this thesis (see section 5.4.1 for further discussion).

With regard to the validity of crime simulations a number of insightful papers have also recently been published. Townsley and Johnson (2008) outline a number of threats to simulation validity – many of which relate to the need for model qualification, validation and verification outlined in section 3.6. Furthermore the authors also highlight the important role of replication within simulation-based research, asserting the significance of both within- and between-model replications discussed in section 3.6.1. Importantly, they also propose that models may be best empirically verified by assessing their ability to produce multiple commonly observed crime patterns. Similarly, Berk (2008) proposes that crime simulations aimed at providing insight must be appropriately validated against known crime data, outlining a typology of model and target equivalence similar to that proposed by Axtell and Epstein (1994) and depicted in Table 3.1.

Of considerable importance to this thesis, Eck and Liu (2008) provide a insightful discussion of the similarities and differences between simulated and empirical experiments. Drawing on Epstein's concept of the generative explanation (Epstein, 1999) (described in further detail in the next section), Eck and Liu examine the simulation methodology from a traditional experimental standpoint. Contrasting the use of simulation against more traditional forms of explanation, the authors propose that the ability of simulation to identify generative explanations of specific crime phenomena (i.e. those micro-mechanisms that are generatively sufficient to produce macroscopic regularities congruent with the target system) positions the simulation model as a substantive scientific instrument. It is this approach that the ABM developed in this thesis follows, providing a test of the generative sufficiency of a number of core premises outlined by the opportunity theories in producing several crime patterns commonly observed in empirical research.

3.7.1 Specific Contributions of This Thesis

The model developed for this thesis aims to extend the previous efforts discussed above. Much like Eck and Liu (2004) state (cited in Groff (2007a, 80)) the approach presented in this thesis does not aim to compete with previous endeavours, but instead complement and capitalise on previous efforts. In doing so, this thesis contributes to the newly emerging evidence base of what hypothesised crime event mechanisms are capable of generating plausible crime patterns.

The approach presented in this thesis does however differ from previous studies in several ways, and as such makes a number of distinct contributions to the field of computational criminology. Primarily, drawing on Epstein's notion of the generative explanation, the model presented in this thesis provides a systematic test of the generative sufficiency of all three opportunity theories in generating multiple independent regularities of crime, across multiple crime types. The model presented in this thesis formalises and examines the macro-level ramifications of three core micro-mechanisms of the opportunity theories identified in section 2.1 – movement (routine activities), decision making (rational choice) and learning (crime pattern theory). Following Groff's (2007b) implementation of the null activities model condition, the model developed implements experimental and control conditions for each mechanism – such that, in the experimental condition agents within the simulation exhibit behaviour representative of the theoretical mechanism, and in the control condition its absence. Using these conditions in conjunction with a computational laboratory-based approach advocated by previous authors, a series of controlled experiments are performed in which the crime patterns that are generated by offender populations acting under distinct behavioural configurations are systematically explored and compared. Using this approach, the model is used to estimate the likely impacts on crime patterns of the three core micro-mechanisms in both isolation and interaction.

Second, in examining the generative sufficiency of these mechanisms, three independent outcome measures - each relating to a given regularity of crime identified in section 2.2 are used. By analysing the outputs of the same simulations against multiple regularities, the equivalence of simulated and empirical data is assessed across multiple dimensions, thus strengthening the confidence (or lack thereof) one can have in the sufficiency of a given mechanism. This approach is consistent with the suggestions of (Berk, 2008; Brantingham et al., 2008; Eck & Liu, 2008; Townsley & Johnson, 2008) who all suggest that the ability to generate patterns congruent with those observed in empirical research is an appropriate step toward establishing the validity of crime event models.

Third, considering the concerns of Elffers and Van Baal (2008) and Brantingham and Tita (2008) an abstract model environment is used. However, in acknowledging the potential importance of the spatial constraints a street network confers on agent activity, as highlighted by Groff (2007b), an abstract representation of a street network is developed. Importantly, where previous efforts have focused predominantly on exploring crime patterns within a single sample environment, the model presented in this thesis permits the exploration of multiple environmental configurations. In doing so, the model environment aims to encapsulate the potential impact a street network may have on the spatial activities of agents, and in turn, the distribution of crime; yet, by examining outcomes over multiple environments, also control for potential environmental effects that might be imposed by the use of a single environment.

In addition, a focus on model simplicity permits the number of within-model replications performed to be orders of magnitude greater than those presented in previous studies. Furthermore, in undertaking large numbers of within-model replications, distributions of outcome measures are generated, thus allowing the statistical significance and magnitude of differences between model outcomes resulting from different mechanisms to be assessed - two important but distinct measurements of simulated data (Axelrod, 2005).

Finally, where previous efforts have focused on models of a single offence type, the model framework presented here applies two variants that permit assessment of the generative sufficiency of the opportunity theories for crimes that occur both against spatially static targets (e.g. residential burglary) and spatially dynamic targets (e.g. street robbery).

Having outlined how the model presented in this thesis differs from and compliments existing applications of computational modelling within environmental criminology, the final section of this chapter outlines the notion of the generative explanation that underpins the research presented.

3.8 Generative Social Science

In this section the rationale of generative social science, the approach applied in this thesis, is discussed. Propositions of the approach that suggest that the computational ABM provides a new kind of scientific instrument capable of falsifying theory are outlined, and the notion of the generative explanation is discussed and compared to more traditional forms of explanation. The concept of generative sufficiency is discussed and the ability of ABM to identify candidate micro-specifications capable of generating known macro-structures is outlined. Finally, it is argued that the generative social science approach provides an ideal framework through which the propositions of the opportunity theories can be explored, and moreover their sufficiency as candidate explanations for commonly observed regularities of crime assessed.

3.8.1 The Generative Explanation

Recent advances in the application of ABM within the social sciences have seen advocates propose that ABM permits a new "third way of doing science" alternate to traditional forms of inductive and deductive reasoning (Axelrod, 2005, 5). This approach sees the agent-based computational model or artificial society, as it has become known (Epstein & Axtell, 1996), as a new scientific instrument that permits a unique experimental method through which social macro-structures of interest can be "computed" (Epstein, 1999, 2006; Hedström, 2005). A branch of analytical sociology, the approach focuses on mechanisms as explanations, and in doing so advocates suggest that such artificial societies allow researchers to systematically establish which micro-level mechanisms can and cannot be viable explanations for observed macroscopic phenomena: "Agent-based models provide computational demonstrations that a given microspecification is in fact sufficient to generate a macrostructure of interest" (Epstein, 1999, 42)

More generally, the generativist[4] views society itself as a form of distributed computational device through which macro-structures are computed from micro-action. The generativist proposes that complex social science phenomena can be understood through the synthesis of their emergence from lower order action and interaction. The central premise of generative social science is as follows: "If you didn't grow it, you didn't explain its emergence" (Epstein, 2006, 8). Consequently, the generativist approaches observed macro-phenomena by attempting to identify what combination of micro-conditions are capable of generating them. Or more specifically, "How could the decentralised local interactions of heterogeneous autonomous agents generate the given regularity?" (Epstein, 2006, 5).

In attempting to answer this question the ABM is employed. Therefore, in addressing the above question the following course of action is proposed: "Situate an initial population of autonomous heterogeneous agents in a relevant spatial environment; allow them to interact according to simple rules and thereby generate – or "grow" – the macroscopic regularity from the bottom up" (Epstein, 1999, 42).

In following this approach it is suggested that theory about unexplained social science phenomena can be tested by building ABMs of the proposed micro-level mechanisms of a system and testing if these mechanism are sufficient to produce observed macroscopic regularities of the target. Such regularities describe those salient macro-level patterns that are consistently observed in the empirical study of the target system. For instance, these might include right skewed wealth distributions, price equilibria, segregation pat-

[4]i.e. he or she who undertakes generative social science

terns, or in the case of this thesis the spatial clustering of crime.

Whereas traditional statistical or equation-based explanations operate in a *top-down* manner, with the identification of associations between aggregate observations used to make inferences about underlying mechanisms; generative social science operates from the *bottom-up*, identifying generative explanations as those hypothesised micro-level mechanisms that produce macro-level output patterns consistent with observed regularities of the target (Epstein, 1999). Applying ABM as its principal scientific instrument, generative social science assesses the generative sufficiency of theory. Generatively sufficient mechanisms are those that when employed by an agent population are sufficient to generate macro-level patterns congruent with the target. The more regularities a mechanism is capable of generating, the greater the confidence one can have in its validity. Importantly, if a mechanism cannot produce such regularities, confidence is reduced, and it may be eliminated as a potential explanation of the target phenomena. Thus, the use of ABM provides a method through which theory can be falsified, a principal requirement of any scientific proposition (Popper, 1963).

Drawing parallels to Mackie's theory of causation (Mackie, 1974), hypotheses deemed generatively sufficient are those which are made up of INUS conditions of the phenomenon being studied. Thus, each condition is in itself insufficient, as it alone cannot cause the observed phenomenon; yet non-redundant, as it is required in this set of conditions for the phenomenon; unnecessary, as it may be replaced by a number of other sets of conditions; but sufficient, as in combination with other conditions will cause the phenomenon.

An important observation regarding this form of investigation is that while generative sufficiency is a prerequisite of causal explanation, the converse is not necessarily the case. Returning to Mackie's theory of causation, clusters of causes or INUS conditions are sufficient to bring about the observed effect, but are not necessary. Thus, while ABMs may identify hypotheses that are generatively sufficient, they cannot be used to infer causal explanation (Epstein, 1999; Hedström, 2005). In discussing this issue, Epstein (2005, 3) succinctly states that "generative sufficiency is a necessary, but not sufficient condition for explanation". This is obviously the case. It is highly probable that a number of different micro-level mechanisms may produce output phenomena consistent with that observed of the target. This is no different from the scientific discipline as a whole – there is no finite limit of the number of potential explanations one can conjure up for a given phenomena. Generative social science aims to use ABM to identify which of those potential explanations are viable candidates. It is only through further empirical experimentation that the most tenable candidate mechanisms can be identified (Epstein, 1999; Hedström, 2005).

The initial task of the generativist, then, is to eliminate those theories that are generatively insufficient, leaving only generatively sufficient candidate explanations. This ability to identify insufficient hypothetical constructs is where the strength of the generative approach lies. Having identified a number of candidate explanations, each should be examined in further detail, considering its plausibility and identifying other potential metrics that may be used to test for the presence of the mechanisms purported using empirical experimentation. As such, the development of generative models guides further empirical observation of the target phenomena, which in turn may identify further potential explanations that can subsequently be assessed for generative sufficiency (Epstein, 1999). While this process is not guaranteed to produce a single viable explanation of a phenomenon, it has eliminated those that are insufficient, implausible or have been falsified through empirical observation, in effect separating the theoretical wheat from the chaff.

To illustrate this approach an example is now provided. Consider three rival hypotheses about how some macro-phenomenon x occurs in the target system T; denoted A_h, B_h and C_h. Each of these hypotheses consists of a series of assumptions about how micro-level interactions of individuals combine to generate the regularity x. Drawing on each of these hypotheses, three ABMs are built; models A_m, B_m and C_m. In each model, agent behaviour is formalised from the three respective hypotheses A_h, B_h and C_h. Once developed, each of the three models are used to perform a series of simulated experiments and their outputs examined in comparison to observed phenomena x. The results of these analyses demonstrate that the output patterns produced by agents operating in A_m differ substantially from those observed in T. However, both B_m and C_m produce outputs that are consistent with the empirical observation of T. Given these results, A_h is considered generatively insufficient and is eliminated as a potential explanation of x. Both B_h and C_h are generatively sufficient and as such, are identified as candidate explanations of phenomena x.

Given these two candidate explanations, we may continue to experiment with a wider range of parameters (for which we have corresponding empirical observations) in an attempt to eliminate either of these hypotheses. Alternatively, we may look for other regularities of T and assess if both B_m and C_m are sufficient to generate them as well as x. In addition, we might attempt to identify meso-level interactions or regularities exposed by models B_m and C_m and generate new corresponding hypotheses; establishing equivalent empirical experiments which can be used to test whether or not they are observed in the target system T.

Extending this initial example, consider that the target system T exhibits several macroscopic regularities; T_{r1}, T_{r2} and T_{r3}. In examining the three proposed explanations of T, model A_m may not produce any of the observed regularities whereas model B_m may only be capable of generating T_{r2} and not T_{r1} and T_{r3}. Conversely, model C_m produces output patterns consistent with all three identified regularities T_{r1}, T_{r2} and T_{r3}. In this example, again model A_m may be eliminated as a likely explanation of T_{r1}, T_{r2} and T_{r3}. Subsequently, both models B_m and C_m are generatively sufficient for T_{r2} but model C_m can also produce patterns similar to those of T_{r1} and T_{r3} as well. In this case while model B_m should not be eliminated, as a there may be other unknown mechanisms not modelled operating that are responsible for T_{r1} and T_{r3}, in isolation it can be eliminated as a candidate explanation for T_{r1} and T_{r3}. At this point it would seem a sensible course of action to assume that model C_m and the associated hypothesis C_h currently offer the most parsimonious and plausible explanation of the target system T. Again, while the above process in no way is making definitive judgements about the actual in-situ mechanisms, it is providing a technique through which competing hypotheses can be prioritised in terms of their plausibility. This in turn may optimise the allocation of real world resources in the empirical investigation of those hypotheses deemed sufficient through simulation.

In application, generative social science has demonstrated its utility in exploring a number of social science phenomena. Epstein (2006) provides a review of a number of these endeavours, which include exploring the dynamics of civil violence (Epstein, 2002), potential strategies for controlling epidemics (Epstein, Cummings, Chakravarty, Singham, & Burke, 2006), and the impacts of cultural change within indigenous communities (Dean et al., 2006).

Having outlined the underlying rationale behind the application of ABM in assessing the generative sufficiency of theory, the following section describes how this approach is applied to assess the viability of the opportunity theories - the task undertaken in this thesis.

3.8.2 Testing the Generative Sufficiency of the Opportunity Theories

Given the approach described above, this thesis applies the methods of generative social science to determine if the micro-level mechanisms of the opportunity theories outlined in section 2.1 offer a viable generative explanation of the macroscopic regularities of crime discussed in section 2.2.

The Micro-level Propositions of the Opportunity Theories

The opportunity theories offer a number of micro-level propositions concerning the crime event (see section 2.1). The routine activity approach describes how offenders and victims traverse their environment and how in turn these spatial and temporal patterns of activity lead to the convergence of the prerequisite elements of crime. Once encountered the rational choice perspective sets out a decision calculus which allows offenders to evaluate the suitability of a given target. In addition, crime pattern theory describes a cognitive mapping mechanism through which offenders develop knowledge of their local environment, which in turn aids in the commission of crime.

The Macroscopic Regularities of Crime

In addition to these hypothetical propositions, a number of known macroscopic regularities of crime exist (see section 2.2). To reiterate, research has shown that crime is both spatially and temporally clustered; that a small number of victims experience a disproportion amount victimisation; and further when aggregate journey to crime curves are observed they follow a characteristic distance decay. These regularities represent the trace effects of the complex system that the crime event is the output of, and thus are those that the micro-level propositions described above purport to explain.

Exploring the Micro-Macro Divide with a Generative Agent-Based Model of Crime

Given the proposed micro-mechanisms of the opportunity theories and the observed macro-regularities of crime, the approach of generative social science seems ideally placed to explore if the former is indeed capable of generating the latter. If the propositions of the opportunity theories do reflect the proximal in-situ mechanisms that are significant in the commission of crime, we would expect a virtual population of offenders operating according to them to generate patterns of crime congruent with those observed in empirical study. Thus, in this thesis a generative ABM is developed and populated with virtual victims and offenders. Offender behaviour is derived from a number of propositions of the opportunity theories, dictating how offenders traverse the environment, make decisions about the suitability of potential targets they encounter, and learn about their local environment. Running this model a series of controlled experiments are performed whereby the mechanisms under which virtual offenders operate are systematically manipulated. Subsequently, the simulated crime data produced by virtual offenders are then compared to the macroscopic regularities of crime previously described. From this analysis conclusions are drawn about the generative sufficiency of the mechanisms formalised, and moreover the validity of the opportunity theories from which they are derived as candidate crime event explanations.

3.9 Conclusion

In this chapter an overview of the simulation methodology applied in this thesis was provided. The logic underpinning the use of simulation within the social sciences was outlined, and two key applications of simulation – to predict and explain were discussed. Subsequently one particular type of simulation, the ABM, was described. The key components and characteristics of ABM were outlined, and the strengths of the approach in exploring the crime event as depicted by the opportunity theories discussed. Furthermore, a number of suggestions concerning both model and simulation outcome validity were then set out.

Subsequently, several recent studies that have utilised ABM in exploring the crime event as depicted by environmental criminology were described, and the insights gained from them in developing the model presented in this thesis highlighted. Finally, the emerging field of generative social science applied in this thesis was described. The notion of the generative explanation outlined, and the strengths of the approach in assessing the viability of potential micro-level explanations of observed macroscopic phenomena discussed. To conclude, section 3.8.2 set out how the generative approach aligns well with both the micro-mechanisms provided by opportunity theories and the macro-regularities of crime commonly observed in empirical study – as such, providing a tool through which the sufficiency of the former in explaining the latter can be systematically assessed. The next chapter now briefly summarises the research presented thus far and outlines how the remainder of the thesis proceeds.

4

Research Overview

This chapter briefly summarises the research presented, reiterates the key research questions, and specifies the methods through which they will be addressed.

4.1 Research Context

Section 2.1 provided a summary of the opportunity theories depiction of the crime event. In examining three key theoretical perspectives, a number of micro-level hypotheses regarding the proximal mechanisms of crime were discussed. These included the spatial and temporal constraints of day-to-day activities described by the routine activity approach; the expected utility calculus outlined by the rational choice perspective; and the awareness space proposed by crime pattern theory. In discussing these theories a number of problems associated with obtaining data at a suitable resolution to test their validity, and in turn their likely impacts on crime, were highlighted.

In section 2.2 a number of consistently observed macroscopic regularities of crime were described. These regularities, which constitute the predictable emergent outcomes of the proximal mechanisms of crime, included the spatial and temporal clustering of crime, patterns of repeat and near-repeat victimisation, and the characteristic journey to crime curve. In discussing these regularities a number of hypothetical explanations for each, as proposed by the opportunity theories were outlined.

Section 2.3 highlighted a number of issues endemic within the social sciences that confound efforts to explore this divide between micro-theory and macro-observation. It was suggested that researchers must go to considerable lengths to rigorously test the validity of the micro-mechanisms provided by the opportunity theories in describing the crime event and furthermore, the macroscopic regularities of crime discussed in section 2.2. The chapter concluded by highlighting the emerging field of crime event simulation and proposing the development of an ABM aimed at exploring the viability of theoretical mechanisms put forward by the opportunity theories.

Chapter 3 then began by providing a brief introduction to the simulation methodology and the development of explanatory models aimed at exploring macro-ramifications of micro-behaviour. The ABM methodology, used extensively in the emulation of complex social systems, was then described. Aligning the characteristics and strengths of ABM with the propositions of the opportunity theories, it was argued that the ABM offered a more holistic approach to the formalisation of such theories than traditional analytical methods; allowing exploration of the complex dynamic interactions proposed by the opportunity theories without the need to suppress unit heterogeneity or simplify nonlinearity. As a result, it was suggested that the application of ABM could overcome some of the problems associated with the ethical, logistical and monetary requirements of empirical observation and experimentation, thus providing additional insight into the micro-macro divide previously highlighted.

Section 3.7 then provided an overview of several previous studies that have applied the agent-based methodology in the study of crime. Drawing on the findings of these studies, the utility of ABM in examining the complex interactions outlined by the opportunity theories was highlighted. Furthermore, in discussing these previous efforts, several key strengths and weaknesses of existing models were identified. In doing so, a systematic test of the generative sufficiency of the opportunity theories in explaining multiple regularities of crime across multiple crime types was proposed. The chapter concluded by describing the field of generative social science that is applied in this thesis with the aim of providing such a test.

4.2 Research Aim and Overarching Research Question

The aim of this research is to apply the approach of generative social science to systematically assess if the micro-level propositions of the routine activity approach, rational choice perspective and crime pattern theory outlined in section 2.1 offer a candidate generative explanation for a number of commonly observed crime patterns. In doing so, the research presented in this thesis answers the following overarching research question:

Are the micro-level mechanisms of the opportunity theories generatively sufficient to explain macroscopic patterns commonly observed in the empirical study of crime?

To address this question a generative ABM of crime is developed. In this model a population of virtual offenders and victims are created, and a number of behavioural formalisms derived from the identified micro-level propositions of the opportunity theories used to dictate their actions. The crime patterns these virtual offenders generate are then compared to several known regularities of crime discussed in section 2.2. In comparing the patterns produced by these virtual offenders to those observed in the empirical study of crime, conclusions are drawn relating to the generative sufficiency of the mechanisms formalised, and moreover the validity of the theories from which they are derived.

4.3 Selection of Micro-specifications and Macro-structures

The following section specifies the micro-specifications and macro-structures of interest – that is, the hypothetical mechanisms to be explored through the virtual population, and the salient macroscopic patterns against which simulated crime data will be compared. In order to focus the research and keep it manageable, the number of mechanisms to be modelled, and the number of regularities the emergent outcomes of such mechanisms are compared against is limited to three of each.

The three offender agent behaviours employed within the model are derived from the three key micro-level mechanisms identified in section 2.1. These behaviours define how agents traverse their environment and encounter potential targets (routine activities); assess those targets for suitability (rational choice); and build up cognitive maps of their activity spaces and the potential targets within them (crime pattern theory). Following a computational laboratory approach, for each of these three mechanisms an experimental and control agent behaviour is developed. The experimental behaviour reflects the presence of the proposed mechanism, and the control behaviour its absence; thus providing an appropriate counterfactual state against which the experimental behaviour can be compared.

In examining the crime patterns produced by virtual offenders operating according to these mechanisms, simulated crime data collected from the model is analysed with respect to three regularities of crime: spatial clustering, repeat victimisation and the journey to crime curve. The selection of these regularities reflects a desire to capture characteristics of the three key components of offending as described by the opportunity theories and depicted in the crime triangle (see Figure 2.1) – that is, the crime place (spatial clustering), the victim (repeat victimisation), and the offender (the journey to crime curve).

Thus, extending the overarching research question, the research presented initially addresses the following three focused research questions:

Focused Research Question 1: *Are the mechanisms of the opportunity theories generatively sufficient to explain the spatial concentration of crime commonly observed in empirical study?*

Focused Research Question 2: *Are the mechanisms of the opportunity theories generatively sufficient to explain patterns of repeat victimisation commonly observed in empirical study?*

Focused Research Question 3: *Are the mechanisms of the opportunity theories generatively sufficient to explain the characteristic journey to crime curve commonly observed in empirical study?*

Subsequently, having addressed these questions, focused research question four assesses if the three theoretical mechanisms formalised from the opportunity theories have differential effects on each of the regularities studied.

Focused Research Question 4: *Do the mechanisms of the routine activity approach, rational choice perspective and crime pattern theory have differential impacts on commonly observed patterns of crime?*

Examining the outputs of two model variants, the final focused research question then assesses if the answers to all of the above questions differ when considering crimes that occur against spatially static targets (e.g. residential burglary) and crimes that occur against spatially dynamic targets (e.g. street robbery).

Focused Research Question 5: *Do these results differ by crimes that occur against static or dynamic targets?*

The computational experiments performed in addressing these questions are now described.

4.4 The Computational Laboratory

Drawing on the strengths of the simulation approach discussed in section 3.4.6, the ABM developed is used to perform a series of controlled experiments exploring the impacts of each of the formalised mechanisms on the three selected regularities of crime.

Having outlined the three experimental agent behaviours (*movement* – routine activities, *decision-making* – rational choice perspective, *learning* – crime pattern theory) and the experimental and control states for each, a traditional 2 by 2 by 2 experimental design is employed. In doing so, the model is used to explore the crime patterns produced by the virtual offending population operating under eight distinct combinations of the three hypothesised offender mechanisms.

In each of these experiments all simulation model parameters are held static except those relating to the current active offender agent behaviours. Furthermore, in keeping with the discussion of simulation replication presented in section 3.6.1, a series of within-model replications are performed for each of the eight experimental model configurations. In each replication, while the size of the environment and agent populations remain fixed, a unique transport network and offender and target population are used; thus, minimising environment specific effects and increasing the generalizability of model findings.

Subsequently, to address focused research question five all simulation experiments are performed using two distinct model variants. The first, simulating crimes that occur against spatially static targets; and the second, crimes occurring against spatially dynamic targets. The simulated crime data generated in each of these experiments are then analysed in a number of distinct ways detailed in the following section.

4.5 Methods of Analysing Simulated Crime Data

In examining simulated crime data, three distinct phases of analysis are undertaken. Each phase addresses a given empirical regularity of crime against which model results are compared. In line with the discussions of simulation and empirical equivalence presented in section 3.6, analysis of simulated crime data aims to assess the qualitative equivalence of simulation and empirical macro-structures of interest (i.e. level 1 of Table 3.1 (Axtell & Epstein, 1994)). To evaluate the extent of each of the three selected regularities the following output metrics are used to analyse simulated crime data. In addition, FRQ4 is addressed through the use of inferential and descriptive statistics that establish the significance and magnitude of differences in such regularities under each configuration of hypothetical mechanisms.

4.5.1 Spatial Clustering Output Measure

In addressing FRQ1 the level of spatial clustering observed in simulated crime data is analysed using the Nearest Neighbour Index (NNI). This method of quantifying spatial clustering is described in further detail in section 6.5.1.

4.5.2 Repeat Victimisation Output Measure

In addressing FRQ2 the distributions of victimisation observed in simulated crime data are examined using the Gini coefficient. This method is described in further detail in section 6.5.2.

4.5.3 Journey to Crime Output Measure

Finally, in addressing FRQ3 the skewness of aggregated journey to crime curves observed in each simulation are analysed using Pearson's coefficient of skewness. This method is discussed in further detail in section 6.5.3.

4.5.4 Assessing Model Robustness

Following the observations made in section 3.6.1 a series of model robustness tests are also performed to ensure that model outcomes are robust to changes both in initial parameters and random number seeds.

4.6 Summary

This chapter has reviewed the research context underlying this thesis. It has set out the aims of the research and reiterated both the overarching and focused research questions. Subsequently, it has specified the methods undertaken in addressing these questions. In doing so, the development of an ABM of crime aimed at exploring the generative sufficiency of the opportunity theories has been proposed. Describing this model, the key micro-level propositions to be formalized have been outlined and the macroscopic regularities against which model outputs are assessed defined. Subsequently, the experimental approach undertaken using the model has been specified, and the output measures through which simulated crime data are analysed have been presented. In the following chapter the ABM developed is described and the decisions made in its development discussed.

5

Model Development

This chapter outlines the development of the primary scientific instrument used in this research - the generative ABM of crime. This model was used assess the generative sufficiency of the identified micro-mechanisms of the routine activity approach, rational choice perspective and crime pattern theory in explaining (1) the spatial concentration of crime, (2) patterns of repeat victimisation, and (3) the journey to crime curve. The underlying decisions made in the development of the model are outlined. The selected level of model complexity is discussed and the justifications for this approach provided. Each of the model elements is described in detail, including the environment and agent specifications. These specifications include a description of the objects contained within the model, namely offenders, targets and the transport network. The parameters associated with each are then outlined and their initialisation conditions specified.

Subsequently, three experimental offender agent behaviours are specified. These behaviours emulate a proposed mechanism derived from each of the three theoretical approaches under study. For each mechanism the underlying theoretical propositions are outlined, a series of conceptual equivalencies are derived, and the computational formalisms developed to represent these conceptual models described. In specifying each of these agent behaviours a control and experimental state are specified. In the experimental state the agent behaviour aims to represent the presence of a given mechanism, in the control state an appropriate counterfactual behaviour, representing the absence of a given mechanism is outlined, thus allowing the impact of specific mechanisms on crime patterns to be explored.

Having described the key model elements and the behaviours employed by the offender agents, the subsequent sections of this chapter outline the simulation logic. This description specifies how the model progresses over time – *the simulation cycle*, and within it, the order in which all agents take actions – *the agent cycle*. The chapter concludes by outlining how the model is used to perform computational experiments.

5.1 Modelling Offences against Static and Dynamic Targets

Two variants of the model presented are developed. The first, which is described in detail in this chapter, simulates crimes that occur against static targets, in this case using an example of residential burglary. The second model variant aims to emulate crimes that occur against dynamic (i.e. mobile) targets (e.g. street robbery). This variant differs from the first model only by activating the movement behaviours discussed in sections 5.6.1 and 5.6.4 within the target population, thus allowing targets to move around the environment in the same way that offenders do. Subsequently, all experiments performed are done so with both model variants and presented in two distinct studies in the next chapter.

5.2 The Model

The ABM used in this research approximates a geographical region populated by both potential offenders and targets. When a simulation is run using the model[1], offenders utilise a transport network to undertake their own unique spatial activities, moving from different parts of the environment to work, socialise and so forth. As offenders traverse the simulation landscape they encounter potential opportunities for offending. When this occurs, offenders make judgements about whether or not to offend based on

[1]At this stage it is prudent to clarify the usage of two key terms throughout this chapter – model and simulation. Here the term *model* describes the ABM itself – that is, the agents and environment; the data-structures, algorithms and logical constructions used to represent them; and the interface used to manipulate and observe them. Simulation is what the model does – a *simulation* is the emulation of a particular set of circumstances as played out using the model.

both characteristics of the target in question, and their own current motivations and knowledge of the local environment. As the simulation progresses multiple heterogeneous offenders explore the environment, making decisions about where and when to offend, and in turn generating unique patterns of crime.

Using this model, a series of controlled computational experiments are performed that explore the generative sufficiency of three hypothetical offender mechanisms proposed by environmental criminology. These mechanisms describe offender movement (routine activity approach), reasoning (rational choice perspective) and learning (crime pattern theory). In examining these hypotheses the decision calculus employed by a virtual offending population is systematically manipulated to reflect the propositions of theory, and the patterns of crime that emerge as a result examined and analysed. By focusing specifically on the sufficiency of these hypothetical mechanisms in producing three known regularities of crime, conclusions are then drawn about their ability to provide viable candidate explanations for three commonly observed crime phenomena.

The model is developed using NetLogo, a freely available cross-platform "multi-agent programmable modeling environment" (Wilensky, 1999) developed at the Center for Connected Learning and Computer-Based Modeling at Northwestern University.

5.3 Model Complexity

Before describing the model it is important to reiterate the ethos that underlies all model development presented here: following Axelrod's (1997a) mantra of "keep it simple stupid" (KISS), the initial model developed in this thesis aims represent everything as parsimoniously as possible. The model presented aims to provide a simplistic emulation of direct contact predatory offending. It is made up of simple entities that, in turn, employ simple rules governing behaviour. While there is no doubt a wealth of other elements that could be added to the model, the research presented here follows the rationale of Schelling (1971, 1978) and Epstein and Axtell (1996) and does not purport to closely mimic any particular locality or reality. Instead, it provides a simple set of robust explanatory tools, with which otherwise untestable hypotheses linking micro-offending behaviour to macro-crime patterns can be explored. Thus, it aims to provide insight by permitting levels of observation and manipulation that are otherwise impossible in traditional empirical research – reducing the complexity and noise of the real world and removing the ethical, logistical and monetary implications associated with empirical experimentation. In essence, the model presented provides a toy world in which appropriately specified mechanisms of theory can be tinkered with in a controlled fashion. By means of inspiration Schelling's *Micromotives and Macrobehavior* (1978) and Epstein and Axtell's *Growing Artificial Societies* (1996) provide compelling examples of how such simple models can tell us something novel and interesting about the complex systems we aim to understand.

Given that the opportunity theories propose a number of micro-mechanisms that purport to explain the distribution of crime, and several regularities are commonly observed in the study of such crime distributions, the goal is to assess if these mechanisms are sufficient to explain such regularities. In developing this model the aim is to imbue a virtual offending population with behaviours that sufficiently formalise a particular hypothetical micro-level mechanism so that its macro-level ramifications can be explored. As such, it is acknowledged that these behaviours do not encompass all hypotheses proposed by a particular theory. While complex models may indeed provide unparalleled insight into certain real world processes, they can also lead to a combinatorial explosion in degrees of freedom, making the exploration and interpretation of model outcomes, and moreover the ability to generalise from them to real world outcomes difficult at best, and impossible at worst.

Considering such simple mechanisms it may be reasonable to assume that the macro-impact of a single micro-mechanism is relatively predictable, especially with respect to a single output phenomenon. It is a considerably bolder claim however to suggest one can predict how multiple interconnected mechanisms (simple or otherwise) might act together in unison across multiple individuals, and moreover how these interconnected mechanisms might influence several independent outcome phenomena. While one could assume that opportunity-based depictions of offending provide explanations for the clustering of crime, patterns of repeat victimisation, and the characteristic journey to crime curve – one might equally well assume that alternative depictions provided by anomie or social disorganisation theory were also capable of generating the very same observations. The model presented here provides a means to test (in a systematic fashion) if indeed those macroscopic structures can be generated by a specific micro-specification. Thus, while the entities and actions of the model presented may be simple - their interaction is not necessarily so, and it is in exploring this interaction that the approach presented provides insight.

Furthermore, a focus on model simplicity also aims to explore the possibility of a Pareto distribution underlying the mechanisms of the crime event. That is, exploration of the notion that perhaps a small number of mechanisms may be capable of explaining a large proportion of observed crime phenomena. This study aims to contribute one component to this effort – by presenting a method through which the viability of purported offender level mechanisms as explanations for commonly observed crime phenomena can be explored. In considering such investigation it may be appropriate to draw an analogy to logistic regression, a technique commonly utilised in the study of both crime and criminality. In applying logistic regression to explore the relationship between two or more observed characteristics, the researcher may include a vast number of independent variables in an attempt to explain variation in the dependant variable. However, the ultimate aim of such an approach is always to explain the greatest amount of variance from the smallest number of variables – in this regard the explanatory ABM presented here aims to be no different. Beyond this epistemological goal, concentrating on model parsimony also provides a number of other distinct advantages:

- *Development Practicality:* Focusing on model parsimony has direct and significant practical benefits. Put simply, models with simple underlying constructs are more easily developed, tested, interpreted and understood than their more complex equivalents. This observation has been stated by several authors within computational criminology, and it is under this rationale that the model presented here proceeds. Furthermore, the ABM approach can be particularly sensitive to unintentional development decisions that unknowingly impact on the observed output behaviour of the model. Such 'ghosts in the machine' can in turn lead to inappropriate inferences relating micro-specification and macro-structure. While the development of simple models does not preclude such problems, the more complex a model becomes, the more difficult such influential but unintentional model assumptions are to identify, isolate and remove.

- *Transparency:* Another goal of the selected approach is to ensure that all model elements can be easily understood and considered by fellow scholars. Transparency aids in replication, a key requirement of experimental progress that applies as much in-silico as it does in traditional empirical enquiry. Providing transparent depictions of the mechanisms of interest also promotes critical and novel thinking about how not only the model functions, but also the real world system it aims to emulate, which in turn may lead to the generation of new theory and hypotheses that can be examined through traditional empirical means. In contrast, the application of overly complex models often dictates that the interactions of model elements can quickly become cognitively intractable to all, even those who have developed the model. Such complexity can make it very difficult to use the model as a means to inspire discussion, and instead, may lead to models being used to simply explore and analyse vast parameter spaces – the theoretical and practical implications of which are not always readily apparent.

- *Incremental Complexity:* The above observations do not preclude the development of more complex models, they do however highlight the advantages of staged model development – here it is argued that simple models should precede complex ones (Townsley & Birks, 2008). It is only when simple models are understood that further complexity should be considered. This approach allows new model elements (or replacements for existing ones) to be adequately examined, tested and their impacts on model outcomes to be systematically analysed. Furthermore, the development of simple initial models, and in turn, their outcomes, can be used as a counterfactual against which an incrementally developed can be compared; thus, allowing the impacts of new model elements to be assessed.

Having outlined the rationale behind the model, its purpose, and the underlying approach taken in selecting and representing its constituent components, the model developed is now specified. Description of the model is divided into two sections, mirroring the key components of ABM discussed in section 3.4: the first outlining the virtual environment in which simulations take place; and the second describing the intelligent agents which inhabit it, and make up the population of virtual offenders through which the hypothetical mechanisms of interest are explored. In presenting each of these model elements, a discussion of both the rationale underlying its inclusion in the model, and a description of the methods through which it is conceptualised in-silico are provided.

5.4 The Simulation Environment

The simulation environment specifies the virtual landscape in which all simulations take place. In keeping with the aim of developing a tractable model of offending, and drawing on the observations of previous research discussed in section 3.7, an abstract simulation environment is adopted. This environment is represented as a simple two-dimensional lattice. When a simulation is initialised, the experimenter specifies the dimensions of the environment, for instance creating a 100x100 environment containing 10,000 distinct locations. This environment contains three key types of object: offender agents, potential targets and transport nodes. The following sections outline both the transport network around which offender agents navigate and the potential targets that are encountered within it. Figure 5.1 depicts a typical simulation environment containing transport nodes, potential targets and a single offender agent.

5.4.1 Transport Network

The first model element considered is that of the transport network that permits movement of agents throughout the environment. When individuals move around their environment navigation can rarely be characterised as Euclidian or 'as-the-crow-flies'. Instead, human movement is greatly influenced by the transport network; paths link origin and destination via footways, bike tracks, roads, streets, intersections, motorways, rivers and even flight paths. These strata of the transport network impose constraints on spatial behaviour, in essence dictating that only a finite number of (plausible) paths

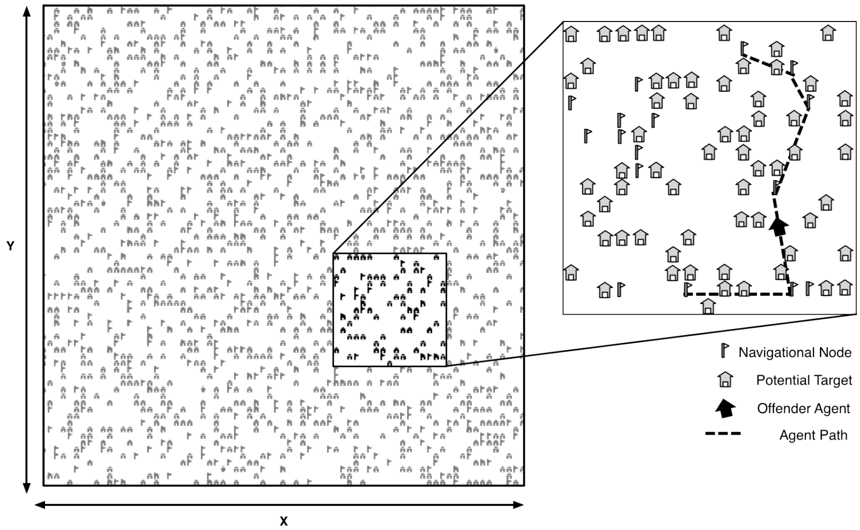

Figure 5.1: The Simulation Environment

exist between any two locations. Moreover, some origin-destination pairs have greater or fewer paths linking them than others, and some of these are more travelled than others. Such spatial constraints lead to queues outside football stadiums, city centre gridlock on Friday afternoons, and tailbacks at motorway on-ramps.

Given that the model presented here aims to explore how the spatial activities of offenders might affect trends and patterns of offending, the model presented aims to approximate a transport network of some form. While this representation may not require a complex hierarchy of pedestrian, private vehicle, and mass transit networks as observed in reality, it is important that it imposes these spatial constraints on the activities of individuals that move around it.

Appropriate Complexity

In developing a simulation environment, two distinct approaches can be utilised in the representation of a transport network. The first option is for a model to make use of one or more GIS data sets to replicate an environment from some locality in the real world. In such models, offenders move around transport networks dictated by real street and intersection data. In implementing these environments, researchers need not worry whether the representation of a transport network sufficiently reflects transport networks in the real world, as it is from these that they are directly derived. Real world environments have been utilised in a number of simulation models of offending to varying degrees. Birks, et al. (2008), Brantingham, et al. (2008), Groff (2007b), Wang, et al. (2008), for example all integrate real transport network data to generate simulation environments, coupling GIS with ABMs of offending.

The alternative approach is for a model to utilise a hypothetical transport network. Commonplace within much ABM research, artificial environments are generated by the simulation experimenter and aim to offer appropriate simplifications of complex infrastructures found in the real world. Like many of the decisions that must be made in developing a computational model of any kind, both approaches have their strengths and weaknesses. These are often dependant upon the ultimate aims of the model, and the framework around which its results are to be interpreted. For the purposes of the explanatory model presented here, an abstract transport network is proposed. This choice reflects a want to avoid a number of potential problems a study of this type might experience as a result of making use of a real environment. A summary of these follows[2].

1. When real GIS data are used to generate simulation environments, it is often the case that only a single environment is used. This is understandable - the 'digitisation' process of real GIS data sets can be difficult, time consuming and relies on the availability of good quality data. By focusing on a single or few environments it can be difficult to make inferences that the patterns of crime being observed in a specific simulation are indicative of the mechanisms under study and not an artefact of a specific environment (Elffers & Van Baal, 2008). Indeed, this is a problem commonly encountered in traditional experimentation. One of the distinct advantages of simulation is that it offers absolute manipulation and thus the ability to manipulate the environment and examine the extent to which observed relationships are consistent over differing environmental settings.

[2]While the following comments relate to the use of GIS data to specify a transport network within the model, the majority could be equally well applied to other complex environmental features drawn from real data.

2. If models are to use real GIS data sets to represent a transport network, appropriately specified agent behaviours that can read, parse and navigate such a network must be developed. Such wayfinding algorithms are not insignificant and can be difficult to design and test.

3. As a direct result of the above observation, the use of real environmental data can also be computationally very demanding, limiting both the number of simulations a model can be used to explore in a reasonable amount of time, and the software packages that can be used to develop such models, which will most likely require some explicit support for GIS linkage[3].

4. The notion of a predictive crime computer is one that is understandably alluring. It is suggested that the use of real environmental data may encourage the examination of simulation outputs through the lens of prediction. The ability to view simulated crime hotspots in real housing estates, neighbourhoods and cities and compare them to empirical patterns is of considerable utility. However, the presence of one realistic element (albeit a highly visible one) does not make a realistic model. In order to derive actionable predictive value from model outputs all other model assumptions must be equally well specified and often such verification is difficult or impossible to undertake.

Having outlined the rationale behind the transport network developed, we now describe its characteristics, constituent components and the constraints it imposes on agents within the model.

Transport Network – Computational Specification

In attempting to approximate the spatial constraints the transport network exacts on a population, the model developed provides a simplistic transport network around which all agents must navigate in order to move from one location to another within the environment. This transport network is represented as a series of discrete transport nodes. These nodes can be thought of as the intersections of some hypothetical road network, such that whenever an agent moves from one location to another it does so from one transport

[3]This observation is rapidly becoming less important as agent-based development environments mature.

node to another. In navigating this transport network, all agents follow a principle of least effort in reaching their destination and all proximal nodes are considered connected (this wayfinding behaviour employed by agents is described in section 5.6.1).

Transport Network Initialisation Conditions

When a simulation is initialised, the user specifies the number of transport nodes required to make up the transport network. Transport nodes are then randomly distributed throughout the environment, thus permitting the model to explore the impact of specific mechanisms over a range of different environments. Only a single transport node can be located at any position on the environmental lattice. Figure 5.2 depicts an example transport network made up of 10 transport nodes.

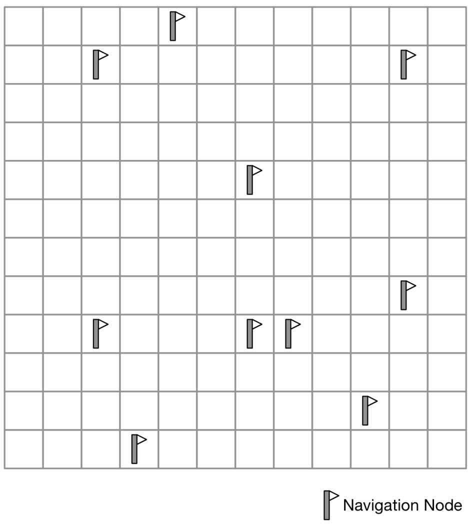

Figure 5.2: Example Transport Network

Having outlined the transport network around which offender agents navigate, a description of the potential targets they encounter is now provided.

5.4.2 Potential Targets

The first model variant described in this chapter aims to emulate offending against targets that do not move. In this case we assume that such targets represent potential opportunities for residential burglary.[4] The targets for residential burglary are residential dwellings. Dwellings offer a range of overt and covert cues about their suitability as targets for crime (Bernasco & Nieuwbeerta, 2005). For instance, some dwellings may lack appropriate security, offer little natural surveillance or be perceived as containing desirable rewards. Conversely, other dwellings may be difficult for an offender to access, or to do so without being detected, or may simply not be perceived as offering sufficient rewards to expend the effort associated with victimising them. Thus, in modelling offending the model must contain potential targets for offenders to evaluate. Furthermore, such representations must permit the characterisation of different target properties, dictating that some targets are more attractive to offenders than others.

Potential Targets – Computational Specification

Within the first model variant potential targets for offending, i.e. residential dwellings are represented as spatially static agents. As offender agents navigate the environment these dwellings are encountered and assessed for suitability as targets for crime. Each target stores a number of parameters relating to its characteristics and current state. A description of these follows.

Target Location: Targets are located at a specific location within the environment, this location is described as a simple co-ordinate pair (x, y) describing the target's position on the environmental lattice.

Target Utility: In addition to its location in the environment, each target stores a parameter relating to its relative suitability as a criminal opportunity. This multivariate indicator is expressed as a target's *utility* and aims to

[4] Although these targets might equally well approximate other static opportunities for crime, such as parked vehicles.

combine the measures of risk, reward and effort associated with its victimisation as outlined by the rational choice perspective. It is this utility value that offender agents employing the rational choice behaviour (described in section 5.6.5) draw upon to assess the suitability of a given target. Utility is represented as a floating point number ranging between zero and one. In conceptualising target utility in this fashion, as target utilities tend towards one targets offer the greatest rewards to offenders while presenting little effort or risk in exploiting them. Conversely, as target utility approaches zero the rewards associated with a target become minimal and/or the effort and risks associated with obtaining them considerable.

Target Victimisation History: Each target stores a record of all victimisation it has experienced during the current simulation. This record includes the simulation time at which victimisation occurred and data pertaining to the offender responsible and their associated characteristics.

Target Initialisation Conditions

When a simulation is initialised, the user specifies the number of targets to be modelled. In the same way that transport nodes are randomly distributed throughout the environment, so are targets. However unlike transport nodes, when targets are initially distributed multiple targets may be located at the same location. This conceptualisation aims to emulate the fact that some locations may offer multiple offending opportunities – these might include flats, apartment complexes or attached dwellings in which several distinct residences exist in the same location. Once targets have been placed within the environment a randomly generated utility value is associated with each. Figure 5.3 below illustrates an example spatial distribution of residential dwellings.

Having described both the transport network that facilitates movement within the environment, and the characteristics of potential targets found within it, the following section provides a description of the agents that make up the model's population of potential offenders and through which the mechanisms of the opportunity theories are explored.

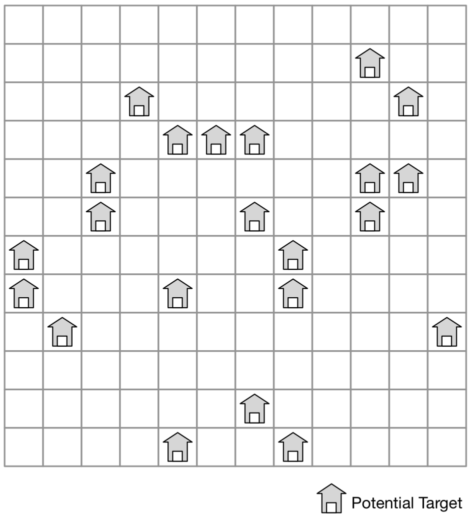

Figure 5.3: Example Target Distribution

5.5 Offenders as Agents

As previously discussed, traditional empirical approaches that aim to gain insight into individual-level offender behaviours may employ a wide range of analytical approaches, these include the analysis of recorded crime data and victimisation surveys; interviews and surveys of known offenders; and evaluations of those interventions which aims to manipulate such purported mechanisms.

In contrast, the ABM approach allows the researcher to synthesise a population of potential offenders, specifying their defining characteristics, preferences and behaviours in order to examine the potential ramifications of these hypothesised constructs. Following this approach, the model represents a discrete population of potential offenders[5] as agents. Each offender agent has its own unique characteristics and acts autonomously based on a series of behaviours defined by the opportunity theories. Given some initial conditions these offender agents then travel around the model environment assessing potential opportunities for offending as they are presented and vic-

[5]While it is acknowledged that it may be acceptable to describe every member of the population as a potential offender, much in the same way one might also be described as a potential vegetarian, for parsimony's sake the model simulates a discrete group of active offenders.

timising those targets deemed sufficiently suitable. Following Cornish and Clarke's (2003) typology of offenders, these offender agents aim to mimic the characteristics of the "mundane" offender who targets those victims that are opportunistically encountered.

Offender agents are made up of three distinct elements, (1) a series of parameters describing their pervasive characteristics - i.e. those which remain fixed throughout a simulation; (2) a series of variables describing their current internal state – i.e. those data which change to reflect the current state of an offender agent; and (3) a series of behavioural algorithms which define how an offender agent acts in particular circumstances. Figure 5.4 below provides an overview of these key offender agent components.

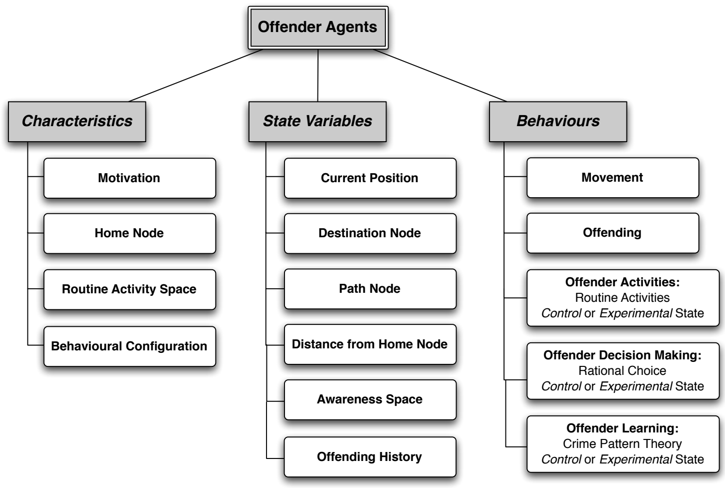

Figure 5.4: Offender Agent Architecture

The following section specifies each of these offender agent characteristics, states and behaviours.

5.5.1 Offender Characteristics

Offender agents store a number of parameters describing their characteristics, these denote features of an offender agent which are set at simulation initialisation and do not change over time as the simulation progresses.

Motivation: The motivation characteristic represents an offender's predisposition to offend at any given time. This value is used in all calculations relating to the decision to offend. Given the probabilistic nature of the model, motivation is simply represented as a probability that an offender is currently motivated to offend *p(motivated)*. As motivation increases offenders are more likely to offend when presented with suitable opportunities. In order to separate the impact of motivation from the fundamental mechanisms studied, in the initial model presented motivation is held static across all offender agents and does not change over time.

Home Node: An offender's home location as allocated at simulation initialisation. It is from this node that an offender begins activities, and in turn, returns to after activities are completed. Furthermore, it is from the home node that all journey to crime distances are calculated.

Routine Activity Space: Each offender's routine activity space defines a series of commonly visited locations. These might encompass an agents place of work, preferred commercial establishments and commonly visited recreational venues. Such routine activity nodes are represented as a list of transport nodes. It is these routine activity nodes that the routine activity behaviour (section 5.6.4) draws on to set out spatial activities for an agent.

Behavioural Configuration: The behavioural configuration of an offender agent denotes the state of each of the three key experimental behaviours (see section 5.6.3). The behavioural configuration of an offender agent is represented as a three digit binary code in the form of 111 or 010 etc., each digit referring the (1) experimental or (0) control state of the three experimental behaviours: routine activities, rational choice and awareness spaces respectively. In combination, the configuration of these three key behaviours describes a single hypothetical offender agent decision calculus.

5.5.2 Offender State Variables

In addition to the static characteristics, each offender agent stores a series of variables that reflect their current state, and change as the simulation progresses. These state variables keep track of an offender agent's current goals, perceptions, awareness and a record of previous actions undertaken within the simulation.

Current Position: An offender agent's current location on the environmental lattice. This is stored as a pair of co-ordinate values (x,y).

Destination Node: The destination transport node of the offender agent's current spatial activity, as specified by the wayfinding behaviour currently employed.

Path Node: The current way-finding destination of an offender agent. The current path node reflects the next transport node an offender agent must travel to in order to reach the destination node of their current spatial activity. To illustrate, if an offender agent's ultimate destination is transport node 12 but must travel through nodes 3, 6 and 22 to reach this location the path node variable keeps track of the current way-finding destination – i.e. 3 then 6 then 22 then 12.

Distance from Home Node: The Euclidian distance between an offender agent's home node and their current location within the environment. When an offence occurs this variable is used to calculate the journey to crime distance.

Awareness Space: A simple representation of an offender agent's awareness of the environment. This awareness space mirrors the environmental lattice, such that each cell within the lattice has an associated awareness described by a probability that an offender is sufficiently aware of that location to exploit targets for offending within it *p(aware)*. The awareness of a given location is proportional to the time spent at that location (this learning mechanic is described by the awareness space behaviour discussed in section 5.6.6).

Offending History: A record of all offences committed by the offender agent within the current simulation. This includes data relating to targets victimised, their location, associated utility and the cycle at which victimisation occurred.

Having outlined the key characteristics and variables that both describe our offender agents and allow them to keep track of their current state within a specific simulation, the following sections provide a description of the behaviours that draw upon both these data and cues from the local environment to determine how offender agents act as a simulation progresses.

5.6 Offender Agent Behaviours

The actions offender agents take within the simulation are defined by a number of key behavioural formalisms. These behaviours outline an offender agent's decision calculus and the actions offender agents take in particular circumstances during a simulation. The model implements five key offender agent behaviours, two general behaviours employed by all offender agents: (1) a *wayfinding behaviour* which describes how offender agents use the transport network to go about their spatial activities, and (2) an *offending behaviour* that outlines the circumstances under which offender agents choose to commit crime. In addition to these two behaviours a further three experimental behaviours are employed by offender agents. In attempting to assess the generative sufficiency of the opportunity theories, these behaviours aim to approximate the three distinct hypothetical mechanisms discussed in section 2.1, outlining how offender agents choose appropriate spatial activities to undertake (routine activities), reason about potential targets encountered (rational choice) and learn about their environment (awareness spaces). When offender agents are initialised each of these experimental behaviours can be set in one of two states; an experimental state in which the hypothetical mechanism of interest is enabled and thus employed by an agent; and a control state where the mechanism is disabled and an appropriate counterfactual mechanism is employed.

The following sections outline these behaviours, beginning with a description of the wayfinding behaviour that describes how all agents utilise the transport network in undertaking spatial activities.

5.6.1 Agent wayfinding behaviour

As previously discussed, the model environment includes a series of transport node objects that emulate a transport network around which agents must navigate in order to go about their day-to-day activities. These transport nodes impose spatial constraints on agent wayfinding typical of a real world transport network. The wayfinding behaviour employed by all agents describes the decision-making process associated with proceeding between an agent's current location and their ultimate destination in the simulation environment[6]. In designing and implementing a suitable wayfinding behaviour three rudimentary observations regarding human navigation were considered:

1. *Navigation between origin and ultimate destination is not typically Euclidian in nature – instead, paths between locations are dictated by the available transport network linking origin and destination;*

2. *The principle of least effort – in general people attempt to minimise the distance travelled in reaching their destination;*

3. *Human wayfinding is not deterministic – i.e. the above application should not become an absolute optimisation problem - from time to time people are likely to take different (but plausible) routes between locations.*

To illustrate Figure 5.5 depicts four potential navigational paths linking transport nodes 1 and 2 in a simple environment. Path A violates observation 1 – in that navigation is purely Euclidian; both paths B and C are congruent with the above observations; path D contains unnecessary backtracking and as such does not conform to a principle of least effort.

[6] The movement behaviour presented here simply describes how agents move between any two transport nodes within the environment, and not how an appropriate destination node is selected – this behaviour is outlined by the routine activity mechanism described in section 5.6.4.

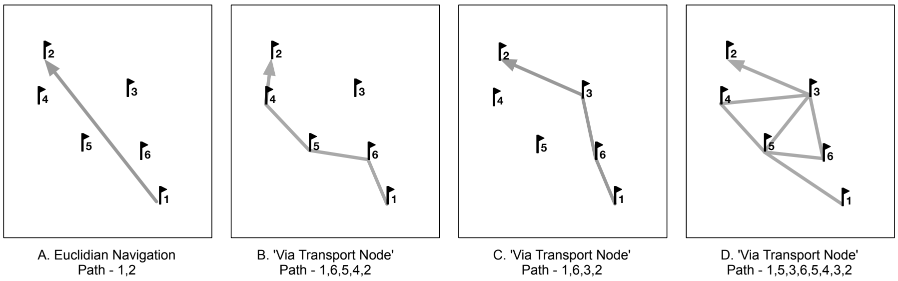

Figure 5.5: Example Agent Wayfinding

While there is considerable research within the field of human wayfinding, and in turn its computational simulation (see for example (Torrens et al., 2012) for a recent review of several implementations), here, in an attempt to reflect the abstract nature of the model developed a simple but novel wayfinding behaviour is presented, permitting dynamic agent wayfinding between any two locations within the environment via the transport network. In operating this behaviour, agents continually survey their local environment and select how best to proceed towards their ultimate destination by designating transport nodes, found to be both close and in the general direction of their ultimate destination, as temporary *path nodes*. Wayfinding between the current location and ultimate destination is then made up of a series of discrete trips between local transport nodes. This wayfinding behaviour is defined by a series of simple actions:

1. Face ultimate destination node;
2. Perceive local transport nodes in cone-of-vision;
3. Select a transport node from cone-of-vision as the current path node (if multiple nodes exist - select one at random, if no nodes exist - extend cone-of-vision);
4. Move towards current path node by one increment per cycle until the current path node is reached;
5. Repeat cycle until destination node is reached.

To illustrate, Figure 5.6 depicts a single offender agent applying this behaviour over multiple simulation cycles to move from transport node 1 to 2.

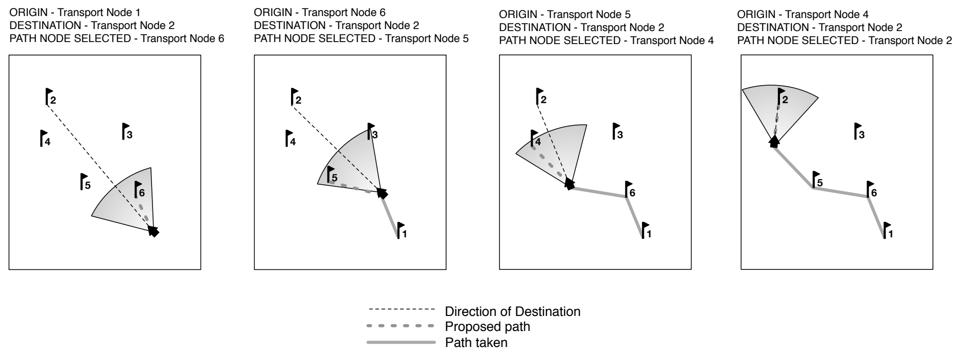

Figure 5.6: Agent Wayfinding Behaviour Example

Testing

Having implemented this behaviour a series of simulation vignettes were run allowing offender agent wayfinding to be scrutinised under a number of different conditions. This process of model verification ensured that the wayfinding behaviour produced ecologically plausible results in keeping with the observations previously discussed. Such vignettes constituted creating a simple environment, inhabiting it with a single or multiple offender(s), specifying both origin and destination nodes, and then examining the path selected by that agent in moving between these two locations.

Having described the offender agent wayfinding behaviour, the following section outlines the circumstances under which offending can occur within a simulation.

5.6.2 Agent Offending Behaviour

As offender agents navigate the environment, they come across potential targets for offending represented by the target objects previously described in section 5.4.2. The following section outlines an offending behaviour employed by all offender agents that draws both its key mechanisms, and logical construction, from the opportunity theory's depiction of offending. This behaviour draws on three further experimental behaviours employed by offender agents, each dictating a component of the proposed offending decision calculus. These experimental behaviours, that are subsequently described, constitute the "theoretical switches" that can be thrown by the researcher (Axelrod, 1995), thus exploring the crime impacts of several differing hypothetical offender strategies.

Returning to our theoretical approach, the offender agent's offending behaviour aims to provide a mechanistic equivalent of the following opportunity-based depiction of the crime event. The routine activity approach states that for a crime to occur a spatio-temporal convergence of motivated offender, suitable target and lack of capable guardian is required. Further, suggesting that rather than searching for potential targets in unfamiliar areas, the majority of offenders commit crime as and when opportunities for offending present themselves during day-to-day activities. The rational choice perspective then proposes that in assessing the suitability of potential opportunities for offending, offenders attempt to maximise some expected utility. This utility is dictated by both an offender's own motivations and the perceptions of risk, effort and reward associated with a given criminal opportunity. However, for a target to be assessed it must first be known. Crime pattern theory describes the awareness space, a cognitive construct that defines how offenders learn about their local environment, suggesting that as knowledge of the local environment increases so does an offenders ability to take advantage of criminal opportunities found within it. From this depiction of the crime event the following key premises are derived:

1. *Crime can only occur when an offender is in the same location as a target;*
2. *The likelihood of crime occurring is influenced by:*
   (a) *An offender's current motivation to offend;*
   (b) *The perceived utility associated with a target (encompassing risk, reward and effort);*
   (c) *An offender's knowledge of the local environment.*

Given this logical assembly of theoretical approaches, a simplified but equivalent offender agent decision calculus that estimates the suitability of a given criminal opportunity[7] is developed. This model can be formally expressed

[7] In this abstraction the assumption is that increases in motivation, target attractiveness and local knowledge all increase the likelihood of offending.

as follows:

$$O_{(x,y,t,\alpha,\beta)} = m_{\beta}^{b_1} \left(\frac{w_{\alpha}^{b_2}}{s_{\alpha}^{b_3} f_{\alpha}^{b_4}} \right) k_{(x,y,t)}^{b_5} \tag{5.1}$$

Where O is some measure of the criminal opportunity found at a convergence of target α and offender β at location *(x,y)* and time t; m is a measure of offender motivation; w the reward; s the risk; and f the effort expected in victimising target α; k an offenders knowledge of the local environment; and weightings b_i the importance that each of these constituent components play in the decision to offend.

For the model developed, the above method is further simplified into a likelihood function[8]. Firstly, metrics of reward, risk and effort are collapsed into a single measure of target utility congruent with the target characteristic previously described in section 5.4.2. Furthermore, given the rational choice perspective's proposition that the presence of a potential guardian increases the risks of detection perceived by offenders, the presence or absence of guardianship is assumed to be captured by the measure of target utility. Thus, targets that have a low utility may do so due to the presence of a potential guardian or place manager[9]. Finally, we assume that weights b_i are all equal.[10]

Each of the above elements of motivation, utility and awareness are then represented as a probability that each criterion is sufficiently met. Thus, the likelihood of victimisation, given a convergence of offender agent and target is expressed as a product of the probabilities that (1) a suitably motivated offender $p(m)$; (2) finds a target of sufficient utility $p(u)$; (3) of which they are sufficiently aware $p(k)$.

$$p(victimisation) = p(m) \cdot p(u) \cdot p(k) \tag{5.2}$$

This proposed model of victimisation can be used to examine the influence

[8]Here we make the assumption that the decision to offend is probabilistic and given the same set of circumstances offenders will not always choose the same course of action.

[9]It is acknowledged that this representation of guardianship fails to capture its dynamic qualities (in that some targets may be guarded at some times and not at others) future studies aim to explore this mechanism in further detail.

[10]While this may well not be the case, it is a logical starting point from which to explore these mechanisms.

of four distinct mechanisms on the occurrence of crime:

1. *The spatio-temporal convergence of victim and offender;*
2. *An offender's motivation to offend;*
3. *An offender's reasoning regarding target utility;*
4. *An offender's awareness of their local environment.*

5.6.3 Experimental Offender Agent Behaviours Overview

With the above overarching offending behaviour in place and these four elements in mind, a series of experimental behaviours were developed, each formalising a theoretical mechanism as described by the opportunity theories. From which the probabilities described in the equation above are derived.

- A *movement* behaviour that outlines spatial activities for all offender agents, and thus dictates where and when offenders and targets converge;
- A *reasoning* behaviour derived which describes how offender agents estimate the utility associated with a presented target;
- A *learning* behaviour that describes how offender agents gain awareness of the locations they visit.

The following sections present a description of each of these behaviours further explicating a *theoretical model* – the mechanism described by theory from which it is derived; a *conceptual model* – a number of key premises derived from the theoretical model; and a *computational model* – the methods through which these key premises are implemented within the ABM. Furthermore, an experimental model condition where the behaviour is enabled, and a control model condition where it is disabled are described.

5.6.4 Offender Agent Behaviour: Routine Activities

Theoretical Model

A key tenet of the routine activity approach states that it is the spatial and temporal characteristics of everyday activities which dictate when and where both offenders and victims are found, when they converge with one another, and as a result when and where crime tends to occur. These day-to-day activities are focused around a number of commonly frequented locations, often referred to as routine activity nodes, which form an individual's activity space. Routine activity nodes include an individual's home, place of work and other commonly visited locations such as recreational venues and/or the homes of friends, family etc.

While all of these locations are visited on a regular basis it is unlikely that such routine spatial activity occurs in an arbitrary order. For instance, most individuals do not travel between work and recreational nodes repeatedly without at some point returning home. In considering human spatial behaviour Golledge and Spector (1978) characterise environmental knowledge acquisitions and, in turn, navigation as 'anchor-point' based, in that many activities start and end at a single node, commonly the home. Furthermore, people tend to either live near to their current activity nodes or develop new activity nodes near to their home location.

Conceptual Model

Given these observations the routine activity behaviour developed aims to formalise the following conceptual model:

1. *Human movement is for the most part characterised by a small number of routine spatial activities that are undertaken repeatedly;*
2. *Most spatial activities are anchor-point based at the home;*
3. *Routine activity nodes are typically located relatively near to home.*

Computational Model

Given these hypotheses the key micro-level action the model aims to emulate is that of the routine activity. In doing so the model allocates all offender agents both a home node and a series of routine activity nodes. A routine activity behaviour is then employed which allows agents to plan routine activities between these nodes in an ecologically plausible fashion.

Experimental Condition - Routine Activities: Enabled

When the routine activity behaviour is enabled all offenders are allocated both a home node and a series of routine activity nodes. These nodes are selected as follows: each agent is first initialised at a random lattice location p within the environment. In reflecting premise 3 of the conceptual model, five transport nodes within distance d of p are randomly selected (d here represents the maximum extent of an individuals activity space within the environment). From these five transport nodes one is randomly selected as an agent's home location. The remaining nodes denote the routinely visited locations of that agent – the agent's routine activity space. Figure 5.7 illustrates the selection of routine activity nodes from some initial location p.

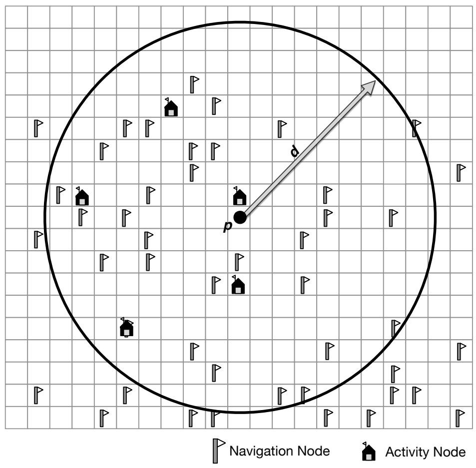

Figure 5.7: Activity Space – Routine Activities *Experimental Condition*

When a simulation begins all offender agents begin at their home location and plan spatial activities using the following simple rules outlined in Figure 5.8 which aim to capture the conceptual model described above.

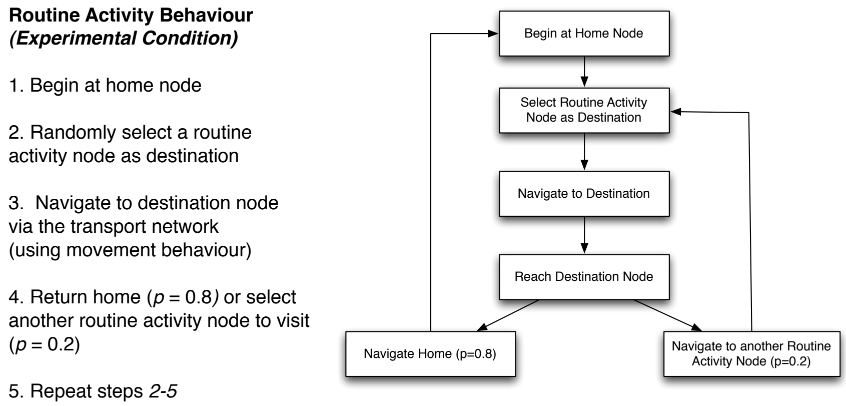

Figure 5.8: Routine Activity Behaviour – *Experimental Condition*

Control Condition - Routine Activities: Disabled

The control condition of the routine activity behaviour provides a counterfactual behavioural state, in which offenders do not undertake routine spatial activities. In this state offender agent's are again initialised at a randomly selected lattice p and select a home node at random. Subsequently, agents move randomly between all transport nodes within their activity space as defined by d[11] (see Figure 5.9).

[11] Note that d is the same distance that those agents with the routine activity behaviour enabled choose transport nodes from within. This ensures that the maximum extents of offender activity spaces under both experimental and control conditions are the same, thus permitting direct comparison between behavioural configurations.

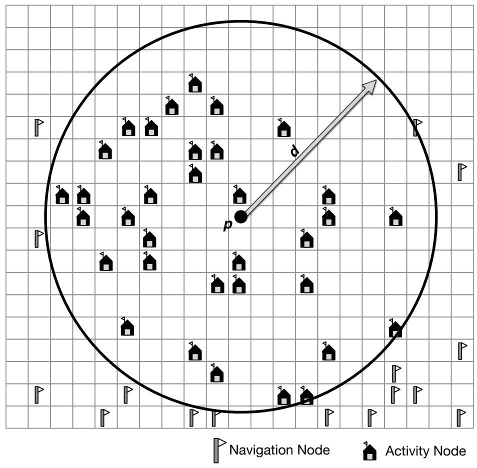

Figure 5.9: Activity Space – Routine Activities *Control Condition*

Agents operating under the control condition plan activities using the following rules detailed in Figure 5.10.

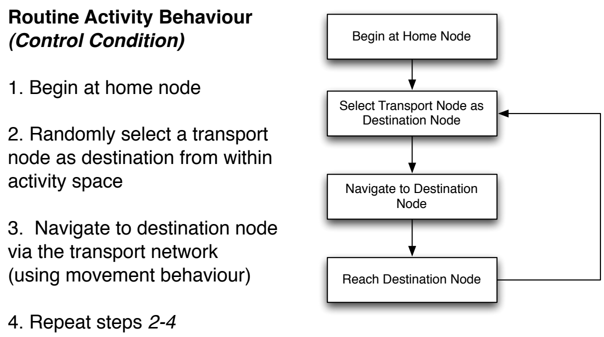

Figure 5.10: Routine Activity Behaviour – *Control Condition*

To further illustrate the resultant impact of these behaviours on agent activities, Figure 5.11 depicts the respective movement paths of a single offender operating under both the experimental and control conditions.

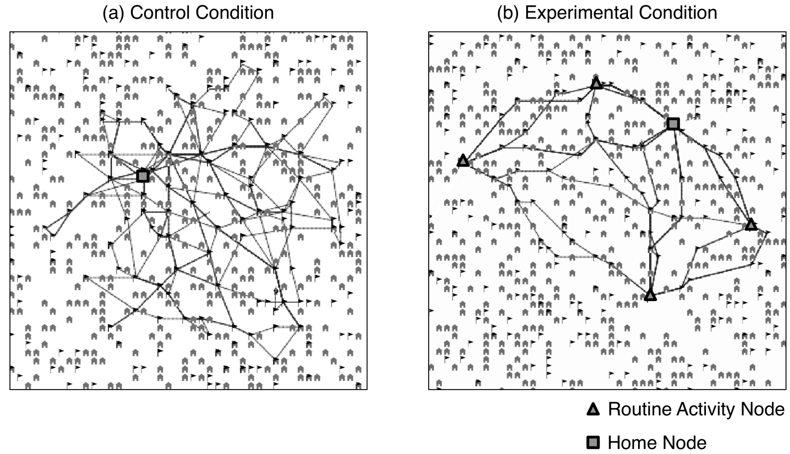

Figure 5.11: Movement Paths of a Single Offender Operating under Routine Activities Control (a) and Experimental (b) Conditions.

Having described the routine activity behaviour that dictates the spatial activities agents undertake within the environment, the following section outlines an agent behaviour derived from the rational choice perspective that allows offender agents to reason about the suitability of potential targets they encounter.

5.6.5 Offender Agent Behaviour: Rational Choice

Theoretical Model

The rational choice perspective describes a decision calculus employed by offenders to assess the suitability of potential targets. This calculus encompasses assessments of the effort required by the offender in victimising a given target, the risks of detection involved in doing so, and the rewards likely obtained as a result. Applying this calculus the rational choice perspective proposes that offenders attempt to optimise expected utility by maximising reward while minimising effort and risk.

Thus, a fundamental implication of the rational choice perspective is that some targets are more attractive to offenders than others. Indeed, given the application of such selection mechanisms we would expect to observe that offenders are most likely to select those targets which are deemed least risky, require least effort and result in the greatest rewards. Given this hypothesis the offender agent rational choice behaviour aims to formalise the following key premises of the rational choice perspective:

Conceptual Model

1. *Target utility is heterogeneous;*
2. *Offenders perceive the rewards, risks and effort associated with victimising a given target in an attempt to maximise utility;*
3. *Those targets that offer the greatest utility are most likely to be victimised.*

Computational Model

Formalising the above conceptual model, a single multivariate parameter is exhibited by all targets characterising the rewards, risks and effort associated with their victimisation. As above, we denote this parameter as a target's utility (see section 5.4.2). As utility increases targets offer substantial rewards while presenting little effort and/or risk, and visa versa. When an offender agent converges with a target its utility is perceived and then used in the offending behaviour equation described in section 5.6.2. Ranging between zero and one, target utility is defined as the probability an offender agent will find a target sufficiently attractive. To illustrate, given a relatively attractive target ($utility = 0.8$) there is a high probability ($p = 0.8$) that the offender in question will find it sufficiently attractive.

Experimental Model Condition – Rational Choice: Enabled

Under the experimental condition all targets within the environment are randomly allocated a utility score between zero and one at simulation initialisation. Thus target utility is heterogeneous.

Control Model Condition – Rational Choice: Disabled

Under the control model condition offenders agents do not assess the relative merits of a given target. Thus, target utility is homogenous and consequently all targets offer equal utility to all offender agents (default = 0.5).

To illustrate Figure 5.12 depicts an example environment under both experimental and control conditions.

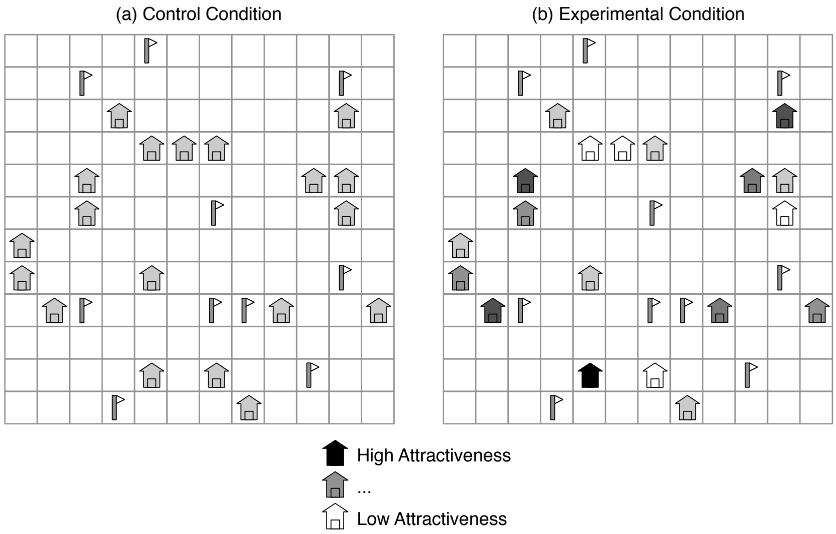

Figure 5.12: Perceived Target Utility under Rational Choice Control (a) and Experimental (b) Conditions

The previous two behaviours have outlined how offender agents within the model move and encounter targets, and subsequently how they perceive their suitability as criminal opportunities. The next section outlines a final behaviour drawn from crime pattern theory's depiction of the awareness space that allows offender agents to learn about their local environment, and, in turn, gain an advantage in offending within those areas that are cognitively known.

5.6.6 Offender Agent Behaviour: Awareness Spaces

Theoretical Model

Crime pattern theory proposes that crime is most likely to occur in areas known to offenders that contain attractive opportunities for offending. Furthermore such cognitively known areas, commonly referred to as an offender's awareness space, are typically located in close proximity to the routine activity nodes of an individual and the paths travelled between them. As an offender spends more time in an area, their awareness of that locality and the opportunities for crime within it increase, reinforcing certain decisions and developing localised templates for successful offending. Given these hypotheses the awareness space behaviour employed by offender agents aims to capture the following key premises.

Conceptual Model

1. *Offenders learn about their environment;*
2. *Knowledge of the local environment increases with time spent there;*
3. *Knowledge of the local environment aids in the commission of crime.*

Computational Model

The model explores the impacts of this cognitive mapping mechanism by providing each offender agent with an awareness of their environment that develops with experience. This awareness space is represented as a spatially referenced two-dimensional matrix of awareness scores ranging from zero to one, mapping directly to the environmental lattice. Such awareness values describe the likelihood that an offender agent will be sufficiently aware of criminal opportunities found at a given location to take advantage of them. For example, given a 3x3 environmental lattice, each offender agent stores an awareness space consisting of nine awareness values. To illustrate, Figure 5.13 depicts such an environment, a spatially orientated depiction of a single offender agent's awareness of it, and the equivalent internal representation stored by the offender agent as an array of awareness scores.

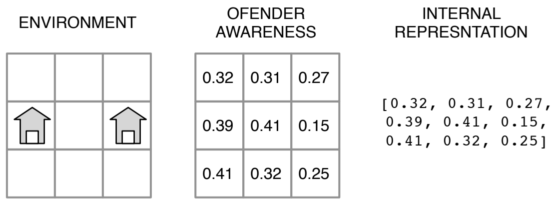

Figure 5.13: Example Offender Awareness Representation

Experimental Model Condition – Awareness Spaces: Enabled.

Under the experimental model condition, as offender agents move across the environment their awareness of visited locations increases. The relationship between time spent at a location and agent's awareness of it is modelled by a common logistic function. Thus, an agent's awareness of any given location can be expressed as:

$$Awareness_{(x,y)} = \left(\frac{1}{1 + e^{-\left(\frac{t_{(x,y)}}{b}\right)}} \right) \tag{5.3}$$

Where $t_{(x,y)}$ is the time spent at location (x, y) and b is the rate at which offender agents learn about the locations they visit.[12]

Control Model Condition - Awareness Spaces: Disabled.

Under the control model condition, offender agents do not build up experience of previously visited location – thus, awareness is static. All agents begin the simulation with a uniform awareness of all locations (default = 0.5). Figure 5.14 graphically depicts the awareness space of a single offender agent under (a) the control and (b) experimental conditions.

Having specified the individual components that make up the model, the following section provides a description of how these model elements interact as a simulation progresses – the simulation logic.

[12]The learning rate of offenders was held static over all simulation configurations, but could be manipulated in further experiments.

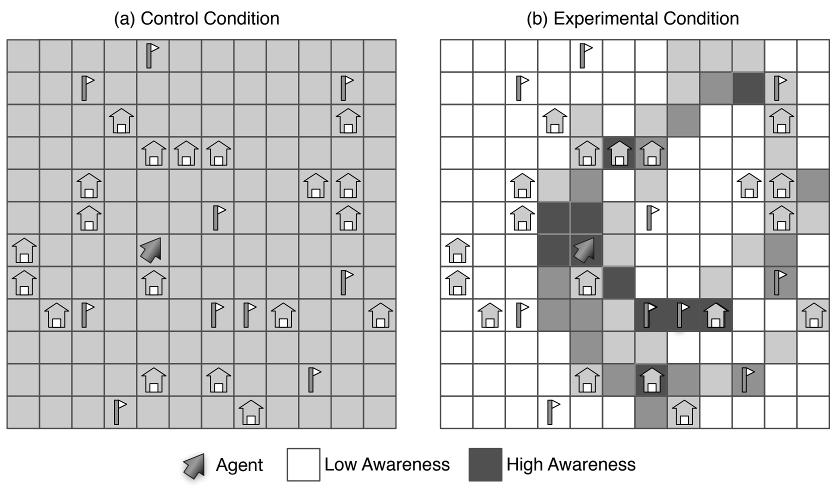

Figure 5.14: Awareness Spaces of a Single Offender Operating under Awareness Spaces Control (a) and Experimental (b) Conditions

5.7 Running Simulations with the Model

The ability to examine systems whose behaviour develops over time is a key attribute of the ABM methodology. Within an ABM time progresses in a series of discreet increments referred to as simulation cycles. At each simulation cycle the model emulates the actions of all agents (which involves each agent undertaking its own cycle of actions – discussed below), and updates a number of internal data structures that record the state of the simulation for both real time visualisation and further analysis once a simulation is complete. A simulation continues until its termination conditions have been met – when this occurs all data relating to the longitudinal action of model elements is then exported to a simulation output data file. Given that the simulation progresses via a sequence of repeated cycles in which all agents perform a further cycle of actions which describe their behaviour for a single artificial time step, the model itself can be seen as a series of iterative embedded cycles. Figure 5.15 provides an illustration of this overarching simulation cycle.

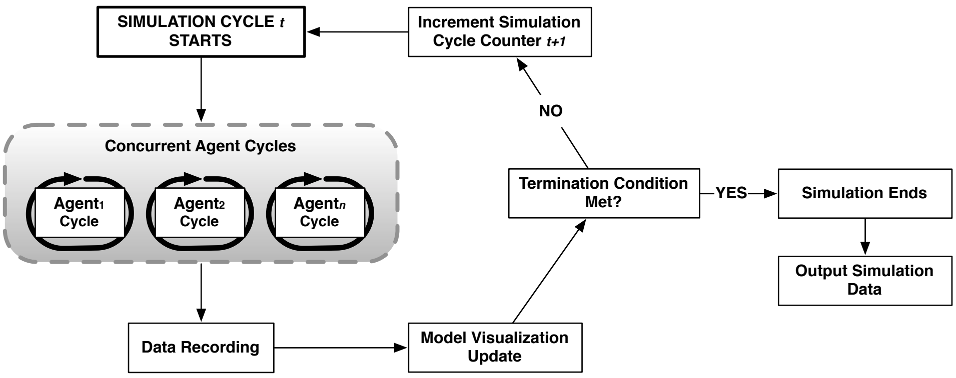

Figure 5.15: The Simulation Cycle

5.7.1 The Simulation Cycle

A simulation cycle consists of the following steps:

1. At the start of each simulation cycle t all agents within the model concurrently perform their agent action cycle (see section 5.7.2).
2. Once all agent activity is complete, output data from the current cycle is collated and where appropriate output to real time simulation output plots and the graphical window.
3. The model checks to see if the simulation termination criteria have been met. For instance if a simulation is to be run for 2000 cycles and $t = 2000$ the simulation ends and outputs all relevant data.
4. The model then increments the cycle count $(t + 1)$

5.7.2 The Agent Cycle

At each simulation cycle every agent concurrently undertakes their own agent cycle - moving, checking for potential offending opportunities, and (when the awareness spaces behaviour dictates) learning about their local environment. Figure 5.16 provides a stylised overview of the key elements of this cycle and the order in which they occur. Subsequently a description of each of the stages of action is provided.

1. **Movement** – All offender agents begin their agent cycle by moving.

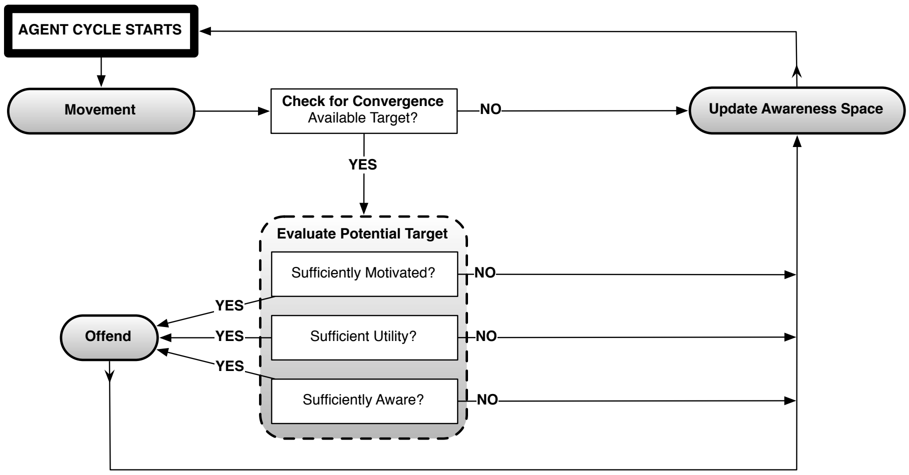

Figure 5.16: The Agent Cycle

As previously described, offender agent movement is specified by two key behaviours: the routine activity behaviour (section 5.6.4) which establishes the overall destination of an offender agent's current activity; and the offender agent wayfinding behaviour (section 5.6.1) which performs real-time way-finding in moving to this selected destination via the transport network. Dependant upon an offender agent's current location the movement element of the cycle involves either moving a single increment towards the current path node, or selecting a new path / destination node and then moving a single increment towards it. What is important is that the first action an offender agent takes at each cycle is to move.

2. **Check for Convergence** – Having moved, an offender agent's next course of action is to check to see if a potential target is present at their new location. If there is no target present, the offender agent skips to step 5 of the agent cycle. Similarly, if a target is present but is being victimised by another offender the offender agents skips to step 5[13]. If an available target is present at the current location the offender agent moves onto the next step in the agent cycle in which the target is assessed for suitability.

[13]This check ensuring that no target can be victimised at the same time by more than one offender (subsequent models may use this mechanism to explore co-offending).

3. **Evaluate potential target** – Having identified a potential target the offender agent activates the offending behaviour to estimate the probability that an offence will occur. Using this behaviour the offender agent evaluates its current motivation $p(m)$ and awareness of the current location $p(k)$ and perceives the associated utility of the target itself $p(u)$. Using the offending model described in equation 5.2 (section 5.6.2) the likelihood of victimisation is calculated as follows.

$$p(victimisation) = p(m) \cdot p(u) \cdot p(k)$$

4. **Offending** – Given $p(victimisation)$, a random number generator is then used to probabilistically determine if victimisation occurs. In cases where the offender agent does choose to victimise the given target a number of internal representations are updated to reflect that offending has occurred. These include updating the offender agent's offending history, the target's victimisation history, and incrementing the global victimisation counter. In addition, a row of data describing all features of the victimisation is written to a simulation output data file.

5. **Learning** – Depending upon the state of the awareness spaces behaviour the final stage of the agent cycle involves each offender agent updating its internal awareness space (described section 5.6.6) to reflect knowledge gained of the current location.

6. **Cycle ends**

Agent Concurrency

The agent cycle described above sets out the actions undertaken by a single offender agent at each simulation cycle. However, the model presented emulates a population of multiple offender agents. In the real world, behaviour is inherently parallel in its execution – i.e. independent individuals do not wait for other individuals to perform actions before they do so. However, given the inherent limitations of current computational architectures[14] the model

[14]This is dictated by the fact that all current CPUs operate in serial – processing one instruction at a time. While computers with multiple CPU cores are widely available – in order to implement true agent concurrency the system would require a CPU core for every agent in the model (which becomes infeasible very quickly), furthermore such im-

implements all agent activity as a pseudo-parallel process. Such concurrency of action is provided by the Netlogo development environment where a function simulates parallel action amongst all agents via a process of turn taking. This implementation allows all agents to proceed through the above agent cycle at (effectively) the same time. In operation this turn taking mechanism divides all agent activities into a series of computable sub-steps, the model then randomly orders all agents and each agent computes a single sub-step in turn, such that once the agent portion of the simulation cycle is complete all agents have performed all sub-steps of their agent cycle. It is important to note that the order in which agents takes turns is randomised at every cycle so that no advantage is conveyed to any agent in the order in which action occurs[15].

5.7.3 Simulation Initialisation & Iteration

Having described the key elements of the model developed and set out the way in which a simulation proceeds over time, the following section provides an outline of how the environment and objects within it are initialised each time the model is used to perform a simulation. Here a specific run of the model (i.e. a single sequence of set parameters, run model until termination condition, analyse output data) is referred to as a single (within-model) replication (see section 3.6.1).

Initialising a simulation requires that the researcher specify a number of model parameters that describe characteristics of the simulation environment, the agents and objects it contains, and how the offender agents within it will behave. The first step in this process involves setting the size of the environment in which the simulation will take place; this is simply specified by the dimensions of the environmental lattice to be used. Once the environmental lattice is generated, the size of the offender agent population and total numbers of targets and transport nodes that it will contain are set. Having specified these parameters, the model randomly distributes

plementations introduce considerable computational overheads in synchronising multiple CPU cores.

[15]In addition to the order of action described by the agent cycle above (move, offend, learn), the agent cycle was tested in a number of other permutations (offend, learn, move etc.) to ensure that the order of agent action did not have unintended impacts on behaviour. In all of these tests no discernible impacts on model outputs were observed.

both targets and transport nodes throughout the environment. At this point each target is then allocated an associated utility value (at a default value if the rational choice behaviour is in the control state, or at random in the experimental state). The final parameter the user specifies is to select a behavioural configuration for all offender agents within the simulation; this is done by setting each of the three experimental behaviours (see section 5.6.3) to either the experimental (enabled) or control (disabled) states described previously. Once the offender agent behavioural configuration has been set a population of offender agents is created and each is randomly allocated a home location within the environment and a series of routine activity nodes (see section 5.6.4 for further detail on how such activity spaces are selected depending upon the state of the routine activity behaviour).

Thus, while the numbers of offender agents, targets and transport nodes, and the behavioural configuration of offender agents remain static across within-model replications, in each replication the spatial distribution of transport nodes and targets, the utility associated with each target, and the home locations and activity spaces of offender agents are different. Furthermore, to ensure that model outputs are not reflective of a particular random number seed, for each replication a different random number seed is used[16]. This variability combined with the probabilistic nature of the model then dictates that in order to examine the impact of a specific behavioural configuration the model is used to run multiple simulation replications. This approach is analogous to placing a population of (behaviourally) similar offenders in a series of different environmental circumstances and examining the range of crime patterns they produce. Running the model multiple times in this way is common practice in ABM research where the outputs of a single probabilistic simulation can often be atypical (Axelrod, 2005). Furthermore, by manipulating the simulation environment at each replication it aims to minimise results being overfit to specific environmental circumstances (Elffers & Van Baal, 2008). In addition, multiple replications permit distributions of outcome measures to be generated, thus providing measures of the variability of outcomes and permitting the estimation of effect sizes between the outcomes of differing behavioural configurations.

[16]The Netlogo random number generator provides an implementation of the Mersenne Twister algorithm, commonly recognised as the most robust random number generator (Matsumoto & Nishimura, 1998).

To illustrate, the model might be used to explore the impact that the routine activity mechanism has on patterns of repeat victimisation. In this example the model would first be initialised with some set size environment and offender agent, target, and transport node populations. In the first series of replications (say 100) all offender agents operate under the routine activities experimental model condition, in the second set the world and object populations remain the same size, but the behavioural configuration of offender agents is altered to reflect non-routine activity (control state) – the model is then run again over a further 100 replications. For each replication a measure of the number of repeat victims is calculated, doing so across all 200 replications produces a distribution of 100 repeat victimisation observations for each of the two behavioural configurations. These distributions can then be analysed and the statistical differences between them, given routine or non-routine activities, identified and quantified.

5.8 Summary

This chapter has provided a description of the key components of the explanatory ABM developed to provide the primary scientific instrument for the studies undertaken in this thesis. An abstract model environment has been described which contains three key types of object – transport nodes that permit travel throughout the simulation environment; potential targets that represent potential opportunities for offending; and a population of offender agents that traverse this environment seeking out viable criminal opportunities. In specifying the offender agent population, a number of individual offender agent characteristics (a) describing the unique pervasive characteristics of each offender agent, and (b) outlining several data structures that allow offender agents to keep track of their current state and goals within a simulation, have been specified. Furthermore, a series of behaviours defining offender agent action have been presented. These encompass a way-finding behaviour that describes how the transport network is used to dynamically route agents between any two locations within the environment, and an offending behaviour that sets out the circumstances under which crime can occur within a simulation. This offending behaviour then draws on three other experimental offender agent behaviours, each inspired by a micro-mechanism proposed by the opportunity theories and identified in section 2.1 – a routine activity behaviour that outlines the spatial activities agents undertake as a simulation progresses; a reasoning behaviour derived from the rational choice perspective that allows offender agents to make decisions about the suitability of a presented target; and a learning behaviour derived from crime pattern theory's depiction of the awareness space, that allows offender agents to learn about their local environment over time, in turn increasing their ability to exploit the targets that exist within it. For each of these behaviours an appropriate counterfactual behaviour has also been presented, thus allowing the model to explore the influence each behaviour might play in the influencing the crime event. Finally, specifying how the model is used to perform simulations, a description of both the simulation and agent cycles have been provided. The following chapter now outlines a number of computational experiments performed using this model which address the key research questions of the thesis, and in turn, their findings.

6
Methods and Findings

The following chapter provides a description of the computational experiments performed using the generative ABM of crime developed, and their key findings. These experiments test several hypotheses concerning the generative sufficiency of the opportunity theories. The results of two key studies are presented, the first utilises an initial model variant that simulates crimes occurring against static targets – that is, those who do not move (e.g. residential burglary), the second study then applies a second model variant to simulate crimes occurring against spatially dynamic targets (e.g. street robbery).

In both of these studies analyses of simulated crime data are identical and divided into three discrete phases. Each explores the generative sufficiency of the identified mechanisms of the routine activity approach (movement), the rational choice perspective (target selection) and crime pattern theory (learning) formalised within the model in explaining one of three commonly observed macroscopic regularities of crime. Drawing from the focused research questions of the thesis, the following hypotheses are derived and tested using each model variant.

Focused Research Question 1 (FRQ1): *Are the mechanisms of the opportunity theories generatively sufficient to explain the spatial concentration of crime commonly observed in empirical study?*

Hypothesis 1 (H1): Crime will become more spatially concentrated as the mechanisms of the opportunity theories are activated.

Focused Research Question 1 (FRQ2): *Are the mechanisms of the opportu-*

nity theories generatively sufficient to explain patterns of repeat victimisation commonly observed in empirical study?

Hypothesis 2 (H2): Greater levels of repeat victimisation will be observed as the mechanisms of the opportunity theories are activated.

Focused Research Question 1 (FRQ3): *Are the mechanisms of the opportunity theories generatively sufficient to explain the characteristic journey to crime curve commonly observed in empirical study?*

Hypothesis 3 (H3): The journey to crime curve will become more positively skewed as the mechanisms of the opportunity theories are activated.

In testing these hypotheses, the model was used to enact a series of simulations where all model parameters were held static aside from those describing the behavioural configuration of agents. The crime patterns produced by offender populations operating under these different behavioural configurations were then examined and compared with respect to the three macroscopic regularities of interest, in turn addressing a respective hypothesis - spatial concentration (H1), patterns of repeat victimisation (H2) and the journey to crime curve (H3).

To answer focused research question 4 (FRQ4): *Do the mechanisms of the routine activity approach, rational choice perspective and crime pattern theory have differential impacts on commonly observed patterns of crime?*, descriptive and inferential statistics were then used to quantify the relative impacts of each behavioural configuration.

Finally, in addressing focused research question 5 (FRQ5): *Do these results differ by crimes that occur against static or dynamic targets?*, the results of experiments performed using both model variants are then compared.

6.1 Model Experimental Configurations

In specifying the hypothetical offender calculi to be manipulated, an offender's behavioural configuration is described by the state of the three experimental agent behaviours: routine activities, rational choice and awareness spaces, each of which can be employed in both a control (disabled) and experimental (enabled) state. Applying a traditional 2 by 2 by 2 experimental design, 500 within-model replications were run for each of these eight distinct model configurations. These experiments were duplicated for both model variants. Table 6.1 provides a summary of each of these configurations. In each replication a simulation was run until the offender population

Table 6.1: Model Experimental Configurations

		Model Configuration							
Theoretical Model	**Computational Model**	000	100	010	001	110	011	101	111
Routine Activity Approach	Routine Activity Movement Behaviour	C	***E***	C	C	***E***	C	***E***	***E***
Rational Choice Perspective	Rational Choice Offending Behaviour	C	C	***E***	C	***E***	***E***	C	***E***
Crime Pattern Theory	Awareness Space Learning Behaviour	C	C	C	***E***	C	***E***	***E***	***E***

E = Experimental Condition C = Control Condition

had committed 1,000 crimes. Additionally, given the initialisation conditions of the model it is important to remember that while the size of the offender agent, target and transport node populations remained fixed across all replications, both the spatial distribution of model entities, and in turn, their characteristics were unique to each. Thus, for each within-model replication a new spatial distribution of targets, transport nodes and offender activity spaces were explored. Furthermore, to ensure robustness to changes in random number seeds, for each replication a different random number seed was used.

For parsimony's sake in describing these model configurations a 3-digit binary code denotes model configuration, each digit relating to the state of one of the three behavioural conditions bestowed upon agents: routine activities, rational choice, and awareness spaces, respectively. To illustrate, the control model configuration where all behaviours operate under the control state is denoted by 000, while the model configuration in which routine activity and rational choice operate under the experimental state, but awareness spaces are disabled by 110. These model configurations are briefly summarised below:

`Model Configuration 000` acts as a base level comparator for all other model configurations. In this model all offenders move randomly around their activity space, consider all potential targets equally attractive, and do not learn about their environment.

`Model Configuration 100` tests the impact of the routine activities mechanism in isolation. In this model offenders follow routine activities in navigating their environment, consider all potential targets equally attractive, and do not learn about their environment.

`Model Configuration 010` tests the impact of the rational choice mechanism in isolation. In this model all offenders move randomly around their activity space, consider the utility of potential targets in assessing their suitability, and do not learn about their environment.

`Model Configuration 001` tests the impact of the awareness space mechanism in isolation. In this model all offenders move randomly around their activity space, consider all potential targets equally attractive, but do learn about their environment.

`Model Configuration 110` In this model offenders follow routine activities in navigating their environment, consider the utility of potential targets in assessing their suitability, but do not learn about their environment.

`Model Configuration 011` In this model all offenders move randomly around their activity space, consider the utility of potential targets in assessing their suitability, and learn about their environment.

`Model Configuration 101` In this model offenders follow routine activities in navigating their environment, consider all potential targets equally attractive, and learn about their environment.

`Model Configuration 111` In the final configuration offenders operate under all three mechanisms proposed by the opportunity theories. Offenders follow spatial routine activities in navigating their environment, consider the utility of potential targets in assessing their suitability, and learn about their environment.

6.2 Model Parameters

An overview of the selected model parameters used in the simulations performed is provided in Table 6.2. Given both the exploratory nature of the model presented and an absence of reliable consistent empirical data, the selection of these parameters reflects common-sense estimations – in that there are likely more targets than active offenders, but less road intersections than targets. To ensure that model results were not specific to the particular parameters selected a series of robustness tests were also performed where several key parameters are manipulated in isolation and the experiments run again (see section 3.6.1).

6.3 Model Output Data

For each within-model replication, data pertaining to all crimes were collected. Table 6.3 summarises the key elements of this data that includes the location and time of each offence, and the characteristics of both target and offender.

6.4 Processing Model Output Data

Given that in each study 4000 simulations were performed (500 within-model replications by 8 model configurations), each capturing data relating to 1,000 crimes, a substantial amount of data were generated by the experiments performed – in total describing four million simulated crime events[1]. In dealing with such large quantities of output data the R statistical package (R Development Core Team, 2011) was used to develop a number of automated analysis scripts, which were used to (1) collate, process and analyse the patterns of crime observed in each replication, (2) aggregate and summarise the results for each set of replications per model configuration and (3) identify and quantify the differences between results observed across differing model

[1] This total does not include robustness tests which explore a further five model variants, including these data brings the running total for study 1 to 24 million distinct crime events analysed. Section 6.9 provides a discussion of the ramifications of such vast quantities of simulation output data that must be appropriately managed.

Table 6.2: Initial Model Parameters

Parameter	Description	Value
World Size	The size of the simulation environment lattice.	100 x 100
Number of Potential Offenders	Number of active offender agents.	25
Number of Potential Targets	The number of potential targets.	2500
Number of Transport Nodes	The number of transport nodes.	1000
Model Terminating Condition	The condition under which the model terminates and the next within-model replication begins.	1000 crimes
Offender Motivation $p(m)$	The probability an offender is sufficiently motivated to offend (see sections 5.5.1 and 5.6.2)	0.1
Number of Routine Activity Nodes	The number of routine activity nodes (including the home) allocated to offenders under the routine activities experimental condition (see section 5.6.4).	5
Radius of offender activity space (d)	Distance from the initialisation location within which activity nodes are selected (see section 5.6.4).	25
Offender Learning Rate (b)	The learning rate applied in the logistic function under the awareness spaces experimental condition (see section 5.6.6).	4°
Return home probability	Probability an offender will return home after visiting a routine activity node under the routine activity experimental condition (see section 5.6.5).	0.8

° The learning rate was selected such that offender awareness of a given environmental lattice approaches 1 after it has been visited 50 times.

configurations. These analyses were divided into three distinct phases, each aimed at quantifying the presence of one of the previously discussed macroscopic regularities of crime, and in turn, testing an associated hypothesis. First, model output data were analysed with respect to spatial clustering; second, the distribution of victimisation amongst targets; and third, the characteristics of journeys to crime. An overview of the output measures used in this analysis follows.

Table 6.3: Model Output Data

Variable	Description	Data Type
Crime Location	The location at which a crime occurs	Coordinate pair (x, y)
Crime Time	Simulation cycle when the crime occurred	Integer
Victim	A unique identifier associated with the target victimized	Alphanumeric ID
Offender	A unique identifier associated with the offender agent.	Alphanumeric ID
Journey to Crime Distance	The Euclidian distance between the crime location and the offender agents home location	Floating point number
Target Utility	The utility value associated with the target victimized	Floating point number (0-1)
Offender Awareness	The offender agent's awareness of the location at which the crime occurred	Floating point number (0-1)

6.5 Outcome Measures

6.5.1 Spatial Clustering Outcome Measure

In addressing hypothesis 1, the location of all simulated offences were collated for each within-model replication and analysed using the nearest neighbour index (NNI), a summary measure of spatial clustering.

The Nearest Neighbour Index (NNI)

When relative comparisons of the spatial clustering observed in multiple crime data sets are required the nearest neighbour index (NNI) offers a viable solution (Chainey & Ratcliffe, 2005). Briefly, the nearest neighbour index of some spatially referenced dataset is calculated by first measuring the mean distance between all closest pairs of points (nearest neighbours). This calculation can be expressed as follows:

$$\overline{d} = \sum_{i=1}^{n} \frac{d_{ij}}{n} \tag{6.1}$$

Where $\overline{d}$ is the mean nearest neighbour distance, d the distance between nearest neighbours i and j, and n the total number of data points. Subsequently, this mean nearest neighbour distance is compared to that expected in a theoretical random distribution. This value is calculated as a function of the size of the study area from which the original data is drawn, and the number of points within that area, and is expressed as:

$$\overline{\delta} = \frac{1}{2}\sqrt{\frac{A}{n}} \tag{6.2}$$

Where $\overline{\delta}$ is the expected mean distance between nearest neighbours in a theoretically random distribution, A is the size of the study from which the empirical distribution is drawn, and n is the number of points within the original dataset. Having calculated both these values the NNI is then represented as a ratio of the two, such that:

$$R(NNI) = (\overline{d}/\overline{\delta}) \tag{6.3}$$

The NNI ratio is capable of delineating between three types of spatial distribution: clustered, random and uniform (see Figure 6.1). Ranging between 0 and 2.15, as the NNI tends towards zero clustering increases, with an NNI of zero representing absolute clustering (i.e. all data are located at the same point in space). NNIs below one indicate clustered distributions. An NNI of one indicates a random distribution, and values greater than one varying degrees of uniformity.

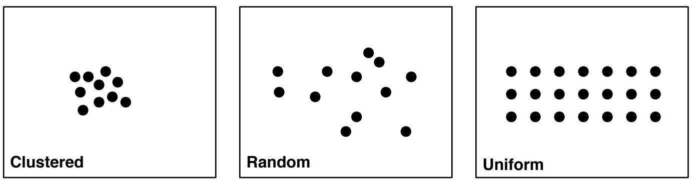

Figure 6.1: Classifications of Spatial Distribution

Having calculated the NNI for all crimes occurring in each simulation replication, a distribution of 500 NNI observations for each of the eight model configurations was generated and the statistical differences between each examined using a one-way analysis of variance (ANOVA). Furthermore, effect sizes (Cohen's D) were calculated to assess the magnitude of difference between each model configuration and the control model configuration (000).

6.5.2 Repeat Victimisation Outcome Measure

In addressing hypothesis 2, the Gini coefficient was used to quantify the distribution of victimisation amongst victims.

The Gini Coefficient

For each within-model replication the count of victimisations per target was collected and the concentration of victimisation measured using the Gini coefficient, a measure of inequality (Gini, 1912). The Gini coefficient is derived from a Lorenz curve that depicts the cumulative proportion of entities receiving the cumulative proportion of some attribute. Briefly, the Gini coefficient G is expressed as the following ratio:

$$G = \frac{a}{a+b} \tag{6.4}$$

where a is the area between the line of equality and the observed Lorenz curve, and $(a+b)$ is the total area below the of line equality (see Figure 6.2). In this case, the Gini coefficient is used to describe the proportion of victims experiencing some proportion of victimisation. When the Gini coefficient is equal to zero victimisation is spread evenly amongst all victims, such that each victim has received an equal number of victimisations. As the Gini coefficient tends towards one, victimisation becomes more concentrated and fewer victims are subject to increasingly disproportionate numbers of victimisations. The Gini coefficient as a measure of victimisation inequality has been used or advocated in a number of criminological studies (Barr & Pease, 1990; Johnson & Bowers, 2010; Trickett, Ellingworth, Hope, & Pease, 1995; Tseloni & Pease, 2005).

Having calculated the Gini coefficient of victimisation occurring in each within-model replication, a distribution of 500 Gini coefficient observations for each model configuration were generated and the statistical differences between each examined using a one-way ANOVA. Furthermore, effect sizes

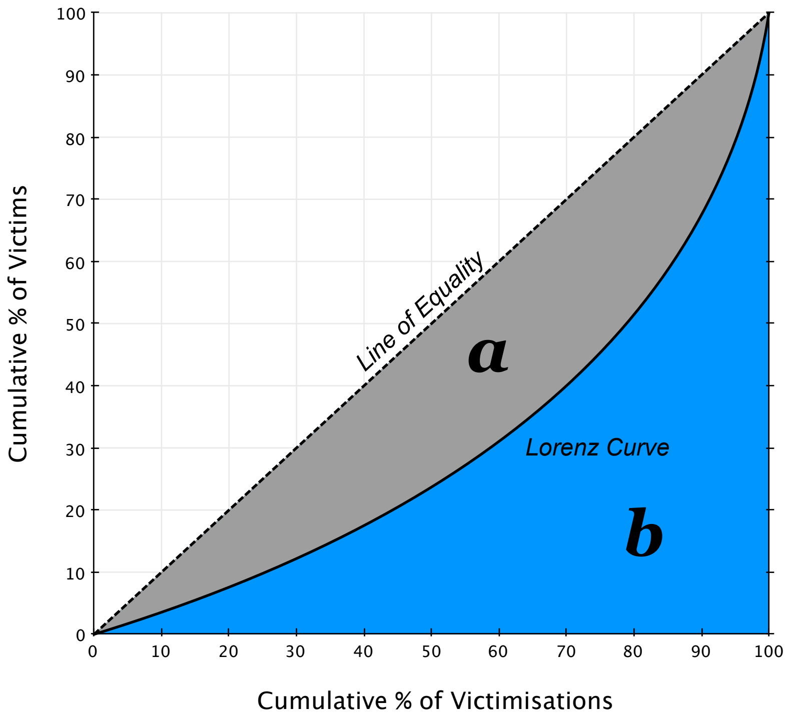

Figure 6.2: Calculating the Gini Coefficient

(Cohen's D) were calculated to assess the magnitude of difference between each model configuration and the control model configuration (000).

6.5.3 Journey to Crime Skewness Outcome Measure

In addressing hypothesis 3, Pearson's coefficient of skewness was used to quantify the skew of journey to crime distributions.

Pearson's Coefficient of Skewness

The Euclidian distance between the crime location and home location of the offender was calculated for each crime occurring in each within-model replication. In keeping with research concerning journeys to crime (see section 2.2.3), a distribution of these distances was then generated for all crimes occurring in each within-model replication as depicted in Figure 6.3.

For each within-model replication the Pearson's coefficient of skewness for

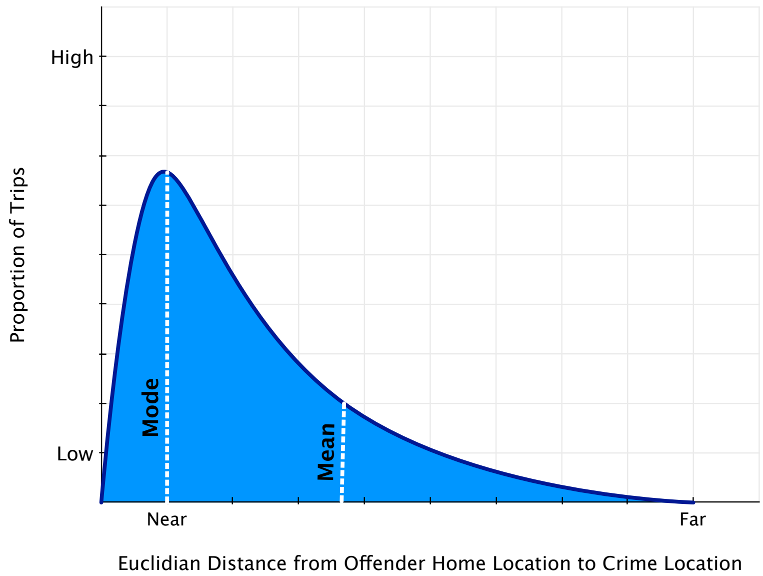

Figure 6.3: Example Journey to Crime Distribution

this journey to crime distribution was then calculated using the following formula.

$$Skewness = \left(\frac{\mu - Mo}{s}\right) \tag{6.5}$$

where μ is the mean distance travelled by offenders, Mo the mode, and s the standard deviation of distances. Subsequently, each model configuration generated a distribution of 500 skewness coefficients and the statistical differences between each were examined using a one-way ANOVA. Furthermore, effect sizes (Cohen's D) were calculated to assess the magnitude of difference in skewness between each model configuration and the control model configuration (000).

6.6 Assessing Model Robustness

In keeping with discussions concerning model validity presented in section 3.6.1 a series of model robustness tests were also performed to ensure that observed results were not unique to initial model parameters (as seen in Table 6.2). In these tests a number of key model parameters were selected (reflecting both model initial conditions and behavioural parameters) – *total number of offenders, total number of targets, total number of navigational nodes, of-*

fender motivation, and number of routine activity nodes – and each, in turn doubled holding all other parameters fixed. For each of these five modified models the entire experimental schedule described above was then re-run and analyses repeated for each modified model.

The rest of this chapter presents findings of the experiments described above. For each of the two model variants (simulating static and dynamic targets – studies 1 and 2 respectively), the focused research questions are addressed, and the derived hypotheses tested.

6.7 Study 1 Findings – Static Targets

6.7.1 Study 1.1 – Spatial Clustering

Hypothesis 1: Crime will become more spatially concentrated as the mechanisms of the opportunity theories are activated.

The location of all simulated offences were collated for each replication and analysed using the nearest neighbour index (NNI). Having calculated the NNI for each replication, a distribution of 500 NNI observations for each of the eight model configurations was generated (see Figure 6.4) and the statistical differences between each examined. Table 6.4 summarises the mean NNI and associated standard deviation for each model configuration. A one-way ANOVA detected significant differences between model configurations, $F(7, 3992) = 17242, p<.001$.

The relative impacts on spatial clustering of each behavioural configuration can be observed by comparing the differences in mean NNIs between each model configuration and the control model (000)[2] (see Table 6.5). First, the greatest increases in spatial clustering are observed when all three mechanisms are enabled (model configuration 111) with a difference in means of 0.383. These results support Hypothesis 1.

[2]Given the acknowledged abundance of statistical power provided by the high number of replications performed, analysis of the magnitude of difference in output measures replaces conventional post-hoc tests of statistical difference.

Table 6.4: Mean and Standard Deviation of Nearest Neighbour Index by Model Configuration (n=500 per model configuration) – Static Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Mean Nearest Neighbour Index***
000	Control	Control	Control	0.51 *(0.03)*
010	Control	*Experimental*	Control	0.48 *(0.03)*
001	Control	Control	*Experimental*	0.27 *(0.03)*
011	Control	*Experimental*	*Experimental*	0.26 *(0.02)*
100	*Experimental*	Control	Control	0.19 *(0.02)*
110	*Experimental*	*Experimental*	Control	0.18 *(0.02)*
101	*Experimental*	Control	*Experimental*	0.128° *(0.02)*
111	*Experimental*	*Experimental*	*Experimental*	0.127° *(0.02)*

* Significant Differences (p<.001) between one or more model configurations
° Values reported at 3 decimal places to illustrate differences

Observing the magnitude of differences given the activation of each mechanism in isolation it is clear that routine activities and awareness spaces play a substantially greater role in the concentration of crime than rational choice (differences in mean NNI of 0.32, 0.24, 0.03 respectively). Furthermore the combination of routine activities and awareness spaces (model configuration 101) produces a difference in mean from the control model that is equivalent to that of all three mechanisms (model configuration 111) with differences in mean NNIs of 0.382 and 0.383 respectively, reinforcing the observation that the rational choice mechanism plays a minimal role in spatial clustering. While the activation of the rational choice mechanism does increase spatial clustering in all model configurations, the magnitude of this increase is substantially less when compared to routine activities and awareness spaces. In examining the magnitude of differences between the control model configuration and all other model configurations, effect sizes (Cohen's D) were also calculated (see Table 6.5). Results of these analyses demonstrate that all model configurations produce large effect sizes from the control model configuration.

Table 6.5: Differences in Mean NNI from control model configuration 000 by model configuration (n=500 per model configuration) – Static Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Differences in Mean NNI from model 000**	**Effect Size (Cohens D) from model 000**
000	Control	Control	Control	0	0
010	Control	*Experimental*	Control	0.03	0.81
001	Control	Control	*Experimental*	0.24	7.87
011	Control	*Experimental*	*Experimental*	0.25	8.54
100	*Experimental*	Control	Control	0.32	10.92
110	*Experimental*	*Experimental*	Control	0.33	11.29
101	*Experimental*	Control	*Experimental*	0.38	14.48
111	*Experimental*	*Experimental*	*Experimental*	0.38	15.01

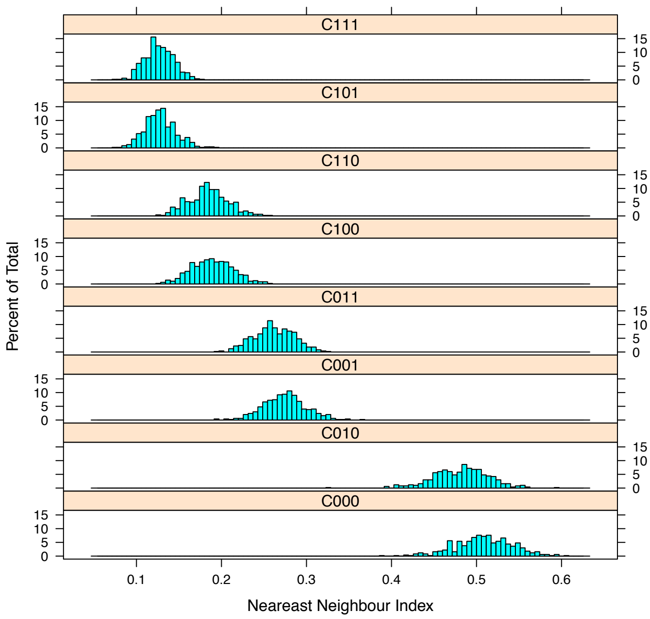

Figure 6.4: Distributions of NNI by Model Configuration (as NNI tends toward 0 greater levels of spatial clustering are observed) – Static Targets

To illustrate the differences in spatial clustering under different model configurations Figure 6.5 depicts kernel density estimation maps (equal grid size and bandwidths) of the spatial distribution of 1000 crimes from two sample simulations, the first using model configuration 000 and the second under model configuration 111.

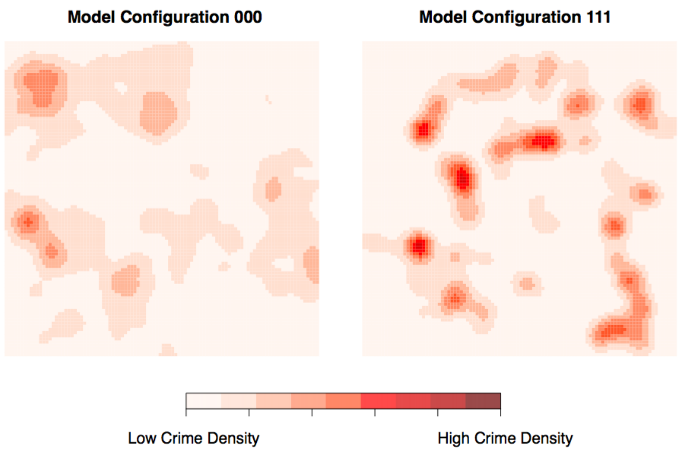

Figure 6.5: Example Spatial Distributions of Crimes Against Static Targets for Model Configurations 000 and 111

6.7.2 Study 1.2 – Repeat Victimisation

Hypothesis 2: Greater levels of repeat victimisation will be observed as the mechanisms of the opportunity theories are activated.

The Gini coefficient of victimisation was calculated for each replication. Subsequently, a distribution of 500 Gini coefficients for each of the eight model configurations was generated (see Figure 6.6) and the statistical differences between each examined. Table 6.6 summarises the mean Gini coefficient and associated standard deviations for each model configuration. Using a one-way ANOVA significant differences in repeat victimisation were detected between model configurations $F(7, 3992) = 8206, p = <.001$.

In establishing the impacts of each model configuration, differences in mean Gini coefficients between each model configuration and the control model 000 were examined (see Table 6.7). Results of this analysis again demonstrate that the greatest difference was observed between model configuration 000 (mean Gini coefficient of 0.27) and model configuration 111 (mean Gini coefficient of 0.47, which equates to around 25% of victims experiencing 65% of victimisations). These results support Hypothesis 2.

Table 6.6: Mean and Standard Deviation of Gini Coefficient by Model Configuration (n = 500 per model configuration) – Static Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Mean Gini Coefficient***
000	Control	Control	Control	0.27 *(0.02)*
010	Control	*Experimental*	Control	0.30 *(0.02)*
100	*Experimental*	Control	Control	0.39 *(0.02)*
001	Control	Control	*Experimental*	0.41 *(0.02)*
110	*Experimental*	*Experimental*	Control	0.42 *(0.02)*
101	*Experimental*	Control	*Experimental*	0.43 *(0.02)*
011	Control	*Experimental*	*Experimental*	0.45 *(0.02)*
111	*Experimental*	*Experimental*	*Experimental*	0.47 *(0.02)*

* Significant Differences ($p<.001$) between one or more model configurations

In assessing the differential impacts of each mechanism the activation of awareness spaces and routine activities results in reasonably sizeable changes in repeat victimisation but much more modest changes result from the rational choice mechanism. To illustrate, comparing the control configuration 000 with activating rational choice (model 010), routine activities (model 100), and awareness spaces (model 001) in isolation results in differences in means of 0.03, 0.12 and 0.14 respectively. Subsequent examination of the impacts of each possible combination of two mechanisms sees small monotonic increases in repeat victimisation with routine activities and rational choice (model 110); routine activities and awareness spaces (model 101); and rational choice and awareness spaces (model 011) producing differences in mean Gini coefficients of 0.15, 0.16 and 0.18 respectively. Again, effect sizes between all model configurations and the control model are large (see Table 6.7).

Table 6.7: Differences in Mean Gini Coefficient and Effect Sizes from control model configuration 000 by model configuration (n = 500 per model configuration) – Static Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Differences in Mean Gini Coef from model 000**	**Effect Size (Cohen's D) from model 000**
000	Control	Control	Control	0	0
010	Control	*Experimental*	Control	0.03	1.73
100	*Experimental*	Control	Control	0.12	7.46
001	Control	Control	*Experimental*	0.14	8.31
110	*Experimental*	*Experimental*	Control	0.15	9.19
101	*Experimental*	Control	*Experimental*	0.16	9.73
011	Control	*Experimental*	*Experimental*	0.18	10.14
111	*Experimental*	*Experimental*	*Experimental*	0.20	11.14

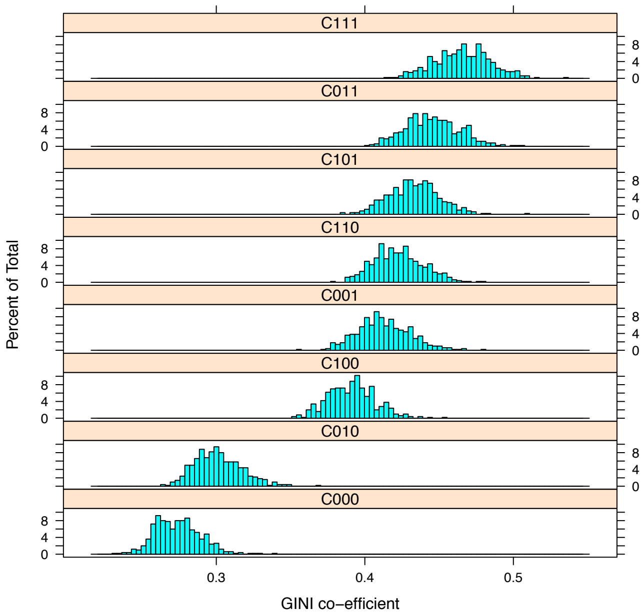

Figure 6.6: Distributions of Gini Coefficients by Model Configuration (as Gini tends toward 1 greater levels of repeat victimisation are observed) – Static Targets

6.7.3 Study 1.3 – Journey To Crime

Hypothesis 3: The journey to crime curve will become more positively skewed as the mechanisms of the opportunity theories are activated.

Trip distances for each crime committed in each replication were calculated and an aggregate journey to crime curve plotted for each replication. Subsequently, Pearson's coefficient of skewness was calculated for each journey to crime curve, a distribution of 500 skewness coefficients for each of the eight model configurations generated (see Figure 6.7), and the statistical differences between each examined. Table 6.8 summarises the mean Pearson's coefficient of skewness and associated standard deviation for each model configuration. A one-way ANOVA detected significant differences in skewness between model configurations $F(7, 3992) = 2341, p = <.001$.

Table 6.8: Mean and Standard Deviation of Pearson's Coefficient of Skewness for Journey to Crime Curves by Model Configuration (n=500 per model configuration) – Static Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**JTC Skewness***
000	Control	Control	Control	0.31 *(0.11)*
010	Control	*Experimental*	Control	0.31 *(0.10)*
011	Control	*Experimental*	*Experimental*	0.31 *(0.13)*
001	Control	Control	*Experimental*	0.32 *(0.12)*
100	*Experimental*	Control	Control	0.75 *(0.13)*
110	*Experimental*	*Experimental*	Control	0.75 *(0.13)*
101	*Experimental*	Control	*Experimental*	0.89 *(0.14)*
111	*Experimental*	*Experimental*	*Experimental*	0.91 *(0.16)*

* Significant Differences (p<.001) between one or more model configurations

In establishing the impact of each behavioural configuration the differences in mean skewness coefficients between each model configuration and the control model 000 were examined (see Table 6.9). Results of this analysis again demonstrate that the greatest difference in mean skewness was observed between model configuration 000 (mean skewness of 0.31) and model configuration 111 (mean skewness of 0.91). These results support Hypothesis

3.

Examining the relative contributions of each mechanism in isolation demonstrates that routine activities generate the most substantial increases in the skewness of journey to crime distributions. Comparing configuration 100 to the control model configuration 000 highlights a difference in mean skewness of 0.44. Moreover, visual inspection further illustrates the primary significance of the routine activity mechanism, demonstrating that in all model configurations where routine activities were enabled journey to crime curves markedly resembled the characteristic distance decay curve observed in empirical journey to crime research (to illustrate Figure 6.8 depicts the journey to crime curves observed for model configurations 000 and 111).

Table 6.9: Differences in Mean Pearson's Coefficient of Skewness from control model configuration 000 by model configuration (n=500 per model configuration) – Static Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Differences in Mean Skewness Coefficient from model 000**	**Effect Size (Cohens D) from model 000**
000	Control	Control	Control	0	0
010	Control	*Experimental*	Control	0.00	0.01
011	Control	*Experimental*	*Experimental*	0.00	0.05
001	Control	Control	*Experimental*	0.01	0.06
100	*Experimental*	Control	Control	0.44	3.73
110	*Experimental*	*Experimental*	Control	0.44	3.62
101	*Experimental*	Control	*Experimental*	0.58	4.68
111	*Experimental*	*Experimental*	*Experimental*	0.60	4.47

With respect to the influence of awareness spaces, when enabled in isolation little discernible effect on skewness is observed (comparing configuration 000 to 001 – difference in mean skewness of 0.01), however in combination with routine activities meaningful increases in skewness are observed - comparing 100 to 101 and 110 to 111 highlighting differences in mean skewness of 0.14

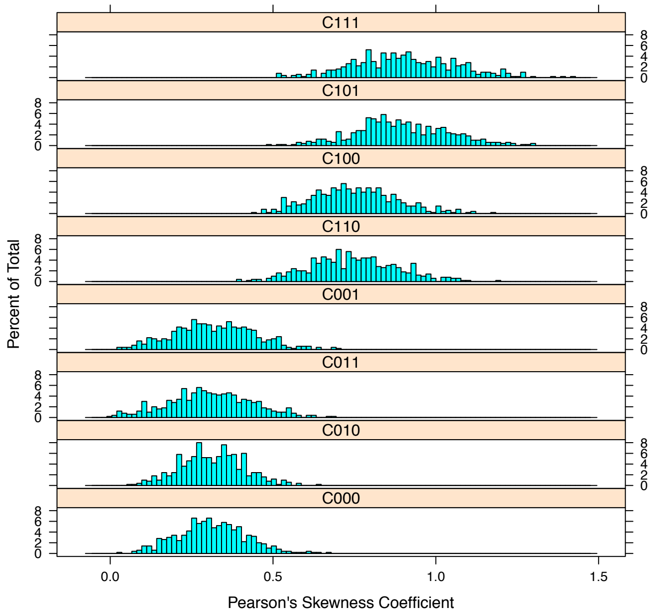

Figure 6.7: Distributions of Pearson's Skewness Coefficient by Model Configuration (n=500) – Crimes against Static Targets

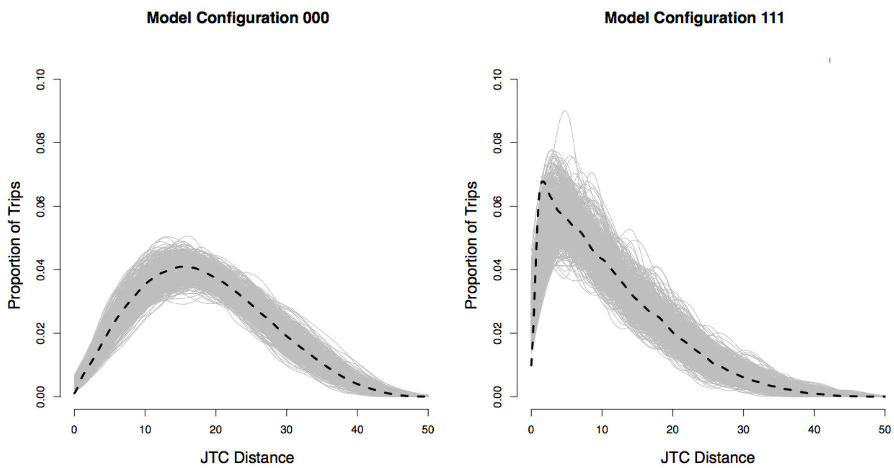

Figure 6.8: Journey to Crime Curves for Model Configurations 000 and 111 (all model replications grey lines (n=500), mean black line) – Static Targets

and 0.16 respectively. Again, activation of the rational choice mechanism does increase skewness (comparing model configuration 101 to 111), but such increases are minimal in comparison to those conferred by routine activities and awareness spaces. Calculating effect sizes (Cohen's D) between the control model configuration and each subsequent model configuration (see Table 6.9) demonstrated large effects in all models where the routine activity mechanism was enabled.

6.7.4 Model Robustness

Examining the robustness of the model presented, several tests of model robustness were performed. Following an approach similar to Groff (2007a) five key model parameters (reflecting both model initial conditions and behavioural parameters as suggested by Fung and Vemuri (2003)) were selected – *total number of offenders, total number of targets, total number of navigational nodes, offender motivation, and number of routine activity nodes* – and each in turn doubled holding all other parameters fixed. All experiments and analyses were then repeated for each of the five modified models. Table 6.10 summarises the results of these experiments, presenting the differences in mean output measures between each model configuration and the control model configuration 000 for the original experiments and all modified models. Analyses of these results demonstrate that significant differences are consistently observed between one or more model configurations across all output measures for all modified models. Furthermore, while the relative importance of routine activities and awareness spaces did swap for a small number of the modified models, the magnitude of contribution of each of the respective mechanisms remained consistent across all – such that for all experiments performed routine activities and awareness spaces continued to confer substantially greater impacts on the formation of spatial clustering, repeat victimisation, and the journey to crime curve than rational choice. Furthermore, the mean differences between model configuration 000 and 111 remained consistently the greatest. Thus, it can be deduced that model results are robust to changes in initial parameters.

Table 6.10: Results of Model Robustness Testing. Difference in Mean Output Measure between each Model Configuration and Control Model Configuration 000 across all Modified Models (n=500 per model configuration) – Static Targets

Output Measure	Model Config	*Original Experiment**	Double Offenders*	Double Targets*	Double Navigational Nodes*	Double Offender Motivation*	Double Routine Activity Nodes*
Nearest	000	0	0	0	0	0	0
Neighbour	010	0.03	0.04	0.03	0.03	0.02	0.03
Index	001	0.24	0.27	0.31	0.24	0.26	0.24
	011	0.25	0.28	0.33	0.25	0.27	0.25
	100	0.32	0.25	0.36	0.35	0.32	0.21
	110	0.33	0.27	0.37	0.36	0.32	0.23
	101	0.38	0.36	0.46	0.42	0.39	0.32
	111	0.38	0.37	0.47	0.42	0.39	0.33
Gini	000	0	0	0	0	0	0
Coefficient	010	0.03	0.03	0.03	0.03	0.03	0.03
	100	0.12	0.09	0.13	0.13	0.12	0.09
	001	0.14	0.17	0.17	0.13	0.17	0.15
	110	0.15	0.12	0.16	0.16	0.15	0.12
	101	0.16	0.16	0.20	0.17	0.18	0.17
	011	0.18	0.19	0.20	0.17	0.21	0.18
	111	0.20	0.19	0.23	0.21	0.22	0.20
JTC	000	0	0	0	0	0	0
Skewness	010	0.00	0.01	0.00	0.01	0.01	0.00
	011	0.00	0.02	0.00	0.02	0.03	0.01
	001	0.01	0.02	0.01	0.02	0.02	0.01
	110	0.44	0.45	0.44	0.45	0.44	0.42
	100	0.44	0.45	0.44	0.44	0.45	0.42
	101	0.58	0.67	0.58	0.58	0.64	0.66
	111	0.60	0.67	0.59	0.58	0.65	0.66

* Significant Differences ($p<.001$) between one or more model configurations

6.8 Study 2 Findings – *Dynamic* Targets

Having explored the initial model of crimes against static targets one logical extension is to explore the same model and hypotheses but instead simulate crimes occurring against spatially dynamic targets – that is, targets that move. Study 2 uses a variant of the model used in Study 1 that models crimes against such dynamic targets (i.e. street robbery). All experiments and analyses from study 1 are replicated and the same hypotheses (H1, H2, H3) tested. A brief description of the model modifications made in emulating crimes against dynamic targets follows.

6.8.1 Model Modifications

Given the simplicity of the model presented, to simulate crimes against dynamic targets the second model variant differs from the first in only one key way – targets are provided with the same routine activities and wayfinding behaviours previously only used for offender agents (see sections 5.6.1 and 5.6.4). Other than this modification, the model is identical to that described in chapter 5.

Thus, all targets are allocated a home location in the same way as offenders. Subsequently, when the routine activities mechanism operates under the control condition targets navigate randomly within the bounds of their activity space, under the experimental condition targets are allocated five routine activity nodes that are visited frequently. The offending calculus is again operated when an offender comes into the same location as a (now mobile) target. While the implementation of this model variant is relatively trivial its computational implications are considerable (see section 6.9). Results of the experiments performed using the second model variant are now presented.

6.8.2 Study 2.1 – Spatial Clustering

Hypothesis 1: Crime will become more spatially concentrated as the mechanisms of the opportunity theories are activated.

Again, the location of all simulated offences were collated for each replication and analysed using the NNI. A distribution of 500 NNI observations for each model configuration was then generated (see Figure 6.9) and the statistical differences between each examined using a one-way ANOVA. Table 6.11 summarises the mean NNI and associated standard deviation for each model configuration. Significant differences between model configurations were again detected, $F(7, 3992) = 11425, p < .001$.

Table 6.11: Mean and Standard Deviation of Nearest Neighbour Index by Model Configuration (n=500 per model configuration) – Dynamic Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Mean Nearest Neighbour Index***
000	Control	Control	Control	0.78 *(0.03)*
010	Control	*Experimental*	Control	0.78 *(0.03)*
100	*Experimental*	Control	Control	0.57 *(0.03)*
110	*Experimental*	*Experimental*	Control	0.57 *(0.02)*
001	Control	Control	*Experimental*	0.54 *(0.03)*
011	Control	*Experimental*	*Experimental*	0.54 *(0.03)*
101	*Experimental*	Control	*Experimental*	0.43 *(0.02)*
111	*Experimental*	*Experimental*	*Experimental*	0.42 *(0.03)*

* Significant Differences (p<.001) between one or more model configurations

The relative impacts on spatial clustering of each behavioural configuration were observed by comparing the differences in mean NNIs between each model configuration and the control model (000) (see Table 6.12). Similar to crimes against static targets, the greatest increases in spatial clustering were observed when all three mechanisms were enabled (model configuration 111) with a difference in mean NNI of 0.36. These results provide further support for Hypothesis 1.

Furthermore, observing the magnitude of differences from the activation of each mechanism in isolation demonstrated that the routine activities and awareness spaces mechanisms again play a substantially greater role in the concentration of crime than rational choice (differences in mean NNI of 0.21, 0.24, and 0 comparing model 000 to models 100, 001 and 010 respectively). The combination of routine activities and awareness spaces (model configuration 101) produces a mean difference from the control model that is again equivalent to that of all three mechanisms (model configuration 111) with differences in mean NNIs of 0.35 and 0.36 respectively, further reinforcing the observation that the rational choice mechanism plays a minimal role in spatial clustering within the model. Further, mirroring the results of the first model variant the awareness space mechanism confers the greatest impact of all mechanisms when considered in isolation.

In examining effect sizes (Cohen's D) between the control model configuration and all other model configurations (see Table 6.12) all model configurations except the model in which only the rational choice mechanism was enabled (model 010) produced large effect sizes from the control model configuration.

Table 6.12: Differences in Mean NNI from control model configuration 000 by model configuration (n=500 per model configuration) – Dynamic Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Differences in Mean NNI from model 000**	**Effect Size (Cohens D) from model 000**
000	Control	Control	Control	0	0
010	Control	*Experimental*	Control	0	0
100	*Experimental*	Control	Control	0.21	7.59
110	*Experimental*	*Experimental*	Control	0.21	7.48
001	Control	Control	*Experimental*	0.24	8.07
011	Control	*Experimental*	*Experimental*	0.24	7.94
101	*Experimental*	Control	*Experimental*	0.35	13.53
111	*Experimental*	*Experimental*	*Experimental*	0.36	13.05

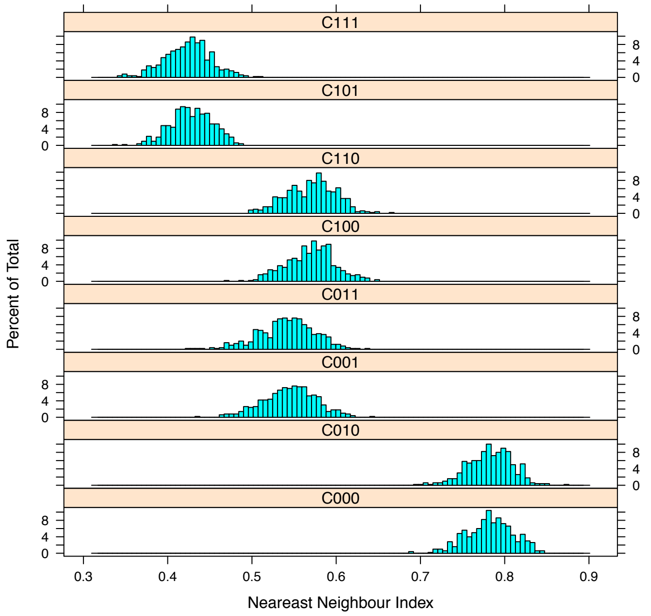

Figure 6.9: Distributions of NNI by Model Configuration (as NNI tends towards 0 greater levels of spatial clustering are observed) – Dynamic Targets

Illustrating the differences in spatial clustering under different model configurations Figure 6.10 depicts kernel density estimation maps (equal grid size and bandwidth) of the spatial distribution of 1000 crimes against dynamic targets from two sample simulations, the first under model configuration 000 and the second under model configuration 111.

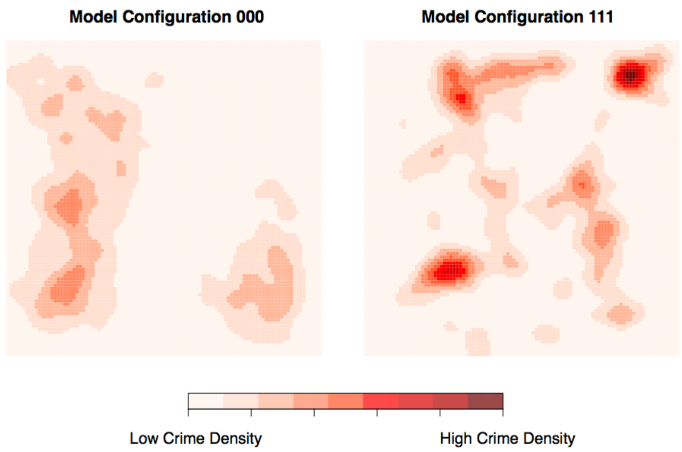

Figure 6.10: Example Spatial Distributions of Crimes Against Dynamic Targets for Model Configurations 000 and 111

6.8.3 Study 2.2 – Repeat Victimisation

Hypothesis 2: Greater levels of repeat victimisation will be observed as the mechanisms of the opportunity theories are activated.

Again the Gini coefficient of victimisation was calculated for each replication, a distribution of 500 Gini coefficients generated (see Figure 6.11) and the differences examined using a one-way ANOVA. Table 6.13 summarises the mean Gini coefficient and associated standard deviations for each model configuration. Significant differences in repeat victimisation between model configurations were again detected $F(7, 3992) = 1649, p = <.001$.

Establishing the impacts of each behavioural configuration, differences in mean Gini coefficients between each model configuration and the control model 000 were examined (see Table 6.14). Results of this analysis demonstrate that while changes in the level of repeat victimisation were relatively modest between model configurations the greatest difference was observed between model configuration 000 (mean Gini coefficient of 0.17) and model configuration 111 (Gini coefficient of 0.25, which equates to around 25% of victims experiencing 50% of victimisations). Therefore, again the presence of all three mechanisms leads to the greatest level of repeat victimisation. These results further support Hypothesis 2.

Table 6.13: Mean and Standard Deviation of Gini Coefficient by Model Configuration (n = 500 per model configuration) – Dynamic Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Mean Gini Coefficient***
000	Control	Control	Control	0.17 *(0.01)*
001	Control	Control	*Experimental*	0.19 *(0.02)*
100	*Experimental*	Control	Control	0.19 *(0.01)*
010	Control	*Experimental*	Control	0.21 *(0.01)*
101	*Experimental*	Control	*Experimental*	0.21 *(0.01)*
011	Control	*Experimental*	*Experimental*	0.22 *(0.02)*
110	*Experimental*	*Experimental*	Control	0.23 *(0.01)*
111	*Experimental*	*Experimental*	*Experimental*	0.25 *(0.01)*

* Significant Differences (p<.001) between one or more model configurations

Table 6.14: Differences in Mean Gini Coefficient and Effect Sizes from control model configuration 000 by model configuration (n = 500 per model configuration) – Dynamic Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Differences in Mean Gini Coef from model 000**	**Effect Size (Cohen's D) from model 000**
000	Control	Control	Control	0	0
001	Control	Control	*Experimental*	0.02	1.16
100	*Experimental*	Control	Control	0.02	1.78
010	Control	*Experimental*	Control	0.04	3.20
101	*Experimental*	Control	*Experimental*	0.04	3.35
011	Control	*Experimental*	*Experimental*	0.05	3.62
110	*Experimental*	*Experimental*	Control	0.05	5.03
111	*Experimental*	*Experimental*	*Experimental*	0.08	6.42

In assessing the differential impacts of each mechanism the activation of all three mechanisms in isolation results in similar changes in repeat victimisation, the greatest being conferred by the rational choice mechanism (differences in mean of 0.04 from rationale choice compared to 0.02 for both routine activities and awareness spaces). Subsequent examination of the impacts of each possible combination of two mechanisms sees small monotonic increases in repeat victimisation with routine activities and awareness spaces (model 101); rational choice and awareness spaces (model 011); and routine activities and rational choice (model 110) producing differences in mean Gini coefficients of 0.21, 0.22 and 0.23 respectively. Analysis of effect sizes (Cohen's D) again demonstrates large effects between all model configurations and the control model (see Table 6.14).

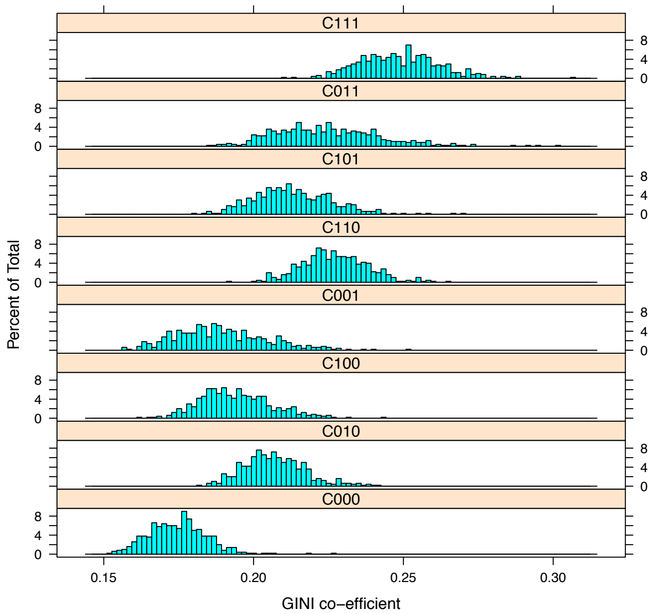

Figure 6.11: Distributions of Gini Coefficients by Model Configuration (as Gini tends towards 1 greater levels of repeat victimisation is observed) – Dynamic Targets

6.8.4 Study 2.3 – Journey to Crime

Hypothesis 3: The journey to crime curve will become more positively skewed as the mechanisms of the opportunity theories are activated.

Trip distances for each crime committed in each replication were calculated and a journey to crime curve plotted for each replication. Subsequently, Pearson's coefficient of skewness was calculated for each journey to crime curve and a distribution of 500 skewness coefficients for each of the eight model configurations was generated (see Figure 6.12) and the statistical differences between each examined. Table 6.15 summarises the mean Pearson's coefficient of skewness and associated standard deviation for each model configuration. A one-way ANOVA detected significant differences in skewness between model configurations $F(7,3992) = 2640, p = <.001$.

Table 6.15: Mean and Standard Deviation of Pearson's Coefficient of Skewness for Journey to Crime Curves by Model Configuration (n=500 per model configuration) – Dynamic Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**JTC Skewness***
000	Control	Control	Control	0.35 *(0.10)*
010	Control	*Experimental*	Control	0.37 *(0.10)*
011	Control	*Experimental*	*Experimental*	0.39 *(0.13)*
001	Control	Control	*Experimental*	0.39 *(0.13)*
110	*Experimental*	*Experimental*	Control	0.74 *(0.11)*
100	*Experimental*	Control	Control	0.75 *(0.12)*
101	*Experimental*	Control	*Experimental*	0.99 *(0.14)*
111	*Experimental*	*Experimental*	*Experimental*	1.01 *(0.15)*

* Significant Differences (p<.001) between one or more model configurations

Examining the impact of each behavioural configuration (see Table 6.16) demonstrates that the greatest difference in skewness was observed between model configuration 000 (mean skewness of 0.35) and model configuration 111 (mean skewness of 1.01). These results further support Hypothesis 3.

Examining the relative contributions of each mechanism in isolation demonstrates similar results to those observed in examining crimes static targets. Again, routine activities generate the most substantial increases in the skewness of journey to crime distributions. Comparing configuration 100 to the control model configuration 000 highlights a difference in mean skewness of 0.40. Again, visual inspection demonstrated that in all model configurations where routine activities were enabled journey to crime curves closely resembled the characteristic distance decay curve (see Figure 6.13).

Again the awareness spaces mechanism in isolation produces little effect on skewness (comparing models 000 to 001 – difference in mean skewness of 0.04), however in combination with routine activities substantially greater increases in skewness are observed - comparing 100 to 101 and 110 to 111 highlighting differences in mean skewness of 0.24 and 0.27 respectively. Activation of the rational choice mechanism does increase skewness (comparing model configuration 101 to 111), but such increases are minimal in comparison to those conferred by routine activities and awareness spaces (difference in mean of 0.02). Furthermore, effect sizes calculated between the control model 000 and each subsequent model demonstrate large effects from all model configurations in which the routine activity mechanism is enabled (Table 6.16).

Table 6.16: Differences in Mean Pearson's Coefficient of Skewness from control model configuration 000 by model configuration (n=500 per model configuration) – Dynamic Targets

Model Config	**Routine Activities**	**Rational Choice**	**Awareness Spaces**	**Differences in Mean Pearson's Coef of Skew from model 000**	**Effect Size (Cohen's D) from model 000**
000	Control	Control	Control	0	0
010	Control	*Experimental*	Control	0.02	0.17
011	Control	*Experimental*	*Experimental*	0.04	0.37
001	Control	Control	*Experimental*	0.04	0.36
110	*Experimental*	*Experimental*	Control	0.39	3.78
100	*Experimental*	Control	Control	0.40	3.78
101	*Experimental*	Control	*Experimental*	0.64	5.56
111	*Experimental*	*Experimental*	*Experimental*	0.66	5.31

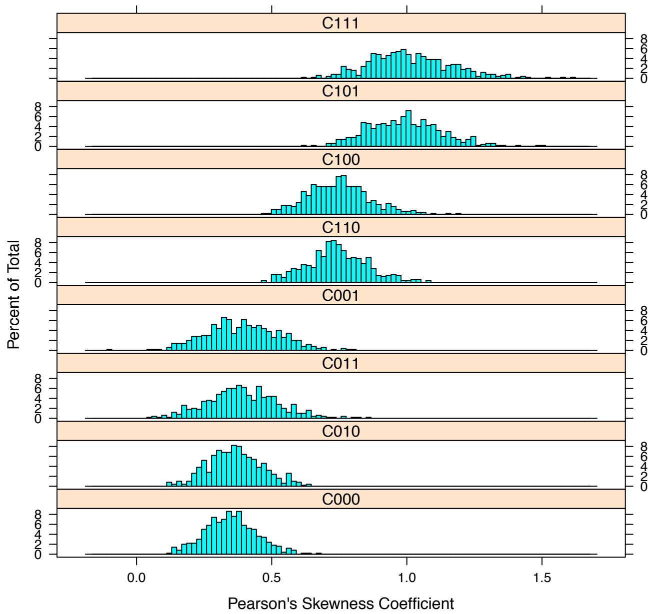

Figure 6.12: Distributions of Pearson's Skewness Coefficient by Model Configuration – Dynamic Targets

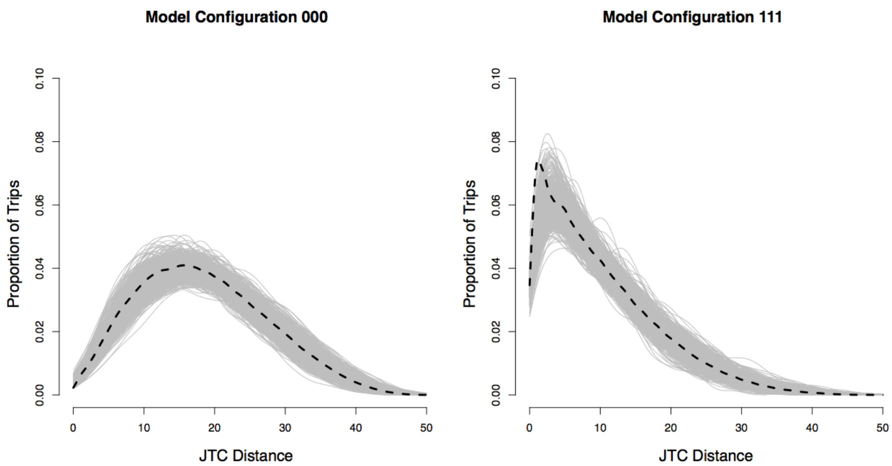

Figure 6.13: Journey to Crime Curves for Model Configurations 000 and 111 (all model replications grey lines (n=500), mean black line) – Dynamic Targets

6.8.5 Model Robustness

Section 6.7.4 describes model robustness testing for the first model variant. Due to time constraints model robustness tests were not performed for the second model variant. This is a direct result of the significant increases in computation time required to run the second model variant, which are briefly discussed below in section 6.9. While this is not ideal, it is hoped that the initial model robustness tests of the first model variant provide a fair indication that the model is not overly sensitive to initial parameter selection. In addition, as each within-model replication uses a different random number seed, it can at least be deduced that the second model variant is robust to changes in random number seeds. However, it is acknowledged that further work (or more specifically time) is required to fully test the robustness of the second model variant's results.

6.9 Model Runtime

As discussed in the previous section, the computational resources required of each model variant presented are substantially different. To illustrate Table 6.17 provides a brief overview of the average computation time required to complete a single within-model replication using both model variants, an estimated time required to perform all within-model replications for each study, and an estimate of the time required to undertake robustness testing of five model parameters (using available hardware).

Table 6.17: Estimates of Computation Time by Model Variant

Model Variant	Average Time to Complete 1 Replication	Computation Time - 500 Replications for 8 Model Configurations*	Computation Time - Robustness Testing - 5 Parameters*
Static Targets	2 minutes	17 hours	4 days
Dynamic Targets	28 minutes	10 days	50 days

*Time to compute estimates based on 8 parallel simulations running on a Dual Quad Core 2.26Ghz Intel Xeon, 16gb RAM

Note that the computational time of the second model variant is orders of magnitude greater than that of the first. This is a result of the substantial increases in computation when all targets are spatially dynamic and must employ the wayfinding and routine activities behaviours described in sections 5.6.1 and 5.6.4. While these agent behaviours may be further optimised for efficiency, such disparities will like always exist as a result of the first model requiring to compute the wayfinding behaviour 25 times (once for each offender) per simulation cycle, and the second 2525 times (once for each offender and target).

7
Discussion

In this chapter, the key findings of the research are discussed. The overarching and focused research questions are restated, their underlying rationale revisited, and the findings of studies performed in addressing them summarised. A number of potential implications for theory, methodology, and policy that result are subsequently described. Finally, several potential limitations of the research presented are discussed, and a series of prospective avenues for further research set out.

The aim of this thesis was to apply an ABM to test the generative sufficiency of micro-level mechanisms provided by the opportunity theories in explaining several commonly observed macro-level patterns of crime. In doing so, the following overarching research question was investigated:

Are the micro-level mechanisms of the opportunity theories generatively sufficient to explain macroscopic patterns commonly observed in the empirical study of crime?

To address this question a generative ABM of crime was developed to explore the three key identified micro-level mechanisms of movement, decision-making and learning derived from the routine activity approach (Cohen & Felson, 1979), rational choice perspective (Cornish & Clarke, 1986), and crime pattern theory (Brantingham & Brantingham, 1993a). Drawing on these mechanisms, an artificial society was created in which offenders traversed a virtual environment encountering potential targets (routine activities); victimising those considered suitable (rational choice); and learning about their local environment and the potential targets within it (crime pattern theory). For each theoretical mechanism, control and experimental agent behaviours were developed, representing the absence and presence of a proposed mechanism; hence providing a counterfactual through which the impacts of specific mechanisms could be assessed via computational experimentation.

Using this model, a series of experiments were performed in which the behaviour of offender agents were systematically manipulated and the emergent crime patterns generated as a result examined and compared to several known macroscopic regularities of crime. Using a computational laboratory-based approach each experiment was replicated 500 times, each replication exploring the impacts of the same theoretical mechanisms in a unique simulation environment inhabited by a distinct population of victims and offenders.

Two model variants were presented, each addressing a fundamentally different type of offending: the first simulating the commission of crime against spatially static targets (e.g. residential burglary), and the second against spatially dynamic targets (e.g. street robbery). Simulated crime patterns produced in these experiments were analysed using a number of commonly used analytical techniques, each aimed at identifying and quantifying the presence of an empirically identified macroscopic regularity of crime. In undertaking this analysis the following five focused research questions were investigated.

FRQ1: *Are the mechanisms of the opportunity theories generatively sufficient to explain the spatial concentration of crime commonly observed in empirical study?*

FRQ2: *Are the mechanisms of the opportunity theories generatively sufficient to explain patterns of repeat victimisation commonly observed in empirical study?*

FRQ3: *Are the mechanisms of the opportunity theories generatively sufficient to explain the characteristic journey to crime curve commonly observed in empirical study?*

FRQ4: *Do the mechanisms of the routine activity approach, rational choice perspective and crime pattern theory have differential impacts on commonly* *observed patterns of crime?*

FRQ5: *Do these results differ by crimes that occur against static or dynamic targets?*

In addressing these questions, this thesis provides a systematic test of the generative sufficiency of mechanisms described by the routine activity approach, rational choice perspective and crime pattern theory in explaining multiple regularities of crime across multiple crime types.

7.1 Summary of Research Findings

Findings of both studies presented in chapter six demonstrate that the identified micro-mechanisms of the routine activity approach, rational choice perspective and crime pattern theory provide a depiction of the crime event that is *generatively sufficient* to explain commonly observed patterns of spatial clustering, repeat victimisation and the journey to crime curve. Simulation experiments show that the greatest levels of these regularities were observed when offenders operated according to all three proposed mechanisms of the opportunity theories. Moreover, the generative sufficiency of these mechanisms was demonstrated across multiple environments and in the context of criminal activities that occur both against static and dynamic targets. In addition, model results were shown to be consistent across several initial robustness tests. In the following section the previously stated focused research questions are addressed.

7.2 Focused Research Questions

FRQ1: Are the mechanisms of the opportunity theories generatively sufficient to explain the spatial concentration of crime commonly observed in empirical study?
The greatest levels of spatial clustering, for static and dynamic targets, were observed when offenders operated according to the identified mechanisms of routine activities, rational choice, and awareness spaces. Thus, demonstrating that the mechanisms of the opportunity theories provide a candidate generative explanation for the spatial clustering of crime.

FRQ2: Are the mechanisms of the opportunity theories generatively sufficient to explain patterns of repeat victimisation commonly observed in empirical study?
The greatest levels of repeat victimisation, for static and dynamic targets, were also observed when offenders were imbued with all three identified mechanisms of the opportunity theories. Thus, demonstrating that the mechanisms of routine activities, rational choice and awareness spaces provide a candidate generative explanation for empirically observed patterns of repeat victimisation.

FRQ3: Are the mechanisms of the opportunity theories generatively sufficient to explain the characteristic journey to crime curve commonly observed in empirical study?
Journey to crime curves, for static and dynamic targets, exhibited the greatest levels of positive skew when offender agents operated under all three proposed mechanisms of the opportunity theories. Thus, demonstrating that the mechanisms of routine activities, rational choice, and awareness spaces provide a candidate generative explanation for the characteristic journey to crime curve observed in empirical studies of offender mobility.

FRQ4: Do the mechanisms of the routine activity approach, rational choice perspective and crime pattern theory have differential impacts on commonly observed patterns of crime?
The model developed demonstrates that the identified mechanisms of the routine activity approach, rational choice perspective, and crime pattern theory, have differential impacts on the each of the macroscopic regularities of crime studied. Furthermore, such impacts differ when comparing offending against static and dynamic targets. Figure 7.1 provides an overview of the relative impact each mechanism confers on the regularities of interest in both model variants investigated.

Primarily, the routine activities mechanism confers the greatest impacts on the three selected regularities, playing a substantial role in 5 out of 6 regularities studied. Interestingly, the two model variants differ in only one key way – levels of repeat victimisation are most influenced by the routine activity and awareness space mechanisms when targets are static. Conversely when targets are spatially dynamic the rational choice mechanism seems to play a

Table 7.1: Relative Impacts of Each Mechanism on Macroscopic Regularities by Model Variant

	Crimes against Static Targets			*Crimes against Dynamic Targets*		
	Spatial Clustering	Repeat Victimisation	Journey to Crime Skew	Spatial Clustering	Repeat Victimisation	Journey to Crime Skew
Routine Activities	***Greater***	***Greater***	***Greater***	***Greater***	Lesser	***Greater***
Rational Choice	Lesser	Lesser	Lesser	Lesser	***Greater***	Lesser
Awareness Spaces	***Greater***	***Greater***	Lesser	***Greater***	Lesser	Lesser

more significant role in explaining repeat victimisation.[1]

FRQ5: Do these results differ by crimes that occur against static or dynamic targets?
As discussed above, when simulating offending against both static and dynamic targets the identified micro-mechanisms of the opportunity theories provide a generative explanation of all three regularities of interest. However, the impacts of the three identified mechanisms do differ between offending types.

Having summarised the key findings of the thesis, a number of implications for theory, methodology and policy are now discussed

7.3 Theoretical Implications

This thesis began by identifying several hypotheses concerning the proximal mechanisms of crime put forward by the opportunity theories. In doing so, it was demonstrated that while considerable empirical support for these theories existed, several problems associated with observation and experimentation limited the rigour with which their underlying hypotheses could be empirically tested at the micro-level.

[1]However, further robustness tests are required to confirm the ubiquity of this result.

In examining the salient findings of a wide range of empirically based research within environmental criminology, a number of consistently observed macroscopic regularities of crime were highlighted. These included the non-uniform spatial and temporal distributions of crime, patterns of repeat victimisation, and the characteristic journey to crime curve. Drawing on Brantingham and Brantingham's (1993b) depiction of crime as a patterned activity that produces patterned outcomes, it was argued that such regurlarities represented the observable, predictable, emergent outcomes of whatever mechanisms were indeed operating *in-situ*.

In an attempt to bridge this divide between micro-theory and macro-observation an ABM of crime was developed through which the generative sufficiency of micro-level theoretical mechanisms in explaining these commonly observed patterns of crime could be assessed.

Results of the simulations performed demonstrate that the mechanisms described by the opportunity theories provide a candidate *generatively sufficient* explanation for the spatial clustering of crime, patterns of repeat victimisation, and the characteristic journey to crime curve, commonly observed in empirical studies. As a result, the primary theoretical implication of this research is that the model provides micro, meso and macro support for the identified hypothetical mechanisms of the routine activity approach, rational choice perspective, and crime pattern theory. By exploring the decentralised interactions of multiple heterogeneous individuals, the model demonstrates that the micro-level interactions of offenders, victims and place described by the opportunity theories give rise to a number of predictable emergent outcomes that closely resemble those observed in the real world. This finding is congruent with crime pattern theory's depiction of the criminal event as a complex system that exhibits patterned outcomes. Of particular note is the ability of the mechanisms formalised to consistently generate all three regularities of interest, across multiple environments, and when examining offending against both static and dynamic targets. The ubiquity of these findings serves to further support the propositions of the opportunity theories as viable generalizable crime event explanations that can be applied to a range of crime types.

Furthermore, by applying a computational laboratory based approach the model was also able to estimate the likely contributions of specific mechanisms in the formation of particular crime patterns. When targets are static, results of the model suggest that both the routine activity and awareness space mechanisms confer the greatest impacts on all three regularities. This finding supports the propositions of the routine activity approach that describe the importance of the crime convergence in explaining the observed incidence of crime. Furthermore, the interplay of routine activities and awareness spaces is of considerable significance - cognitively known areas are a direct result of those which are commonly visited and as a result, the awareness space mechanism serves to reinforce the spatial activities of an individual.

As such, the model provides a computational demonstration of the proposed interactions of activity and awareness spaces provided by Brantingham and Brantingham's pattern and geometry of crime theories. In particular, returning to the hypothetical offender-target-environment scenarios depicted in Brantingham and Brantingham (1981), patterns of crime produced by the model closely mirror the expected distributions of crime described in cases 7, 8, 9 of the theory (Brantingham & Brantingham, 1981, 44-47), demonstrating that above and beyond the hypothesised mechanisms, the interactions which occur between them produce patterns of crime congruent with those both expected by theory, and observed in reality. These findings provide significant support for the geometric theory of crime's depiction of aggregate crime patterns and the underlying mechanisms which give rise to them.

Further observations are also congruent with the opportunity based depictions of the crime event provided by environmental criminology, which suggest that while the most attractive targets are more likely to be victimised, target utility alone is unlikely to be sufficient to predict victimisation. Rather, targets both attractive and located within the cognitively known operating area of motivated offenders are those who face the greatest risks of victimisation (Cohen & Felson, 1979; Hindelang et al., 1978).

A further interesting finding is the limited impact that the rational choice mechanism had on levels of repeat victimisation when targets were static. This observation has potential implications for the theoretical mechanisms of event dependence (boost) and risk heterogeneity (flag), suggesting that event dependence is likely to play a significant role in explaining repeat victimisation in crimes such as residential burglary.[2]

When targets are spatially dynamic (e.g. street robbery, assault), the routine activities and awareness spaces mechanism remain most significant in explaining the spatial clustering and the characteristic journey to crime curve. However, when examining repeat victimisation across both model variants, the results of study 2.2 suggest that the rational choice mechanism confers the greatest impact on repeat victimisation (relative to the routine activity and awareness space mechanisms) when targets are spatially dynamic.[3]

In considering why this might be the case three potential explanations are proposed, the first relating to the characteristics of the underlying mechanisms being studied, and two further which relate to potential limitations of the ABM presented.

The first potential explanation concerns the increased complexity of interactions which occur in the commission of crime against dynamic targets – that is, when both offender and victim activity is, as a result of the routine activities mechanism, nonlinear. To illustrate, consider a static target with a relatively low utility found within the cognitively known activity space of offenders. Over time, as the target is repeatedly encountered by a particular offender, the offender becomes increasingly more aware of it. In this scenario, eventually all but the most unattractive targets will likely be victimised, and after an initial victimisation the chance of a subsequent victimisation can only increase (until at least some upper bound of awareness is reached).

Conversely, dynamic targets are likely to be encountered less frequently by the same offender in the same location, simply as a result of them not always being in the same place at the same time. In these cases, the relative utility of a target may play a more significant role in determining whether victimisation occurs. To be considered viable, targets with relatively low utility require offenders to not only converge with them, but also to do so in cognitively well known crime places which facilitate offending.

[2] This hypothesis could be further investigated using the existing model by establishing whether repeat victims were repeatedly targeted by the same or different offenders.

[3] This finding however, requires further investigation via robustness testing.

In essence, this relationship can be described as follows. Each time an offender encounters the same (static) target, the likelihood of victimisation increases as a result of the awareness spaces mechanism. Conversely, when encountering dynamic targets the likelihood of victimisation depends on both the utility of the target and the offender's knowledge of the place in which convergence occurs. Thus, targets become more or less attractive to offenders depending on where and when they are encountered, highlighting the importance of place, and in turn offender's awareness of it, in considering the spatial and temporal distribution of suitable criminal opportunities. Relating this observation again to the boost and flag explanations of repeat victimisation, the model results thus suggest that when targets are spatially dynamic, risk heterogeneity may play a more significant role in repeat victimisation than event dependence.

An alternative way to consider this finding is to ask not why the rational choice mechanism might be more significant in explaining repeat victimisation against dynamic targets, but instead, why the routine activities and awareness spaces mechanisms seem less important relative to when targets are static. One potential explanation concerns the implementation of routine activities within the model itself. Currently the temporal aspects of routine activities are somewhat underdeveloped, offenders undertake spatial activities in only a semi-structured fashion (the key pseudo-temporal element being the likelihood of returning home after each activity). This limited conceptualisation of temporal constraints is likely to have little impact on crimes occurring against static targets, as these are encountered at the same location irrespective of time. However, when considering crimes against dynamic targets the lack of temporal constraints for offender and victim activity may underestimate the repeated convergence of certain victims and offenders that might result from overlapping spatial and temporal characteristics of activities, thus reducing the impacts that routine activities might play in levels of repeat victimisation.[4]

A further possible explanation relates to a lack of formalised, shared activity nodes within the environment. Crime pattern theory suggests that certain societal nodes described as crime generators repeatedly draw certain

[4] Given the links between activity and awareness spaces discussed above this may also limit the impact of awareness spaces on repeat victimisation.

activities and as a result, bring together victim and offender, thus leading to greater numbers of potential crime convergences. Within the model presented routine activity nodes are randomly allocated from the environment to all offenders and victims (when dynamic), with no predisposition for certain nodes to be shared by agents. Thus, the inclusion of such nodes might lead to the repeated convergence of dynamic victims and offenders at predictable locations, and in turn increase levels of repeat victimisation. Both of these potential explanations can be explored further using additional model elements and are discussed briefly in the extensions section below.

In summary, the primary theoretical implication of this thesis is that the identified mechanisms of the opportunity theories offer a candidate explanation that is generatively sufficient to explain why offending against both static and dynamic targets tends to be spatially clustered, experienced by a relatively small number of repeat victims, and why the aggregate journey to crime curve tends to follow a characteristic distance decay relationship. In demonstrating how the micro-hypotheses of theory are capable of generating macro-patterns observed in reality the model provides support for the propositions of the routine activity approach, rational choice perspective, and crime pattern theory, at micro, meso and macro levels. Recalling Jeffrey's (1993) criticism of the routine activity approach as providing a "description of [crime] events and not an explanation" (p492), this thesis demonstrates that the proximal descriptions of the crime event provided by the routine activity approach, rational choice perspective and crime pattern theory do provide an explanation of several widely observed crime phenomena – a generative explanation.

Observations beyond this primary implication, such as those described above, serve to highlight the strengths of the simulation approach in generating novel and interesting hypotheses that should be further explored through both computational and empirical study. Having discussed the key theoretical implications of the experiments performed throughout this thesis, the following sections outline a number of potential methodological and policy implications.

7.4 Methodological Implications

This thesis has demonstrated how computational ABMs of the crime event can be used to assess the generative sufficiency of theoretical crime event micro-specifications, and in turn, estimate the likely impacts of important theoretical processes in the formation of particular crime patterns. In keeping with the work of previous authors within the field of computational criminology, this research further highlights the suitability of simulation approaches in exploring the validity of hypotheses that describe complex unobservable interactions of the crime event.

Epstein's approach of generative social science applied in this thesis seems to offer considerable promise to those who wish to apply ABM in exploring and testing the viability of criminological theory. Given that much is known about the macroscopic patterns of crime, the criterion of generative sufficiency seems an eminently suitable method through which micro-level hypotheses can be prioritised in terms of their plausibility as explanations for known crime patterns.

In addition, the application of simulation as a computational laboratory as undertaken here and advocated by previous authors also demonstrates considerable utility. By permitting the systematic manipulation of model elements, controlled computational experimentation affords a suitable method through which theories about unobservable mechanisms can be assessed in ways that are, for the most part, impossible through traditional experimental means. While the inferences that can be made from computational experiments are different from those related to empirical experimentation, when appropriately framed, the computational model provides a unique point of triangulation through which theories describing the crime event can be explored. Importantly, relative to other forms of experimentation, simulation remains monetarily, ethically, and logistically inexpensive. Thus, while the simulation experiment will never replace traditional empirical enquiry, and should never aspire to, in the future it may provide a viable compatriot to existing approaches that is capable of easily, quickly and cheaply prototyping theoretical proposition; in turn, prioritising theory in terms of its plausibility prior to further empirical investigation.

7.5 Policy Implications

When considering potential policy implications of explanatory models such as the one presented in this thesis appropriate caution should be taken in making inferences from simulation outcomes to the real world. The approach to modelling presented here favours parsimony in order to explore the underlying dynamics of several theoretical propositions. As such its implications are primarily theoretical.

Importantly the model developed in this thesis has demonstrated generative sufficiency not causal explanation. Thus, there may well be other mechanisms not formalised here that are equally capable of generating the macroscopic patterns of crime studied, and as such offer an equally viable explanation for the patterns of crime we commonly observe in empirical study. This, however, is not unlike other methods of enquiry where previously unobserved constructs may be responsible for observed effects.

For policy implications to be derived from the model presented here further testing in a considerable greater number of scenarios and against a greater number of regularities is required. While such experiments will never establish causal explanation the greater the flexibility of the mechanisms in producing plausible outcomes the greater the confidence we can have that that they do indeed sufficiently reflect those processes operating in the real world. Furthermore it is obvious that, as ever, further empirical investigation will be required to explore the validity of model-driven insight.

Therefore, the primary policy implication of this thesis is that the depictions of the crime event provided by the opportunity theories have been supported and as such, crime prevention techniques that draw upon them such as situational crime prevention (SCP), problem-oriented policing (POP) , and crime prevention through environmental design (CPTED) are likely to be effective in reducing crime (just as they have demonstrated to be).

7.6 Model Development Observations

Having described the key findings and implications of the research presented, this section outlines three key observations regarding the use of computational modelling that became evident in undertaking the research presented in this thesis.

First, from the outset, researchers must be explicit about the purposes of models being developed. The development of computational models is constrained by three key factors: the imagination of the researcher, their technical ability, and the computational resources available to them. This creative potential is a double-edged sword; while ABM offers considerable flexibility, the numerous directions in which a model may progress dictate that researchers must exercise considerable self-control in selecting what should and should not be modelled. For them to be useful, models must be transparent and should start out simple, only incrementally increasing their scope in a systematic fashion (Townsley & Johnson, 2008). In taking this approach, each additional model component can be appropriately justified (*why should it be included?*), specified (*how should it be included?*), and implemented (*how was it included?*). The emergent nature of ABM dictates that each additional model component can have considerable and often unforeseen impacts on model outcomes. Indeed, this is often the very phenomenon one is interested in. However, as a result, model enhancements require extensive testing to ensure that what was initially specified has been appropriately implemented. While the time and resources required to perform simulation experimentation are likely considerably less than those associated with real world experiments, development of an ABM still requires considerable investment by researchers. It is crucial at the outset to specify a model's aim and what inferences can be made from its output behaviour. Asking questions such as what will the analysis of model output data tell us, will they inform theory, practical intervention, predict behaviour, or all of the above, will make the viability of certain inclusions and exclusions easier to assess. The focus of the model described in this research was to assess the validity of several identified mechanisms provided by the opportunity theories as a generative explanation of several characteristics of crime. Therefore, model elements were limited to operationalisations of several core identified mechanisms of those theories.

Second, one should not overlook the considerable utility derived from the process of model building. Translating theoretical construct into computational equivalents forces the researcher to consider all the concepts, entities and interactions of a given hypothetical mechanism. Thus, modelling promotes the rigorous specification of theory. This process of theory formalisation can highlight logical inconsistencies that may otherwise be overlooked, and has lead to considerable debate in the development of the model presented in this thesis. Furthermore, the requirement of formalisation serves well to highlight theories that lack adequate specification. Those theoretical constructs that cannot be operationalised and examined in an artificial society, where perfect measurement and manipulation is possible, are those that are likely to be very difficult to test in reality.

Finally, another key observation made during this thesis relates to the importance of appropriate simulation data management and analysis protocols. As previously discussed, simulation experimentation can generate vast quantities of data that must be managed and analysed. To illustrate, the results presented for study one require data describing in total 24 million distinct crime events[5]. Data relating to these and their subsequent analysis required roughly 75,000 data files and 20 gigabytes of disk space. In managing these data a number of procedures were undertaken to ensure that simulated data was adequately prepared, analysed and catalogued. These procedures are briefly summarised below.

Standardised recording: simulation output files should necessarily be standardised, specifying both what will be recorded and how will it be recorded. It is likely unrealistic to record every computational step performed during every simulation – especially when large numbers are performed. Thus, standardised output recording should be established that is appropriate to the research questions the model aims to address. In the model presented in this thesis the recording of simulated crime data aimed to mirror that of recorded crime data (albeit without errors in reporting and recording) thus allowing commonly used analytical techniques to be applied to simulated crime data in the same way that they are applied to recorded crime data.

Standardised analysis: For the output of numerous within-model replications to be analysed and aggregated at suitable levels for reporting, the analysis of simulation output data must be standardised and automated. This requires developing suitable computational routines that will process, analyse

[5] 6 model variants (1 original + 5 modified robustness test models) x 8 model configurations x 500 within-model replications x 1000 crimes per replication.

and summarise simulated crime data. In line with observations made by Axtell and Epstein (1994), researchers should not underestimate the workloads involved in developing suitable methods for processing and analysing simulation output data. To illustrate, at the completion of the research presented in this thesis, the R code developed to process and analyse simulation output data was equivalent in size to the NetLogo code that described the model itself. Furthermore, the time spent in computing such analysis was not insignificant.

Data Cataloguing: Once simulated data are recorded, processed and analysed they must be appropriately catalogued, so that they can be recalled when required. For each set of experiments output files produced by the model were stored in a standardised repository. In addition to the raw model output data, and its subsequent analyses, each repository stored the source code associated with the model used to generate data, and a summary of all model parameters used in each simulation.

7.7 Limitations and Methodological Critiques

The results of this study should be interpreted in the context of several potential limitations. These limitations, relating to both the model developed and more generally the application of ABM and generative social science, are summarised below.

The first potential limitation of the model presented relates to the underdeveloped nature of temporal constraints applied to agent routine activities. Currently, the model specifies routine activities by allocating agents routine activity nodes, however it does not create any particular temporal schedule beyond the likelihood of returning home after certain activities. As previously discussed, this simplification may impact on model outcomes in a number of ways, especially when considering crimes that occur against dynamic targets where the temporal characteristics of activities may more significantly impact on the spatio-temporal distribution of victim-offender convergences. Moreover, if the model is to be used to assess generative sufficiency in explaining temporally based regularities such as the time course of repeat victimisation (Polvi, Looman, Humphries, & Pease, 1991) or the spatio-temporal clustering of near repeats (Johnson et al., 2007; Townsley et al., 2003) it is likely that a more developed representation of temporal constraints on routine activities will need to be developed.

Another potential limitation concerns the current depiction of offender motivation as uniform and static. While this initial model assumption effectively disentangled the effects of offender motivation from the underlying mechanisms explored, it is unlikely to reflect real world offending populations. With this in mind however, the variation in crime phenomena generated given a population of uniformly motivated offenders seems particularly noteworthy. Nevertheless, further model development should explore the impact that differing representations of offender motivation have on model outcomes.

Similarly, the assumption that target utility is randomly distributed throughout the environment should be further explored. The law of spatial dependence states that things that are spatially proximate are more likely to be characteristically similar (Tobler, 1970). Thus, the current depiction of target utility may impact on model outcomes. For instance, randomly distributed target utility may underestimate the likely influences of the rational choice mechanism on the spatial clustering of crime, as some offenders may find themselves within particularly fortuitous circumstances as a result of the clustering of target utility. As a result, extensions to the existing model should investigate the impacts of different spatial distributions of target utility.

While these three limitations are likely to have influenced model outcomes it is important to remember that the aim of this research was to present an initial parsimonious model that allowed the impact of identified theoretical mechanisms to be explored. In order to assess the impacts of these proposed model modifications, the outcomes of further models should necessarily be compared to this initial model, thus providing a counterfactual. However, such comparisons significantly increase computational requirements and as a result were considered beyond the scope of this study. To illustrate, in exploring the influence of spatially autocorrelated target utility, all simulation experiments would need to be replicated first within simulation environments in which target utility was randomly distributed, and secondly where target utility was spatially autocorrelated, thus doubling the required number of within model replications that need to be performed.

More generally, the approach of generative social science applied in this thesis is also still in its infancy. Given its relatively recent introduction, the generative explanation lacks much of the rigour associated with its statistical equivalent. While this should not dissuade researchers from potential applications within criminology, especially given its demonstrated strengths, improper applications of new techniques can undermine credibility; therefore, understanding and clearly communicating the purposes of any model is paramount. With regard to generative social science, the key here is to ensure that the audience for model results understand the difference between generative sufficiency and causal explanation.

One specific limitation of the generative social science approach to modelling crime relates to the quality of data describing the crime event from which regularities are derived, and in turn, against which model outcomes are compared. As previously discussed, the limitations of crime data are well acknowledged (Maguire, 2007). Thus, in assessing equivalence of simulated and empirical data researchers must interpret levels of correspondence appropriately. In discussing this issue Eck and Liu (2008) rightly point out that without adequate modelling of the crime recording process, quantitative equivalence between simulated and recorded crime data should be interpreted with scepticism.

It is suggested however, that this limitation may not impact as greatly on explanatory models, such as the one presented in this thesis that aim for qualitative equivalence, than those models which aim for quantitative equivalence. Consistent with existing studies utilising recorded crime data, the current model makes the necessary assumption that unreported and unrecorded offences do not conform to a unique set of distributional characteristics distinct from those observed in recorded crime data. Nevertheless, the more realistic a model becomes, the more thought that will be required in addressing this issue in a hope of minimising threats to model validity. Furthermore, as the number of empirical regularities against which model outcomes are assessed increases, the ubiquity of certain regularities will need to be carefully considered to ensure that empirical patterns are indeed reflective of the underlying mechanisms and not the processes through which crime is reported and recorded. This will likely involve triangulation of multiple data sources including recorded crime, victimisation survey, and offender self report data; estimates of the likely impacts of reporting and recording practices; and eventually, as Eck and Liu propose simulation of reporting and recording practices.

Another common criticism of ABM is that model outcomes can only ever reflect initial assumptions explicitly made by the model developer – that is, *you only get out what you put in*. This is simply not the case, it is obvious that through the interactions of initial assumptions further, novel outcomes can be observed. For instance, in the models presented, at no point are agents directed to repeatedly victimise certain homes or concentrate their efforts in certain hot-spot locations, yet we observe both high levels of spatial clustering and repeat victimisation when agents operate according to the three mechanisms studied. Furthermore, the approach of generative social science addresses much of the basis for this criticism by appropriately framing the interpretation of model outcomes; by comparing the outcomes of specified micro-mechanisms to known macro-patterns one is able to assess the plausibility of those initial assumptions, so they may in turn be better refined, or eliminated as potential explanations for observed phenomena.

A further criticism of the agent-based approach relates to the primary direction of causality explored using ABM. Emergence in the current model is unidirectional – in that specified micro-behaviour gives rise to observed macro-structures, but macro-outcomes have little impact on micro-behaviour. In the real world macro-patterns affect individual behaviour. For instance, with regard to the crime event, some locations will likely attract and repel offender and victim respectively because of their known properties as good crime places. As such, the initial model presented fails to capture some of the likely feedback mechanisms operating in-situ. Acknowledging this limitation, a number of methods can be envisaged through which it may be, at least partially, addressed with the use of macroscopic constructs that influence individual agent action. For example, Wang et al. (2008) developed a tension surface which encodes the macro-patterns of crime emerging from the micro-level, and through which micro-action is influenced in a top-down manner.

Another limitation of computational modelling relates to the computational resources needed to run large numbers of simulation experiments. While simulation is cheap relative to many other experimental methods within the social sciences, the application of computational models does often require that researchers invest considerable time or computational power[6] in performing simulation experiments. Unfortunately, such computational resources are not commonly found in the academic departments of criminology and criminal justice. In the study presented, the computational capacity available limited the extent of robustness tests that could be performed, dictating that for the second model variant, which was considerably more computationally demanding than the first, robustness tests could not be performed within a reasonable time frame. Furthermore, where robustness tests were performed the parameter space explored was necessarily small in order that such tests were manageable. As such it is acknowledged that further explorations of the parameter space should be undertaken for both model variants, assessing the robustness of model findings and estimating the likely impacts of differing initial conditions in a wider range of circumstances.

Finally, the validity of the model presented in this thesis has only been assessed using within-model replication. An obvious next step is to undertake between-model replication of the same underlying model assumptions using other computational architectures, thus ensuring that findings are not unique to the presented implementation. It is hoped that the documentation provided throughout this thesis will assist those who might wish to undertake this endeavour.

Having discussed a number of potential limitations of the research presented, the following section sets out a number of avenues for further research, several of which aim to address the concerns discussed above.

7.8 Recommendations for Further Research

Having explored the research questions posed in this thesis, a wide range of potential avenues for further research using the existing model are apparent. As such, it is hoped that this thesis has detailed the first of several research efforts using the model presented. A number of these potential lines of

[6] These two requirements are obviously intrinsically linked, at least in theory. Anecdotally, the author has however observed more computing power producing more complex models, which in turn require the same or more time to execute – a property of software development that is in no way unique to agent-based models of social science phenomenon.

enquiry are now briefly described.

7.8.1 Exploring Further Regularities:

Extending this research, the initial goal is to further explore the emergent properties of the existing model. While additional theoretical mechanisms could be incorporated and assessed for generative sufficiency, or the existing computational equivalents of those studied here developed further, the first aim is to explore which other regularities of crime can and cannot be generatively explained by the parsimonious mechanisms described here. For example, assessing the generative sufficiency of these mechanisms in producing two other commonly observed characteristics of residential burglary: the typically short time-course of repeat victimisation (Polvi et al., 1991) and the spatio-temporal clustering of burglary offences (Johnson et al., 2007; Townsley et al., 2003). By extending the regularities against which micro-level mechanisms are validated the confidence that researchers can have in the sufficiency of theories increases.

7.8.2 Longitudinal Analysis of Simulation Trace

The results of the experiments presented in this thesis have concentrated on the macroscopic outcomes of agent populations operating under a number of theoretically inspired behaviours. The study of these patterns presented has been purely cross-sectional; a potential extension of this research is to further explore the underlying trace that generates such patterns using longitudinal analysis.

7.8.3 Combining Model Variants:

A further suggested application of the current model is to combine both variants presented into a single model in which targets can be both spatially static and dynamic. In doing so, dynamic targets representing civilians could be distributed amongst static targets, representing their homes. One key ramification of combining model variants in this way is that it could facilitate a more advanced exploration of guardianship, such that the utility of static targets could be modified by the presence or absence of home owners, thus capturing the inherently dynamic nature of guardianship (Reynald, 2011). Furthermore, this new model could also be used to explore the impact of informal guardianship by modelling individual's ability to disrupt the crime commission process both against fellow civilians and their homes.

7.8.4 Advanced Temporal Representations:

As previously discussed, currently the temporal aspects of the model are the most underdeveloped. One obvious model extension would provide temporal constraints to routine activities as implemented by Groff (2008) and Wang et al. (2008). In doing so, agents could be allocated temporal schedules that reflect the timings of day-to-day activities. This would permit further examination of temporal patterns of crime such as those described in section 2.2.1.

7.8.5 Exploring the Impact of Crime Generators:

In the hope of addressing another potential model limitation discussed in section 7.7, a further model extension could implement crime generators within the simulation environment. Crime generators could be added to the existing model as routine activity nodes and added to the routine activity spaces of all offenders and victims, thus exploring the impacts of such shared activity nodes on macroscopic patterns of offending

7.8.6 Autocorrelated Target Utility:

A further model extension could explore the impact of spatially autocorrelated target utility – such that targets close to one another would share similar utility scores. In this way different neighbourhoods within the environment could be defined with similar utility profiles. Such model additions could then be used to explore a number of phenomena such as the edge effects described by crime pattern theory (Brantingham & Brantingham, 1993b).

7.8.7 More Advanced Representations of Target Utility:

The current model collapses the metrics of risk, reward and effort into a single measure of target utility. One potential model extension is to model all of these features of a given target separately. In addition, target utility is currently static and does not change; further models could explore dynamic target utility. For instance, given a more advanced temporal representation, static targets for could exhibit different utility at different times throughout a simulation day, reflecting the presence or absence of guardianship provided by residents (Cohen & Felson, 1979).

7.8.8 Variable Offender Motivation:

The current model explores the dynamics that occur given a uniformly motivated offender population. As previously discussed, this representation of offender motivation is one that is unlikely to reflect real world offending populations. Further model extensions could explore the impacts of dynamic offender motivation. Furthermore, the model could be used to represent the provoked, mundane and anti-social predator offenders suggested by Cornish and Clarke (2003). In doing so, different classes of offender agent could be provided with differing behaviours, for instance providing some offenders with a more refined target search strategy that allows them to actively search for targets rather than simply victimising those opportunistically encountered during day-to-day activities. Similarly, different classes of offenders might have different learning rates, which reflect their ability to more rapidly ascertain which targets are suitable for offending.

7.8.9 Offender Effectiveness and Adaptation:

The current model assumes that when the offending calculus deems a potential target sufficiently suitable it is victimised. This representation is simplistic – offenders are clearly ineffective on some occasions (an observation attested by the frequency of attempted burglaries found within recorded crime data). Following a similar approach to Wang, Liu and Eck (2008), further model extensions could better represent the commission process, and in addition might allow offenders to be encouraged or discouraged from committing crime based on their previous successes and failures.

7.8.10 Spatially Specific Activity Nodes:

Following the approach taken by Groff (2007a), another potential model extension could split the simulation environment into a series of zones, such that agent home locations are drawn from identified residential areas and work and recreational nodes from other suitable zones. This clustering of the location of certain types of activities nodes is likely to be a better reflection of the distribution of activity nodes found in the real world where it is unlikely that residential, commercial and industrial premises will be randomly distributed. This model extension might better formalise the overlap of particular societal routine activities undertaken at different times of the day.

Having undertaken the initial experiments presented in this thesis and demonstrated the generative sufficiency of the opportunity theories, the model extensions listed above could be implemented and their impacts systematically assessed by comparing modified model outcomes to those produced in this thesis. Thus permitting the incremental and systematic development of model complexity, and in turn, the exploration of new hypotheses.

7.9 Concluding Remarks

The research presented in this thesis has demonstrated how computational agent-based models of society can be used to gain insight into the potential ramifications of theoretical crime event mechanisms, and, in particular, assess their plausibility in explaining patterns of crime that are commonly observed in empirical study.

Having highlighted the current difficulties facing those who aim to test the propositions of the opportunity theories, the approach described provides a distinct but complimentary method of triangulation to existing endeavours. In addition, by building on the observations of previously developed computational models which aim to explore the crime event, the model presented here aims to contribute to the burgeoning field of computational criminology.

The approach of generative social science proposes that to explain some macroscopic phenomenon one should ask: *"How could the decentralised local interactions of heterogeneous autonomous agents generate the given regularity?"* (Epstein, 1999, 41). In the artificial societies in which offenders operate according to mechanisms outlined by the routine activity approach, rational choice perspective and crime pattern theory, crime clusters in hot spots, with targets that are both attractive and located within the cognitively known activity space of one or more offenders experiencing repeated victimisation. Furthermore, when aggregate journey to crime curves are observed they follow a characteristic distance decay curve. Thus, findings of the simulations presented demonstrate that the identified mechanisms of the opportunity theories provide a generative, and as such, candidate explanation for several commonly observed patterns of crime.

While the importance of empirical experimentation cannot be overstated, computational approaches such as those presented here may provide a complimentary and comparatively inexpensive method for theoretical prototyping. Establishing mechanisms that offer viable generative explanations for crime increases our ability to identify those hypotheses most likely to reflect real-world mechanisms, and diminishes the likelihood of pursuing mechanisms that are unable to explain commonly observed crime patterns. While this approach is only capable of demonstrating the generative sufficiency of theory, assessing which theories offer a sufficient explanation of commonly observed outcomes is of obvious utility. Not only for testing theory, but also in highlighting those theories that lack adequate specification of the mechanisms through which they propose observed outcomes come about. Without revision, such theories are likely of little use in developing either simulation or, more importantly, crime prevention intervention.

While some may lament the fact that simulation relies on assumptions concerning the mechanisms of crime – so does intervention. Indeed, in several ways intervention and simulation are very similar. Both provide viable methods to test the validity of proposed theory – each with their own respective strengths and weaknesses. Yet the relative savings offered by simulation, monetarily, ethically and logistically, necessitate that we must continue to investigate its application as a preliminary tool capable of assessing the risks associated with pursuing particular theoretical propositions. Given the wealth of potential explanations for crime and criminality proposed within the criminological literature, theory validity is implicitly variable. Prioritising theoretical mechanisms in terms of their plausibility may help to guide necessary, but in many cases expensive, empirical activity. Drawing on Sherman's *what works* nomenclature (Sherman et al., 1998), simulation might provide us with a suitable way to initially establish which mechanisms proposed by theory *can and can't work.*

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