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Simulation for Theory Testing and Experimentation: An Example Using Routine Activity Theory and Street Robbery

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Abstract Achieving a better understanding of the crime event in its spatio-temporal context is an important research area in criminology with major implications for improving policy and developing effective crime prevention strategies. However, significant barriers related to data and methods exist for conducting this type of research. The research requires micro-level data about individual behavior that is difficult to obtain and methods capable of modeling the dynamic, spatio-temporal interaction of offenders, victims, and potential guardians at the micro level. This paper presents simulation modeling as a method for addressing these challenges. Specifically, agent-based modeling, when integrated with geographic information systems, offers the ability to model individual behavior within a real environment. The method is demonstrated by operationalizing and testing routine activity theory as it applies to the crime of street robbery. Model results indicate strong support for the basic premise of routine activity theory; as time spent away from home increases, crime will increase. The strength of the method is in providing a research platform for translating theory into models that can be discussed, shared, tested and enhanced with the goal of building scientific knowledge.

Keywords Theory testing · Simulation · Agent-based models · Geographic information systems · Experiment

Introduction

Achieving a better understanding of crime events in their spatio-temporal context is an important research area in criminology with major implications for improving policies and developing effective crime prevention strategies. Theoretical advances under the rubric of opportunity theory have highlighted benefits of a shift in focus from the criminal motivation of people to the contexts in which crime events occur

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(Brantingham and Brantingham 1981; Eck and Weisburd 1995; Weisburd 2002). Because these approaches focus on the crime event and not the intrinsic motivations of the actors, they produce concrete and immediate strategies for both policy and practice (Akers 2000; Cullen and Agnew 1999; Felson 1987; Vold et al. 2002). Implementation of these strategies holds the promise of swift reductions in crime rates.

Routine activity theory (Cohen and Felson 1979), in particular, has received a great deal of attention and its crime reduction potential is widely recognized.[1] Accordingly, there have been many attempts over the last twenty-five years to empirically validate routine activity theory. Despite applying a variety of methodologies, these studies have produced inconsistent support for the theory. Their shortcomings stem from: (1) the lack of individual-level data and (2) the inability to adequately model the complex and dynamic interactions of individuals that produce observed crime patterns. To their credit, these studies have generated a rich literature of evidence upon which to base the identification and operationalization of relevant constructs for the current investigation.

This research demonstrates a new approach to testing routine activity theory (Cohen and Felson 1979) using simulation modeling. The assumptions of routine activity theory are operationalized and implemented in a model of street robbery events. The crime of street robbery is a natural choice for this type of model because it involves the interaction of individuals in a public area (e.g., sidewalk, parking lot, etc.). In addition, it is an instrumental crime (for economic gain), and thus more likely to be the result of a rational decision than an expressive crime (e.g., assault) (Clarke and Cornish 1985; Walsh 1986).

The following sections provide the rationale and methodology for constructing simulation models based on theory. The section entitled ''Meeting the Challenges Discovered by Previous Research'' discusses previous tests of routine activity theory and provides an introduction to simulation as an alternative methodology. The criminological concepts that underpin the model are identified in the ''Theoretical Basis for the Conceptual Model.'' Although routine activity theory is the focus of this research, rational choice theory contributes concepts important to representing offender decision-making. A section on ''Implementing a Model of Street Robbery'' provides a description of how those constructs are implemented in an agent-based modeling (ABM)/geographic information systems (GIS) framework. The analysis strategy and findings are detailed in the ''Analysis'' and ''Findings'' sections. Implications are discussed in the final two sections.

Meeting the Challenges Discovered by Previous Research

Cohen and Felson's (1979) original formulation of routine activity theory has become the most frequently cited basis for examining the connection between social

[1] Environmental criminology is another important theory that emphasizes place characteristics and offender travel in the convergence of victims and offenders in space-time (Brantingham and Brantingham 1981, 1990; Brantingham and Brantingham 1978). Other theories relevant to micro level modeling include lifestyle theory (Hindelang et al. 1978) and the criminal event perspective (CEP) (Meier et al. 2001). However, the focus on one theory for the initial model precludes a full examination of these theories.

structural changes that have affected routine activities and crime.[2] In their seminal work, Cohen and Felson hypothesize that it was the shift away from home-based activities that produced the increase in crime that occurred after World War II. An increase which occurred despite improvement in the socioeconomic indicators historically associated with crime (e.g., unemployment and education). As originally conceptualized, routine activity theory identifies the convergence of *motivated offender*, *suitable target*, and the lack of a *capable guardian* at a particular place and time as the core elements necessary for a crime to occur (Cohen and Felson 1979). The authors also recognize the importance of *routine activities* in shaping the spatio-temporal structure of convergence of victim and offender. They emphasize that crimes occur when the normal everyday activities of offenders and victims converge without a capable guardian present.

A wide variety of studies have attempted to validate routine activity theory and these studies provide a strong foundation for the current research. Some have employed macro-level data to approximate the construct of routine activities (Cohen 1981; Messner and Blau 1987; Miethe et al. 1991). Others have relied on survey data collected from individuals (Miethe et al. 1987; Osgood et al. 1996), and still others have combined micro- and macro-level variables to represent routine activities within a social structure (Cohen et al. 1981; Kennedy and Forde 1990; Miethe and McDowall 1993; Rountree and Land 1996; Sampson and Lauritsen 1990; Sampson and Wooldredge 1987). As mentioned earlier, these studies have found inconsistent support for the theory. The studies suffer from three main shortcomings: (1) failure to consider the spatio-temporal structure of routine activities, (2) measurement issues, and (3) the inability to accommodate dynamic, individual-level interactions. These issues are addressed in more detail next.

Although the importance of spatio-temporal elements in routine activities is often acknowledged, the spatial structure and timing of these activities has been widely overlooked.[3] Indeed none of these studies incorporated the dynamic, spatio-temporal interaction of offenders, victims, and potential guardians at the micro level; an omission that was most likely driven by a lack of data. In a commendable effort, two studies attempted to address these issues through the inclusion of gross measures to capture the timing of routine activity (e.g., separating daytime from nighttime activities) (Kennedy and Forde 1990; Miethe and McDowall 1993). However, the spatio-temporal structure of routine activities is a core component of routine activity theory and must be more comprehensively measured if its role in the convergence of offenders and targets is to be better understood.

A variety of measurement issues arise when attempting to test routine activity theory (Cohen et al. 1981; Miethe et al. 1991; Sampson and Wooldredge 1987). As Bursik and Grasmick note “it has been notoriously difficult to collect reliable and valid indicators of its central components” (1993, p. 77). Other measurement issues include: ecological fallacy; overlapping operationalization of constructs; difficulty with adequately measuring the construct of routine activities; and a reliance on official data and victimization surveys that have widely recognized flaws. When tests

[2] The extensions to the original 1979 version of the theory are not incorporated into this first effort (Felson 2001, 2002). This was done in order to make the results of the model easier to interpret.

[3] Two studies (Miethe and McDowall 1993; Sampson and Wooldredge 1987) emphasized how opportunity structure changed across areas but neither measured how the spatio-temporal structure of routine activities impacted the observed distribution of crime.

are done using macro-level data, they are susceptible to the ecological fallacy which states that the characteristics of an area cannot necessarily be inferred to individuals. Consequently, macro-level data are generally unsuitable for testing a micro-level theory such as routine activity (Eck 1995).

Regardless of the level of analysis, all studies have struggled with measuring the construct of routine activities as isolated from other constructs being measured. This problem is related to general issues that have arisen when attempting to clearly link empirically measured variables to particular constructs (e.g., single person households are associated with less informal social control and with less guardianship) (Cohen et al. 1981; Miethe et al. 1991). These issues make it difficult to test the theory because data issues rather than theoretical ones can be employed to dispute contrary evidence (Miethe et al. 1991, 1987). In addition, the reliance on official data and victimization surveys, which have well-known drawbacks, makes conclusions drawn from studies using those sources susceptible to the usual caveats (Gove et al. 1985).

Finally, all of the previous tests reviewed here suffer from the inability to adequately model the complex and dynamic interactions of individuals that produce observed crime patterns. Routine activity theory is essentially a micro-level theory with macro-level implications; it characterizes crime patterns as resulting from the decisions of individuals made in the context of a particular situation (Eck 1995). The methods of previous studies were simply not able to accommodate the complex, non-linear nature of constantly changing individual-level interactions and the manner in which crime patterns emerge from those interactions (Liu et al. 2005).

A New Approach for Modeling Crime Events and Crime Patterns

Simulation modeling offers an alternative method for capturing the dynamic interactions among individuals taking place at the micro level and their relationship to macro level patterns.[4] Some researchers view simulation as a third way of conducting social science research in addition to the more traditional verbal and mathematical/statistical representation of theories (Gilbert and Terna 1999; Ostrom 1988). In this tradition, simulation allows for the exploration and elaboration of theory (Dowling 1999; Eck 2005; O'Sullivan 2004). Like other modeling approaches, simulation modeling involves the creation of a simplified representation of a social phenomenon (Gilbert and Terna 1999). The most familiar type of model is a statistical one (e.g., a regression model) in which input data are 'run' via a statistical program and values are output that describe the relationships among the input data. In contrast, simulation models are themselves computer programs that incorporate the critical aspects of the social phenomenon being modeled. The program is run and the output data are analyzed using standard statistical techniques. Some advantages of simulation models include the ability to examine the ''entire dynamical history of the process under study'' since information about the dynamics can be collected as the model runs (Axtell 2000). In addition, simulation allows heterogeneity among individuals that more closely approximates the variety found in everyday life and is able to accommodate the non-linear relationships present in dynamic and complex interactions (Dibble C, unpublished paper; Epstein and Axtell 1996; Gilbert and Terna 1999).

[4] Simulation modeling, as discussed here, comes from the complex systems science tradition (see Holland (1995) for an introduction).

Agent-based models are one type of simulation that employs a bottom-up approach, in which agents are imbued with unique characteristics and general behavioral rules and macro-level patterns emerge from their interactions (Epstein and Axtell 1996; Gilbert and Troitzsch 1999). An agent "can be thought of as an autonomous, goal-directed software entity" (O'Sullivan and Haklay 2000, p. 13). Agents most often represent people but can also be organizations, neighborhoods, governments, etc. The characteristics of agents can be randomly assigned so that specific societal averages are produced and the possibility of systematic bias is all but eliminated. Individual agents in the model interact with each other based on a set of decision rules. Their characteristics are dynamically changed as a result of those interactions. Traditionally, agents interact in an artificial world, although the value of leveraging GIS data to provide a 'real' landscape is gaining recognition since artificial landscapes do not take into account the impact of the environment on agent behavior (Brown et al. 2005; O'Sullivan and Haklay 2000).

Additional scientific strength is added when simulation models are implemented within a computational laboratory framework (Dibble 2006, unpublished paper; Epstein and Axtell 1996; Gilbert and Terna 1999; Macy and Willer 2002).[5] Computational laboratories enable experiments to be conducted and replicated. Aspects of the agents, society, and the landscape can be held constant or systematically varied in order to provide a level of control impossible to attain using traditional social science methods. These characteristics of computational laboratories facilitate the creation of a variety of simulated experiments, featuring different conditions or applying various prevention scenarios, which are then evaluated. An additional advantage is that compared to empirical research, simulations have minimal cost.

Agent-based modeling also has some limitations. One is that the findings are constrained by the assumptions and rules on which the model is based. In this way agent-based models reflect the quality of the theoretical and empirical research available, data sources, and the choices about how they are implemented in the model. Specifically, the relationships depicted, data sources, parameter values, and decision rules within the model all influence the relationships observed within the model and the outcomes. Agent-based models rely on random numbers and random number distributions to provide a stochastic element to the simulation. Similar to the choice of parameter values, the choice of distribution (e.g., Uniform, Poisson, Normal, etc.) and the moments of the distribution (e.g., mean, standard deviation, etc.) have implications for model results. Another limitation concerns the meaning of findings from an artificial society. They do not represent an empirical test of the theory but rather the extent to which the theory is plausible.

Recently, a small body of research has emerged that makes use of simulation models to explore crime-related issues. Efforts by Epstein et al. (2001) on civil violence and Wilhite (2001) on protection and social order provide interesting approaches to modeling how the interactions of individual agents are related to emerging patterns of violence or protection. Within criminology, work has begun on conceptualizing the application of simulation in environmental criminology (Brantingham and Brantingham 2004; Brantingham and Groff 2004) and explaining crime patterns (Eck 2005). Simulation is being applied to study both physical and

[5] The term *computational laboratory* refers to the software tools to create and evaluate models through systematic experimentation and descriptive analysis of output data (Dibble 2006, unpublished paper; Epstein and Axtell 1996; Gilbert and Terna 1999).

cyber crime (Gunderson and Brown 2003) as well as drug markets (Olligschlaeger and Gorr 1997; Perez and Dray 2005). Two other efforts implement theory, one is based on a general model of crime on a GIS-based raster grid (Wang et al. 2004) and the other uses routine activity theory to study street robbery in one neighborhood (Liu et al. 2005). Rather than offering competing paradigms, these approaches represent a healthy variety of complementary approaches (Eck and Liu 2004).

The approach taken in this paper extends previous efforts in several ways. First, the steps involved in building a simulation model are thoroughly explained to aid in replication. Second, a set of experiments is conducted to provide the first direct test, albeit in an artificial society, of Cohen and Felson's core assertion that shifts in routine activities away from home, increase crime rates. Each experiment holds the number of motivated offenders and suitable targets constant, only the amount of time spent at home varies. Third, software integrating ABM and GIS is used to explore how agent travel on a real street network impacts the frequency of convergence of the elements necessary for a crime to occur. GIS software excels at managing data about space and ABM is superior at keeping track of time; together they allow exploration of space-time relationships. Finally, the new approach allows examination of how the convergence of heterogeneous agents translates into aggregate rates of street robbery.

The remainder of the paper details how a computational laboratory using ABM/GIS can be employed to address the following research questions: (1) Does the shift of routine activities away from home increase the incidence of street robberies?; and (2) What is the impact of increasing time spent away from home on the spatial pattern of street robberies? In order to facilitate interpretation, the initial model is made as simple as possible, implementing only the core concepts of routine activity.

Theoretical Basis for the Conceptual Model

Although the approach advocated here is novel, the process of developing models to represent reality is not. Models have a long history of use in the social sciences (Gilbert and Terna 1999; Gilbert and Troitzsch 1999; Schelling 1971; Simon 1952). While models vary in how faithfully they represent reality, they typically operate on the principle that simpler is better; thus a primary goal of modelers is try to assemble the most parsimonious model to answer a question. The degree to which the theory is represented in the model provides the structural validity of the model (An et al. 2005; Manson 2001). Simulation models, in particular, start with simple models and then systematically add complexity to ensure that the dynamics are well understood before continuing (Macy and Willer 2002).

Following those earlier modeling efforts, the building of the simulation model detailed here begins with the identification of the most basic theoretical propositions of routine activity theory. Once these are identified, the next step is to develop a conceptual diagram that captures both the essential constructs and how they are related to one another. The constructs and their relationships are then formalized so they can be coded in a computer program. In some cases, the constructs are formalized as clearly stated verbal guidelines that underlie the behavior of agents, their interactions with other agents, and their interaction with the environment. In other cases, the definition of these constructs takes the form of mathematical equations for evaluation of specific situations an agent encounters during the course of a simulation. Where theory is not detailed enough for implementation or does not address an issue, empirical research is used to enhance the representation of behavior within the model. The final step in building the simulation is implementation of the model via a software package that integrates ABM and GIS.

Fortunately, there is rich background literature to guide the development of an agent-based model of street robbery. Appropriately, the model relies mainly on routine activity theory for definition of the core concepts. Since routine activity theory does not address offender decision-making, rational choice perspective is employed to develop the decision rules applied in the model (Clarke and Cornish 1985, 2001). The next sections serve a dual purpose providing the basis for both the conceptual model and the formalization of behavioral rules.

Routine Activity Theory

The four elements of a crime discussed earlier provide the main constructs of the model (Fig. 1). There are two types of people in the model, civilians and police. Civilians take on roles representing the three major elements of crime (i.e. offenders, targets and guardians). The fourth element, routine activity, is influenced by the amount of time an individual spends away from home and the network of streets available for travel. Once convergence occurs, factors such as guardianship and suitability of target are considered by the offender when making the decision whether or not to commit a robbery.

Table 1 and the next few paragraphs provide a detailed account of how each of the above constructs is translated into a formal verbal description and then how that description is implemented in the model. Beginning with motivated offenders,

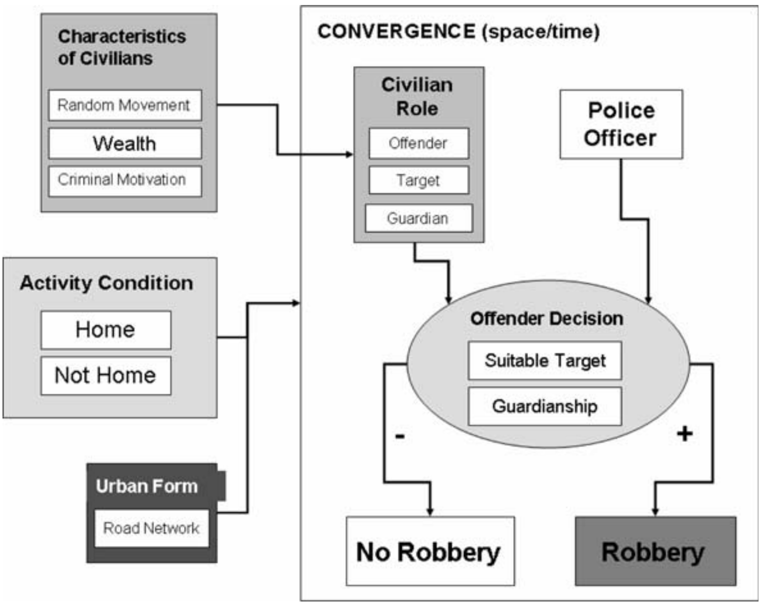

Fig. 1 Conceptual model of street robbery

Table 1 Formalization of theoretical concepts

Theory	Theoretical concept	Verbal operationalization of concept	Implementation
Motivated Offender			
Routine activity	There is a supply of motivated offenders	Research indicates that approximately 20% of the population has participated in crime. This is the proportion of the population that has achieved a state of 'readiness' to commit a crime[a]	Twenty percent of agents have criminal propensity
Rational choice			Only agents with criminal propensity make decision to offend
Rational choice	Offender makes decision to offend using bounded rationality and considering the availability of suitable targets without capable guardians	Individuals with criminal motivation decide to offend based on the suitability of targets and the level of guardianship. The decision itself is not necessarily lengthy or rational but rather based on a form of 'bounded rationality' in which offenders choose the first opportunity that is convenient and meets some minimum requirement for risk and reward	Agents with criminal propensity compare wealth of other agents at node with own wealth
Suitable target			
Routine activity Rational choice	Suitable target is an individual who is visible, accessible and has perceived value	Visibility and accessibility requirements are met if an individual is on the street. The individual also must be perceived as having at least as much money as the motivated offender so there is some potential for gain	Agents with criminal propensity evaluate all other agents at the same node based on the formula below: $S = (W_T - W_A) + P_S$
Capable guardian			
Routine activity Rational choice	Formal and informal guardians factor into level of guardianship	Other individuals at the same place affect the decision to offend. Police have a high deterrent affect because they raise the risk of getting caught. Other individuals can also have a deterrent effect depending on whether they have the potential to intervene in the crime	Each potential offender agent evaluates guardianship at a node • If cop present, no crime • Use formula to evaluate informal guardianship: $G = (N_A - 2) + P_G$
Routine activities			
Routine activity	Social structure	As social structure shifts the locus of routine activities away from the home, risk of personal victimization rises	Average time spent away from home for all agents is systematically varied

[a] Two studies that examined total lifetime participation rates for serious crimes are averaged to get the propensity applied in the model. McCord (1979) found a participation rate of 16.9% for males and Blumstein and Gaddy (1982) found a rate of 22.8% among males and females, an average of those is 19.8%

routine activity theory assumes they are ubiquitous. In making the decision to offend, they evaluate the level of guardianship and whether or not a suitable target is present. Targets, on the other hand, are more fully described. The theory identifies visibility, accessibility, ability to self-protect, and potential for financial gain as the most important characteristics in determining target suitability. The specifics of what constitutes capable guardianship are not addressed, but the theory suggests that the deterrent value of some types of individuals is higher than other types. For example, formal guardians such as police officers have greater influence because they are more likely to intervene.

Cohen and Felson view the construct of routine activity as the key *dynamic* element in determining aggregate crime rates because it affects the particular configuration of offenders, guardians and targets in a situation. Changes in routine activities directly impact the frequency of convergence among these elements which in turn, increases or decreases overall street robbery rates resulting from 'direct-contact predatory violations'.[6] In addition, the theorists postulate that if the frequency of convergence increases, crime may increase even if the absolute number of motivated offenders remains constant. The central premise of routine activity theory then is that as individuals spend more time away from home, crime will increase.

Offender Decision-making

Since routine activity theory assumes a supply of motivated offenders and does not address the decision to offend, the rational choice perspective supplies the theoretical basis for offender decision-making in the model.[7] Rational choice defines criminal behavior as a two-step process. The first step involves the decision to participate in criminal acts. The result of this step is a state of ''readiness'' to commit crime. The second step involves the decision to commit a specific crime and is influenced by the situational factors that exist in a particular context. This research focuses on the second step in the process, the decision to commit a specific crime and assigns agents in the model a criminal propensity indicator that signifies they are at this stage.

There are several components of rational choice that inform the model. At the core of the theory is the concept of rationality in decision-making. The theorists advocate for a notion of rationality that is very broad, stating that ''even if the choices made or the decision processes themselves are not optimal ones, they may make sense to the offender and represent his best efforts at optimizing outcomes'' (Clarke and Cornish 1985, p. 163). In other words, offenders rely on a form of 'bounded rationality' when making the decision to commit a specific offense.[8] Rational choice perspective also assumes that, except for the commission of crimes, offender routine behavior is essentially similar to that of non-offenders.

The theorists also emphasize the value of models and particularly of formalizing process in models. Clarke and Cornish (1985, p. 149) specifically acknowledge the heuristic value of models that incorporate the role of situational aspects of criminal

[6] Following Glaser, they define 'direct-contact predatory violations' as crimes where ''someone definitely and intentionally takes or damages the person or property of another'' (1974, p. 4).

[7] Following Epstein and Axtel (1996) this research does not specifically address how individuals make decisions but rather examines the effect of specific individual behaviors on macro-level social patterns.

[8] Bounded rationality, in particular, lends itself to investigation via agent-based models (O'Sullivan and Haklay 2000).

behavior by stating "[t]hey do not have to be 'complete' explanations of criminal conduct, but only ones 'good enough' to suggest new directions for empirical enquiry or crime control policy." In addition, Clarke and Cornish suggest models should be crime specific and include situational factors (1985, 2001); accordingly, this research focuses on street robbery rather than robbery in general and includes both individual and situational factors.

Implementing a Model of Street Robbery

The following section details how the theoretically based rules and relationships discussed earlier are implemented in a basic model of street robbery. This stage of model building highlights the attributes that make agent-based simulation a powerful tool for exploring spatio-temporal behavior. Specifically, the ability to represent a group of agents as autonomous decision-makers that are involved in dynamic interactions is essential to modeling complex systems of individuals such as those producing crime. The decisions made by agents at one point in time affect the information considered by agents in subsequent turns. For example, when agents are robbed they have less money; the next time they are in a situation with a motivated offender they may be perceived as a less suitable target. This change occurs as the program is running, and its impact is immediately incorporated. The outcome of the model is a set of measurements describing individual and societal crime rates and the distribution of crime events.

Software, Study Area, Duration, and Data

The model is built using Agent Analyst software which combines two of the most popular packages for ABM and GIS. The Recursive Porous Agent Simulation Toolkit for Python (RepastPy) (North et al. 2006) provides the ABM capabilities which are integrated with ArcGIS (ESRI 2005). After Agent Analyst is added into ArcGIS as a toolbox, the program can read from and write to shapefiles, the program's native file format for geographic information.

Although the model can be implemented with any street network, the initial implementation is situated in Seattle, Washington which provides the data for the model landscape. Seattle is the largest city in the state of Washington with a population of 564,945 persons in 2000 (U.S. Census Bureau 2000) and two-thirds of the city is bounded by water. Input data to the model consists of: (1) a GIS layer that describes the Seattle street network; and (2) parameter values to assign societal and agent characteristics and provide a stochastic element to decision-making.

The street network of Seattle provides the basis for agent movement in the model.[9] Because of software limitations, this layer is converted to a set of nodes that represent the street intersections. Instead of traveling along streets, civilians and police in the model move from street intersection/node to street intersection/node. There are 16,035 nodes in Seattle, and these locations represent places among which agents travel and at which a street robbery may occur.

9 The inclusion of a non artificial network on which agents move is critical to representing the impact of the street network on travel and subsequently on the opportunity for convergence. For a more thorough treatment of the technical aspects please see Groff (2007).

Since this is a simulation model, data representing the state of society and individual agents can be collected continuously and/or at custom intervals (e.g., daily, monthly, etc). Data are collected about individual civilians, nodes (places) and society at daily intervals during the model and at the completion of each model run (Table 2). During the model run, agent level variables are collected to describe the time spent away from home, victimization, offending, wealth levels, and whether or not the civilian was assigned criminal propensity. Cumulative totals of the results of agent interactions are also collected for society as a whole. These variables describe: the frequency of street robbery; the number of times more than one agent is at a node; the extent to which police deter crime; offending rates among civilians with criminal propensity; and victimization rates for all civilians. In addition, data from the simulation are collected at the street node level. All these data are written to two types of files, text files and shapefiles. CrimeStat and ArcGIS are used to analyze and visualize the results. The model is run for one year which allows the exploration of changes that might be occurring in the behavior of individual civilians and society over time.

Hypotheses and Experiments

Two hypotheses are tested via five theoretically based experimental conditions. Each experimental condition represents an increase in the societal average for time spent on routine activities away from the home (i.e., 30%, 40%, 50%, 60% and 70%).[10] The two hypotheses examined are:

H_1: As the average time spent by civilians on activities away from home increases, the aggregate rate of street robbery will increase.

H_2: As the average time spent by civilians on activities away from home increases, the spatial pattern of street robberies will change.

The first hypothesis tests the core assertion of routine activity theory—crime rates will increase as time spent away from home increases. The second hypothesis explicitly examines the spatial structure of street robbery locations by comparing the spatial pattern produced under each of five experimental conditions.

Implementation of the Model

In addition to the input data describing Seattle, 12 exogenous parameters are set prior to the model run.[11] Table 3 describes and provides the rationale for each of the

[10] Using data from 1966, Cohen and Felson calculated the average time spent away from home to be 7.74 h per day (32%). Since the goal is to test increases in time spent away from home from that point, the experimental conditions begin at 7.2 h per day spent away from home (30%) and increase by 10% with each subsequent condition to a high of 16.8 h per day (70%).

[11] The values of several of these parameters are assigned using random number generators (RNGs). In simulation models, random numbers have two main functions: (1) provide a stochastic element into what would otherwise be deterministic models of human behavior and (2) enable the replication of model results through assignment of a random number seed at the start of a simulation. The seed is the starting point for all random numbers that are produced during the course of a model run. A particular seed produces the same sequence of numbers each time. This attribute enables testing of the robustness of model outcomes since in simulation modeling the results of a single model run are vulnerable to being atypical (Axelrod 2006). This research applies an explicit random number seed based on the Mersenne Twister algorithm, currently considered to be the most robust available, as the basis for all random number distributions used in the model (Ropella et al. 2002).

Table 2 Outcome data from model

Variable name	Description	Level of measurement
Societal-level outcome		
TotRob	Total number of robberies	Ratio
RobRate	Average number of robberies per population	Ratio
TotIntersections	Total number of intersections (i.e. situations with a motivated offender and one or more 'at risk' civilians)	Ratio
TotDeterred	Total number of robberies deterred by a police's presence	Ratio
TotOffenders	Total number of civilians with criminal propensity that commit a robbery	Ratio
TotVictims	Total number of civilians who are victims of street robbery	Ratio
TotRepeatVictims	Total number of civilians who are repeat victims of street robbery	Ratio
AveAwayTime	Average amount of time agents spend away from home	Ratio
Individual-level process		
AwayTime	Total time spent away from home	Ratio
TotOff	Total robberies committed	Ratio
TotVict	Total times robbed	Ratio
Criminal Propensity	Presence or absence of criminal propensity	Dummy
WealthBegin	Beginning amount of wealth	Ratio
WealthEnd	Ending amount of wealth	Ratio
Place-level process		
TotRobPlace	Total number of robberies	Ratio
TotVisits	Total number of times an agent stopped	Ratio
TotalNodeswRob	Total number of street nodes that had a robbery	Ratio
TotNodeswMultRob	Total number of street nodes that had more than one robbery	Ratio
MeanRobPlace	Mean robberies per street node	Ratio
MeanVisitsPlace	Mean visits per street node	Ratio

parameter values in the model. The choice of parameter values is a critical aspect of all models that deserves special attention because of the potential impacts on the model outcomes. Parameterization of simulation models, while often based on empirical data, must sometimes rely on the experience of the researcher (Liu et al. 2005). For this study, every attempt is made to assign realistic model parameter values but in cases where there was no evidence available a simplified representation was used. For example, choosing a normal distribution for wealth does not represent the actual distribution in Seattle; however, it offers a widely recognized operationalization as a starting point (Axelrod 2006; Epstein and Axtell 1996).

Societal-level Characteristics

Society has only two types of people, police and civilians. Police agents have only one role, that of a formal guardian. Formal guardians are assumed to be capable guardians and automatically satisfy the presence of a capable guardian condition. To accomplish their mission of crime prevention, police agents randomly move along streets. Police never commit crimes in this model and they are never targets.

Six of the parameters in the model apply to society and include the numbers of civilian and police agents, the unemployment rate, the rate of criminal propensity, the time an offender waits before committing another offense, and the random number seed. The number of civilians and police had to be large enough to ensure that two or more agents would sometimes end up at the same one of the 16,035

Table 3 Parameters in the model

Variable	Rationale
Society level	
Number of agents = 1000	Represents a balance between ensuring there are enough agents so that interactions can occur and the computational overhead from using more agents
Number of police = 200	Chosen to ensure that police would be present at some of the convergences that occur across the 16,035 places in Seattle
Unemployment rate = 6%	The unemployment rate of six percent is based on the 2002 unemployment rate for Seattle (Bureau of Labor Statistics 2003)[a]
Rate of criminal propensity = 20%	Given that 20% of the population has committed a crime, 20% of civilians are assigned criminal propensity using a uniform distribution (Visher and Roth 1986)
Time To ReOffend = 60	Parameter value chosen as a starting point since the author could find no empirical data on which to base time to reoffend
Random Number Seed = 100 (seed also tested at 200, 300, 400 and 500)	An explicit random number seed based on the Mersenne Twister (MT) algorithm is used as the basis for all random number distributions used in the model. MT is currently considered to be the most robust in the industry (Ropella et al. 2002)
Agent level	
Societal Time Spent Away From Home = 30% (40%, 50%, 60%, 70%)	Assigned based on a normal distribution with a mean of 432 min (for the 30% condition) and a standard deviation of 10% of the mean (SD = 43)
Initial Wealth = 50	Initial wealth is assigned with a mean of 50 and a standard deviation of 20 units
Amount of wealth received each payday = 5	No empirical evidence available
Amount of wealth exchanged during robbery = 1	No empirical evidence available[b]
Situation level	
Guardianship perception = $U(-2,2)$	The guardianship perception value can add or subtract zero, one or two guardians from the actual number present. This represents the stochastic element in the offender's perception of the willingness of a guardian to intervene
Suitable target perception = $U(-1,1)$	The value in suitable target can increase or decrease the suitability or leave it unchanged. This enables the offender to sometimes decide a target is not suitable even when they have more wealth

[a] Since the jobs data are from 2002, the corresponding year's unemployment rate is employed

[b] A request to the Seattle Police Department for the average amount of cash taken during street robberies remains unanswered

nodes but small enough to be computationally feasible. The choice of 1,000 civilian agents and 200 police agents met that balance. In accordance with the criminal careers literature, 20% of civilian agents are assigned a 'readiness' to commit a crime that is positive; and thus are the only civilians who evaluate each situation for its potential to commit a street robbery. Since even motivated offenders do not offend continuously, a minimum time of one hour is required before an offender can commit another robbery.

Agent-level Characteristics and Behavior

The civilian agents represent the general population of the city. At the start of the simulation, all civilian agents are randomly assigned a starting home location, a wealth level, a criminal propensity indicator, and an allocation of time to spend away from home. Amount of time to spend away from home and initial wealth are assigned using random normal distributions.[12] Amount received each payday and amount of wealth exchanged are fixed.

Following routine activity theory, a civilian agent can assume one of three possible roles, offender, target, or informal guardian. The particular role a civilian agent assumes is driven by their individual characteristics and the contextual dynamics of the specific interaction. All civilian agents begin each day at home where, by definition, they cannot be involved in street robbery either as a victim or offender. For this initial model, civilians in the model begin each day at home and then travel randomly. They are at risk of committing or being a victim of street robbery whenever they are away from home.[13] After they spend their allotted time at home, they travel for the rest of the model day. Wealth is included in the model as the basis for determining whether the civilian is a suitable target. Every 2 weeks, all civilian agents receive five units of wealth.

Each of the civilian agents is randomly assigned a percentage of time to stay away from home. While the time each agent spends away from home is unique, the time for society is controlled. This agent characteristic is the basis for the experiments testing societal trends in time spent away from home. A random normal distribution is used to assign each of the civilian agents a percentage of time to be away from home so that the mean for society as a whole is 30%, 40%, 50%, 60% or 70%.

Since routine activity theory recognizes the importance of the frequency with which the elements of a crime converge in generating crime events but does not elaborate on the space-time structure of human activity, this model of crime events characterizes both the distribution and movement patterns of individuals as random. Civilian and police agents are distributed randomly across the street nodes in Seattle and both follow a 'random walk' in which the agents move one randomly chosen node each minute of the model (Chaitin 1990). When an agent (civilian or police) is moving, each adjacent node has an equal chance of being selected and the civilian can backtrack as well as go forward along the network. Those with criminal propensity travel along the same street network and visit the same locations as other civilians and as police agents. To illustrate the dynamics of the decision to offend, more detail is provided in the next section regarding the behavior of agents with criminal propensity.

Decision to Offend

At each tick of the model, only those agents with criminal propensity (one at a time) who are traveling consider the following aspects of their situation (Fig. 2):

[12] The choice of distribution (e.g., normal, poisson, etc.) and the mean and standard deviation used to assign values affect the allotment of the characteristics across all the agents. While the choices made here are not necessarily reflective of the actual distributions they offer an easily understood base for comparison.

[13] The simple depiction of agents at home or not at home provide a baseline from which to compare more complex representations of agent travel behavior (Groff 2007).

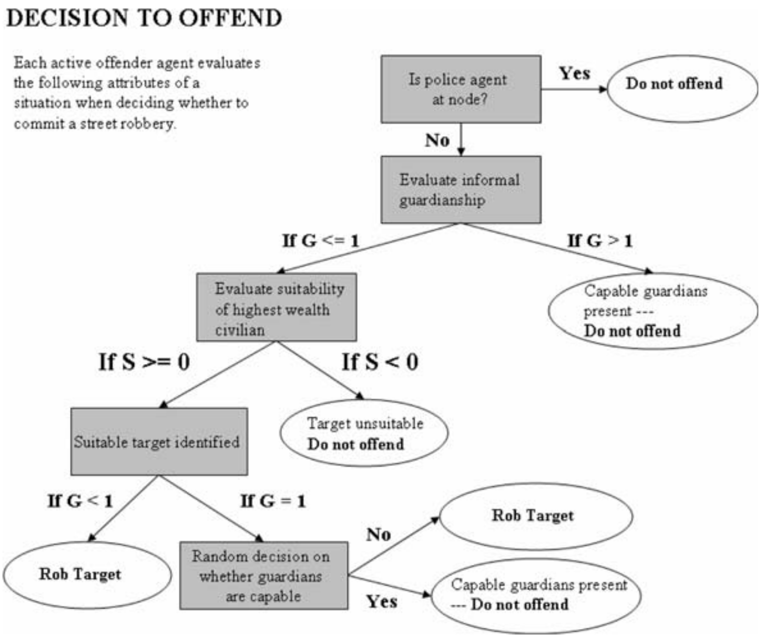

Fig. 2 Model of decision to offend

(1) Is there a police agent at the node?
(2) What is the level of informal guardianship at the node?
(3) Is there a suitable target at the node?

The level of guardianship and the availability of a suitable target are evaluated via two equations. For computational reasons, guardianship is the first situational element considered by the active agent. If there is a police agent at the same node, the active agent decides not to offend because a capable guardian is present. However, if there is no police agent and there is at least one other civilian agent at the node, the level of informal guardianship is evaluated further via the formula in Eq. (1). First, the total number of civilian agents at the location is considered minus the active agent and the potential target. This adjustment reflects the unlikelihood that an offender would act as a potential target's guardian and the inability of the target to be its own guardian. Uncertainty in how offenders perceive the 'capableness' of the other civilians is incorporated into the formula through the addition of a stochastic term P_G that can either increase, decrease, or leave unchanged the active agent's perception of the level of guardianship in a situation. This introduces a stochastic element into the offender's perception of whether other civilians at the node are capable guardians or not.

$$G = (N_A - 2) + P_G \tag{1}$$

If $G < 1$, then there is a lack of capable guardians so condition evaluates to True
If $G = 1$, then make a random decision—condition could evaluate to True or False
If $G > 1$, then capable guardianship is present so condition evaluates to False

Where:
G = Guardianship
N_A = Number of agents at node
P_G = Perception of capability of guardians who are present (uniform random number between –2 and 2)

In reality, the presence of capable guardians is most likely evaluated along a continuum. On one end of the continuum a police officer is present on the street corner. At the other end, the potential offender is alone with a suitable target. More frequently, situations are somewhere in between.

Finally, the active agent considers whether there are suitable targets at the node using Eq. (2). All other civilians who are away from home and at the same node are evaluated using wealth as the primary criteria for identifying a suitable target.

$$S = (W_T - W_A) + P_S \tag{2}$$

If S > = 0, then there is a suitable target so condition evaluates to True
If $S < 0$, then no suitable target present so condition evaluates to False
Where:
S = Perceived suitableness of target
W_T = Wealth of target
W_A = Wealth of active agent (potential offender)
P_S = Offender perception of target suitability (uniform random value between –1 and 1)

If at least one other agent's wealth exceeds the active agent's wealth, the evaluation of the civilian with the highest wealth continues via the formula above. The error term P_S represents the influence of other factors on the offender's perception of the relative suitableness of a target and its value can either increase or decrease the perceived suitability of the target. It is worth noting that other agents with criminal propensity who are at the node are included in the active agent's evaluation and can become victims. If $S < 0$, there is no suitable target at the node, and the active agent does not commit robbery.

To recap, for situations in which there is a suitable target, the decision to offend hinges on the level of informal guardianship. If G = True, then there is a lack of capable guardians so the decision is to rob the suitable target identified. If G = False, the amount of guardianship is too high, and the decision is not to offend. But if $G = 1$, the decision could go either way. In these cases, the active agent makes a random decision whether to commit the street robbery. When an agent commits a robbery, one unit of wealth is taken from the victim and transferred to the offender. Once each civilian with criminal intent has evaluated their situation, the model time advances, agents move and the decision structure is repeated.

Analysis

Both traditional and spatial analysis techniques are used to examine the results of the model runs. Descriptive statistics such as mean, median, and standard deviation are used to characterize the results of each of the experiments. As is customary practice, an ANOVA is applied to determine if there is a significant difference among the RobRates for the five experimental conditions across the two movement types (Axelrod 2006). Finally, the resulting spatial patterns of robbery events are examined.

At the agent level, descriptive statistics are generated to test the relationships among time spent away from home (AwayTime), total number of victimizations (TotVict), and total number of robberies committed (TotOff). These statistics are examined for the total population and then just for agents with and without criminal propensity.

Two approaches to describing the spatial distribution of street robberies are taken. A visual comparison is made of the resulting crime patterns using a kernel density. Kernel density surfaces offer a means of evaluating the existence of global trends in the distribution of street robberies and for comparing the relative density of robberies across experimental conditions. To create a kernel density, a temporary grid is laid over the entire study area and a density value for each cell in the grid is computed using a circular 'neighborhood' (Bailey and Gatrell 1995; Mitchell 1999; Williamson et al. 2001).[14]

In addition to the kernel density, formal tests of the spatial distribution of crime events are employed using Ripley's K function. Ripley's K is applied to compare the clustering of robberies and visits to places at different scales. Typically, the K function for complete spatial randomness (CSR) is helpful in identifying whether the observed pattern is significantly different than what would be expected from a random distribution (Bailey and Gatrell 1995; Levine 2005). A known weakness of comparing the observed distributions to CSR is that most human-generated patterns are non-random (e.g., population, housing, etc.) (Levine 2005).

In this research, CSR cannot be used to evaluate the clustering in street robbery events because the locations at which data are collected are constrained to a fixed set of locations representing the intersections in Seattle.[15] Since the CSR algorithm randomly places points anywhere within the study area boundary, it would be inappropriate to compare the clustering in robberies and number of visits, which are constrained to the street nodes, to a randomly generated CSR. However, a K function can be generated from the pattern of street nodes thus revealing the extent of the clustering intrinsic to the street network. Comparing the K function for street intersections to CSR answers the question of whether the intersections are more clustered than would be expected under CSR. Taking this one step further, the K function for street robberies can be compared to the one for intersections to find out if robberies are more clustered than the street intersections.

Another aspect of the same discussion involves the role of the street nodes in structuring the initial distribution of police and civilians since agents also can only be allocated to a street node (and not to any location within Seattle). In this way, the structure of the street network conditions both the original distribution of agents and their movement. Since the agents are randomly assigned to nodes and they move randomly during the simulation, the distribution of robberies should be similar to that of the network nodes if space alone determines where street robberies occur.

[14] The term kernel refers to size of the 'neighborhood' (also called bandwidth) that is taken into account when computing the density. The total number of street robberies within the bandwidth are summed and divided by the area under the circle. The resulting value is assigned to the current cell.

[15] Thanks to Ned Levine for pointing out this issue.

To check this, the *K* function for nodes is compared to the *K* functions for both robberies and visits.

Findings

The creation of the street robbery model enables the exploration of routine activity theory's propositions via simulation. Two research questions are addressed in the analysis. The first asks whether the shift in routine activities away from home increases the incidence of street robbery. The second examines the spatial pattern of street robberies as members of society spend more time away from home. This section describes the behavior of the model and summarizes the findings of the tests. The robustness of the findings is then evaluated by running the model using five different random number seeds and systematically varying key parameter values for each seed.

General Description of Model Outcomes

Data describing nine attributes of places and society are collected to characterize the results from the model runs across the five experimental conditions. Societal-level changes in the number of street robberies and convergences of agents in space-time (i.e. opportunities for street robbery) are in line with what routine activity theory would predict; both values increase with time spent away from home (Table 4). The number of times the presence of a police agent prevents a robbery from taking place also increases as the societal time spent away from home increases because police have more chances to act as a capable guardian. More in-depth examination reveals how the number of intersections, street robberies, and robberies prevented by police across experimental conditions are related (Table 4). As time away from home increases, the number of convergences displays the highest rate of increase, followed by the number of robberies, and the number of robberies deterred by police presence.

Testing Routine Activity Theory

A One-way ANOVA is applied to test the hypothesis that robberies will increase as time spent away from home increases. By comparing the means across the five experimental conditions, it is possible to determine if the average number of robberies per agent (RobRate) increases as the time spent away from home increases. The results of the ANOVA indicate there are significant differences on the rates of street robbery across the experimental conditions (Table 4).[16] However, the test does not provide information on which of the conditions were significantly different.

Results from post hoc tests employed to identify which experimental conditions are significantly different from one another are inconsistent (Table 5).[17] Beginning

[16] Because of the positive skew to the distribution of robberies, additional tests regarding the equality of means were conducted. Both the Brown-Forsythe and the Welch tests for equality of the means are significant at .000. These tests are preferable to the *F*-test when the equality of variances assumption is violated as it is here (SPSS 2002).

[17] The Levene statistic is significant indicating the variances are significantly different among the groups. However, ANOVA is robust in the face of this violation when the group sizes are equal which they are in this research (Newton and Rudestam 1999; Shannon and Davenport 2001). A Tamhane's T2 post hoc test is used because it does not assume equal variances.

Table 4 Change in street robbery events across experimental conditions

	Condition				
	30%	40%	50%	60%	70%
Target time to spend away from home (hours)	432 (7.2)	576 (9.6)	720 (12)	864 (14.4)	1008 (16.8)
Actual time spent away from home	436.9	580.2	723.5	866.8	1010.1
Base model (robbery rate per 1000 agents)***	54.637	76.032	95.219	118.085	139.007
Societal-level					
Total Robberies	54,637	76,032	95,219	118,085	139,007
Total Intersections	1,454,341	2,050,761	2,631,149	3,238,760	3,835,299
Total Robberies Deterred by Police	1,532	2,148	2,693	3,430	4,040
Model time at home (minutes)	1003.09	859.79	716.51	573.21	429.91
Model time spent away (minutes)	436.91	580.21	723.49	866.79	1010.09
Place-level					
Mean visits per street node	9,733	12,904	16,088	19,253	22,423
Mean robberies per street node	3.41	4.74	5.94	7.36	8.67
Percent of street nodes with a robbery	83% (N = 13,376)	87% (N = 13,925)	89% (N = 14,309)	91% (N = 14,531)	92% (N = 14,683)
Percent of street nodes with more then one robbery	70% (N = 11,157)	76% (N = 12,175)	81% (N = 12,995)	83% (N = 13,303)	85% (N = 13,572)

*** Difference among one or more of the groups is significant at $P < 0.000$

Table 5 Post hoc tests of mean differences (seed = 100)

(*I*) Randomization condition	(*J*) Randomization condition	Mean difference (*I* – *J*)	Standard error	Significance
30% Time away	40% Time away[a]	–21.39	5.584	0.001
	50% Time away[a]	–40.58	6.607	0.000
	60% Time away[a]	–63.45	7.903	0.000
	70% Time away[a]	–84.37	9.129	0.000
40% Time away	50% Time away	–19.19	7.351	0.088
	60% Time away[a]	–42.05	8.534	0.000
	70% Time away[a]	–62.98	9.681	0.000
50% Time away	60% Time away	–22.87	9.236	0.126
	70% Time away[a]	–43.79	10.305	0.000
60% Time away	70% Time away	–20.92	11.180	0.470

[a] Significant differences were found between experimental conditions *I* and *J*

with the 30% condition, there is significantly less crime in societies in which individuals spend 30% of their time away from home when compared to each of the other conditions. Other significant differences exist between the 40% condition and both the 60% and 70% conditions; as well as between the 50% and the 70% conditions.

Spatial Distribution of Street Robberies across Places

The spatial distribution of street robberies is addressed via descriptive statistics, examination of the outcome pattern, and a quantitative description of the concentration of robbery events. The spatial distribution of agent movement and robberies across intersections reveals both increased concentration and a slight increase in spread, as time spent away from home increases (Table 4). Looking first at the summary statistics for places in Seattle, the mean visits per intersection increases at the same rate across all experimental conditions as does the mean robberies per intersection. However, both the percentage of intersections with only one robbery and those with more then one robbery have their largest increase between the 30% and 40% conditions.

The spatial pattern of robberies is examined across all five conditions using kernel density (Fig. 3).[18] A visual inspection of the map series indicates support for the second hypothesis. At 30% time spent away from home, a few areas of concentration appear. As civilians spend more time away from home, the densities of those original concentrations increase while new areas of higher density appear. This pattern reflects both the increased frequency of the convergence of the elements necessary for a crime to occur and the larger travel areas of agents as they spend more time away from home.

[18] A bandwidth of 1,320 feet (one quarter mile) and a cell size of 100 feet are the basis for all kernel density surfaces. The quarter mile distance is often employed to represent the potential walking area for individuals in urban areas and by extension their potential area of interaction (Calthrope 1993; Duaney and Plater-Zyberk 1993; Nelessen 1994). The surfaces are generated in ArcGIS version 9.1 and the output is in robberies per square mile (Mitchell 1999).

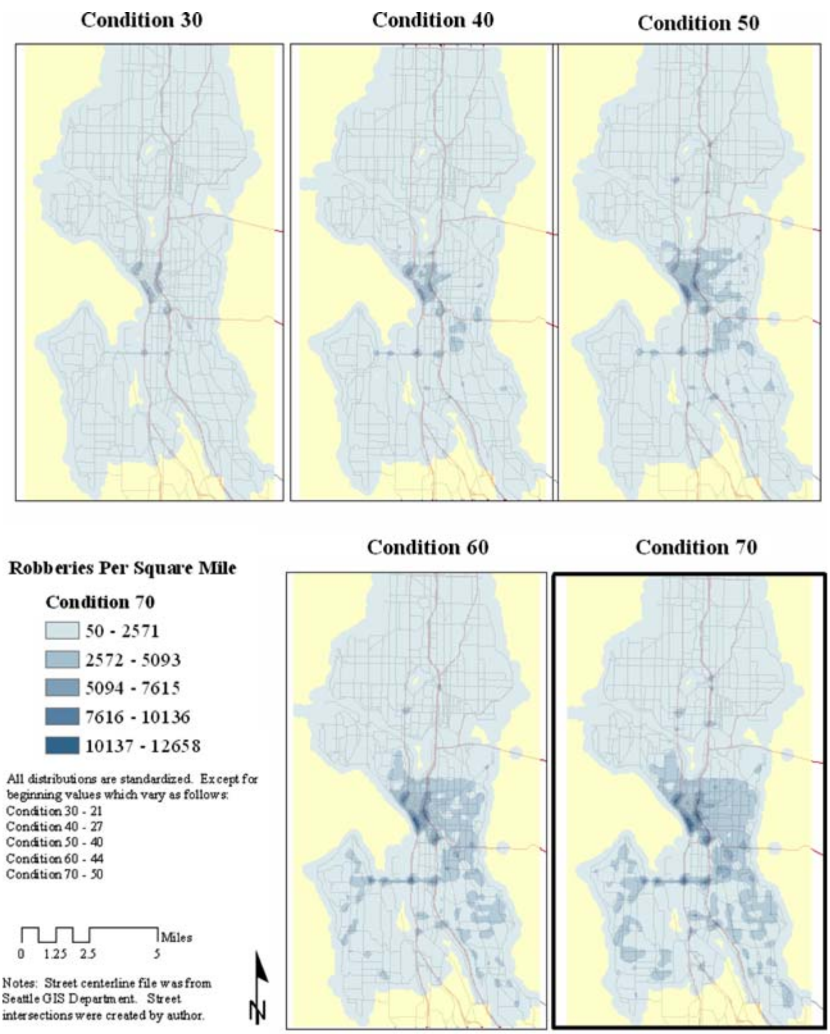

Fig. 3 Kernel densities for modeled street robbery events

Results of the Ripley's K function indicate that there is a high degree of concentration in street robbery locations across all five conditions.[19] Figure 4a compares the concentration of street robberies generated from each of the five experimental conditions to the concentration of the street network's nodes and to a reference distribution describing the amount of concentration that would be expected under CSR.[20] Concentration in street nodes increases until approximately one and one-half miles when it levels off for about a half mile and then begins to decline. The graph

[19] The reported Ripley's K functions are generated using CrimeStat III. No edge correction is applied since approximately three quarters of the perimeter of Seattle is bounded by water.

[20] The CSR K function distribution is generated by using a uniform random number generator to create 100 distributions with the same N as the observed distribution, in this case N=16,035 (Levine 2005). A significance level of $P < 0.05$ is used. The random distribution generated under CSR is truly random in that any location can be selected, not just an intersection.

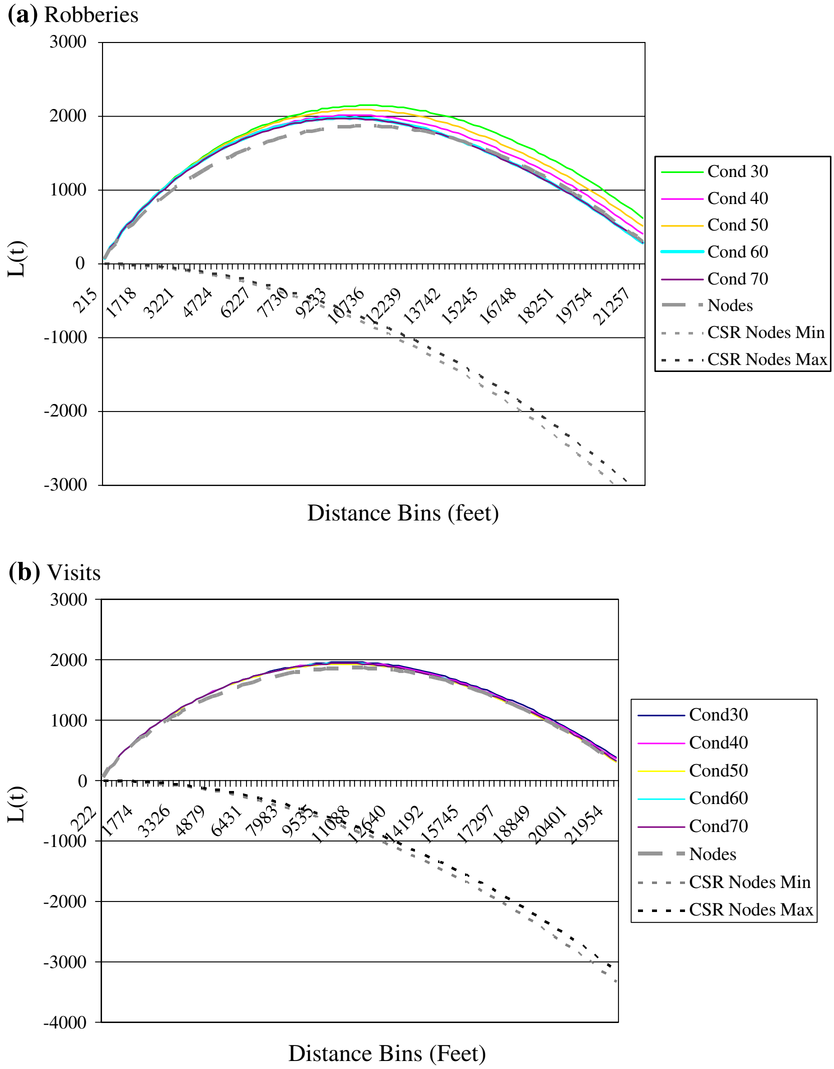

Fig. 4 Ripley's *K* results across experimental conditions (**a**) Robberies (**b**) Visits

reveals that street nodes are significantly more concentrated than would be expected under CSR.

The street robbery distribution lines for each experimental condition follow a similar pattern to the line for all street nodes. All six lines are identical until about 800 feet when the robberies become more clustered than the street nodes. This pattern continues until about 2.25 miles when the robberies in the 60% and 70% conditions converge with the line for street nodes. The lines for the 30%, 40% and 50% conditions remain more concentrated than the street nodes at all distances and the difference between concentrations is consistent. Robberies are most concentrated when society spends 30% of time away from home, and the concentration decreases as time spent away from home increases.

Data characterizing the total number of visits experienced by each node offer a means of quantifying agent travel patterns. Comparing the distribution of all agent movement with the distribution of robberies provides a test of whether the two distributions are different. Figure 4b suggests that the pattern of visits across nodes is very similar to that of street robberies. However, the lines describing visits are closer together indicating there is even less difference in the concentration of the distributions for visits than there is for street robberies. These results suggest that street robbery incidents tend to occur where many agents routinely converge but that robberies have other factors contributing to their greater concentration that are not accounted for by the structure of the street network.

Overall, the results of the K function suggest support for the important role that the street network plays in the concentration of street robbery. Specifically, they illustrate that street nodes are significantly more concentrated than would be expected under CSR and that their intrinsic clustering is responsible for the majority of clustering in both agent travel and street robberies. This finding underscores the importance of considering the street network in any evaluation of the concentration of travel (i.e., visits) and street robberies that are produced by the model. That being said, the results also suggest that there are situational factors at work in generating the observed robbery patterns. Even though the agents (both civilians and police) are randomly distributed across street intersections at the beginning of the simulation and then move randomly from node to node over the whole model year, there is additional clustering in the distributions of street robbery events that cannot be accounted for by the pattern of street nodes.

Some Comments on the Robustness of the Model

Sensitivity testing is essential to quantifying the robustness of the model results and is conducted by varying the initial parameters and the random number seed (Manson 2001). In this study the following tests are conducted: the values of five of the parameters (i.e., number of police, time to wait before able to re-offend, initial wealth distribution, perception of target suitability random term, and the perception of guardianship random term) are increased; the model runs are repeated for all five experimental conditions; and a one-way ANOVA is applied to analyze the results. While the absolute number of street robberies increased or decreased depending on the parameter being varied, in all cases the original significant differences between the groups remained, demonstrating the robustness of model results to changes in initial parameters (Table 6). Finally, the entire sensitivity testing process of varying the five parameter values is repeated four more times using different random number seeds to test the effect of changing the random number seed on the outcomes of the model. An analysis of the output demonstrates that model results are robust to changes in the random number seed.[21]

Discussion

This paper presents a new approach to formalizing and testing criminological theory that relies on simulation. To demonstrate the methodology, a simulation model of

[21] The results of the sensitivity tests with random number seeds of 200, 300, 400 and 500 are available upon request.

Table 6 Parameter testing results

	Condition				
	30%	40%	50%	60%	70%
Target time to spend away from home (hours)	432 (7.2)	576 (9.6)	720 (12)	864 (14.4)	1008 (16.8)
Actual time spent away from home	436.9	580.2	723.5	866.8	1010.1
Base Model (robbery rate per 1000 agents)***	54.637	76.032	95.219	118.085	139.007
Parameter verification					
Increase number of police to 1000***	54.148	72.502	91.474	110.752	131.611
Increase time to wait before re-offending to 1 day***	31.682	37.358	41.403	44.551	47.134
Increase societal wealth distribution (mean = 100 and SD = 50)***	58.937	79.097	100.195	121.916	143.241
Increase impact of random term representing perception of target suitability $U(-10,10)$***	42.093	56.688	73.931	87.699	103.353
Increase impact of random term representing perception of guardianship $U(-4,4)$***	51.427	72.520	89.590	108.469	128.618

*** Difference among one or more of the groups is significant at $P < 0.000$

street robbery is developed based on the core propositions of routine activity theory. The model is then used to conduct a series of experiments to test whether the outcomes match what the theory predicts.

Previous attempts to test routine activity theory, although generally supportive, have produced mixed results. None of the tests were able to sufficiently address the spatio-temporal structure of routine activities, satisfactorily deal with measurement issues, or effectively capture the dynamic nature of interactions at the micro-level. This research addresses all three of those issues by relying on simulated individuals that interact on the streets of Seattle, Washington.

Routine activity theory's basic premise, crime will increase as individuals spend more time away from home, is strongly supported by model results and the finding is robust even when the initial parameter values are systematically varied. Although the absolute number of robberies fluctuates as parameters are changed, the relative relationship between increasing time spent away from home and the rate of street robberies remains significant.

Previous research has recognized the role of the built environment in general to structuring movement (Capone and Nichols 1976; O'Sullivan 2004) and to concentrating population-related variables (Bailey and Gatrell 1995; Levine 2005). This research finds the street intersections are significantly more clustered than would be expected by chance. Taking this clustering into account, the pattern for street robberies exhibits additional clustering beyond what is explained by the street network but only at certain distances. At these distances, the clustering is instead related to the characteristics of the agents who converge and participate in situations in which a street robbery occurs.

Although this initial implementation of the method is simple, it accomplishes several essential functions. First, it makes the process of theory testing transparent by formalizing model specifications. Subsequent researchers have a concrete record of how theoretical constructs are operationalized in the model. Second, the model provides a base upon which to build more complex explorations of street robbery. Third, the method replaces artificial landscapes prevalent in agent-based models with the street network of Seattle. In doing so, the research takes an important step toward more realistically ‘situating’ simulation and measuring the street network’s influence on spatial patterns of street robbery. Fourth, the use of a series of controlled experiments to test the model illustrates the potential for this type of research to refine theory by systematically varying one aspect while holding all others constant.

New questions could be explored by building additional analytical capability into the base model. The incorporation of activity spaces for civilians represents an important and necessary enhancement to the initial model. Rather than traveling randomly, individuals could be assigned home, job, and other locations among which they could travel (Groff 2007). The spatial distribution of homes, jobs, recreation and services in Seattle could serve as the basis for the distribution of agents’ activity nodes in the model. In this way, the activity locations of agents in the model would reflect the activity spaces of the civilians of Seattle.

The behaviors and awareness levels of agents could be expanded and made more nuanced. Enhancing the behavior of existing police agents would enable tests of the effectiveness of different patrol strategies (e.g., hot spot policing) in reducing or displacing crime. For example, a researcher could compare the results of the previous simulation in which police patrol randomly to a hot spots policing strategy in which police are assigned areas where street robbery is highest (Sherman and Weisburd 1995; Weisburd and Green 1995). In addition, a wider range of place characteristics and neighborhood-level perceptions of areas could be incorporated into the dynamic decisions of individuals. This would enable more richly textured micro-level situations in which agents interact as well as incorporate important micro and macro-level elements that impact how a situation is perceived.

At the individual level the impact of guardianship on the decision to offend could be studied intensively. Specifically, the role of place managers and intimate handlers as guardians could be tested in a computational laboratory (Eck 1995; Felson 2001, 2002). For example, a researcher could change the weightings of different types of agents (e.g., police, known agents, place managers etc.) to determine the effect on the decision to offend while holding everything else constant. In the same vein, the role of criminal propensity could be explored further by assigning the attribute using a distribution rather than a presence/absence characteristic. Propensity could then vary based on circumstances and success in previous robbery attempts.

Despite the potential value of simulation as a research platform, serious questions remain about evaluating models (Manson 2001; O’Sullivan 2004). Manson (2001) identifies two types of validity that are important, structural and outcome validity. The evaluation of structural validity is more straightforward and involves the question of how well the model as implemented embodies the theory or theories from which it was constructed. Outcome validity is less easily assessed. However, Eck and Liu (2004) offer a common sense approach to evaluating outcome crime patterns. They suggest that based on the literature, crime patterns should exhibit: (1) a high degree of clustering; (2) concentration of crime in relatively few places; (3) relatively few offenders responsible for most of the crime; (4) rather few victims accounting for most of the victimization and (5) non-static patterns of crime over time. When results from a model share characteristics with empirical ones, its credibility increases. However, matching distributions is not a sufficient criteria for validation since a different model could also produce comparable patterns (Troitzsch 2004). Given the relative novelty of the approach, the potential for developing better methods of verification and validation is wide open.

Focusing on simulation models as tools to aid in explanation and understanding rather than prediction avoids many of the thorniest questions of model validation. In this role, simulation models become aids to the refinement of theory prior to empirical testing and are especially useful in identifying ‘gaps’ in theory (O’Sullivan 2004). The model can be manipulated and the subsequent changes in macro level rates and patterns can be observed and matched to what would be theoretically expected (Eck and Liu 2004). In addition, simulation models have the potential to reduce research costs by saving empirical tests for the strongest theories. After all, simulated theory testing takes place in an artificial world and thus is not capable of conferring empirical validity to a theory (Paternoster 2001).

Conclusion

The research methodology employed here provides a unique framework for promoting more comprehensive and rigorous tests of theories about human behavior at both the micro- and macro-levels of analysis. Because the method requires the formalization of theoretical concepts, it has the potential to generate a common language with which to describe those concepts, and to stimulate the construction of well-defined models that can be discussed and tested further. The findings from the example model of street robbery specified and tested here demonstrate clear support for the plausibility of the basic premise of routine activity theory and in doing so provide the foundation for the development of additional, more richly specified models of criminal and spatial behavior. Advanced models are likely to produce concrete, public policy relevant findings addressing both the situational elements of crime and the structure of routine activities in general. The potential for crime reduction from these findings is high because the situational aspects of the crime event can be altered far more quickly and easily than ones involving the root causes of criminal motivation (Akers 2000; Cullen and Agnew 1999; Felson 1987; Vold et al. 2002).

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