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Adding the Temporal and Spatial Aspects of Routine Activities: A Further Test of Routine Activity Theory

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Routine activity theory identifies the routine activities of individuals as important to understanding the convergence of elements necessary for a crime to occur. Two recent studies have demonstrated how geographically aware agent-based models can be used to provide a virtual rather than empirical laboratory for testing theory. Those studies trace the development of three versions of a basic street robbery model with different representations of routine activities (random, temporal constraints, and spatio-temporal constraints). This research uses the existing model to test whether the core premise of routine activity theory (i.e., as time away from home increases so will street robbery) holds true under the different versions of activity spaces. The findings indicate that temporal and spatial constraints have separate and unequal influences on the incidence of crime. These results substantiate the key role of spatio-temporal constraints in determining the opportunities for and incidence of street robbery events.
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Introduction

Cohen and Felson put forward a "routine activity approach" to studying crime (Cohen and Felson, 1979, p. 588). At the macro level, their approach ties social changes to crime rates. More specifically, they posit that the shift in routine activities away from home-based activities was the source of the crime rise experienced during the 1960s and 1970s. At the micro level, they identify the role of individuals' *routine activities* as facilitating or hindering the convergence of *offenders*, *targets*, and *capable guardians* at the same time and in the same place.

The micro–macro aspect of routine activity theory has led to its wide application in macro-level empirical research but not at the micro level. Difficulties in obtaining individual-level data as well as shortcomings in available statistical techniques have precluded micro-level testing. The lack of individual-level data to characterize human travel behavior in general and the situational elements of crime events in particular, is an ongoing barrier (Huisman and Forer, 1998; O'Sullivan and Haklay, 2000). Likewise, the identification of modeling tools capable of capturing the dynamic nature of human activities and interactions of individuals when they converge remains a hurdle. Thus the empirical validity of the theory is still in question (Eck, 1995; Akers, 2000)

In response to these challenges, some researchers have turned to simulation modeling as an alternative approach. Although modeling in general has a long been applied to examine social science phenomena, simulation has not (Harvey, 1969; Golledge, 1983; Gilbert and Terna, 1999; Gilbert and Troitzsch, 1999). This has begun to change as software has evolved and become more accessible. In response, criminologists have recently begun to explore how agent-based models can inform the study of crime (Xue and Brown, 2003; P.L. Brantingham and P.J. Brantingham, 2004; P.L. Brantingham and Groff, 2004; Eck and Liu, 2004). The inherently spatial nature of human movement and interaction, as well as the role of place in influencing those elements, require that models of crime incorporate space as well as time (Groff, 2007b).

Recent advances in technology have enabled simulation agents to be "situated" in a particular spatio-temporal milieu (e.g., agents travel along a street network and react to the characteristics of a real environment). For example, the software product Agent Analyst links a geographic information system (GIS) with an ABM software package (i.e., ArcGIS (ESRI, 2005) and RepastPy (North *et al*., 2006). The combination of ABM and GIS is necessary in order to move away from the use of artificial landscapes and instead model individuals in their environment (Albrecht, 2005; An *et al*., 2005; Brown *et al*., 2005).

Two recent studies use these developments to explore routine activity theory. Basically, they create a virtual world that works according to routine activity and then test whether the outcomes match what the theory would predict. The first study implemented the assumptions of routine activity theory (Cohen and Felson, 1979) in a simulation model and then tested them via controlled experiments to discover whether the theoretically predicted outcomes match the model outcomes (Groff, 2007a). The model building process used in the study emphasized simplicity, focusing on the elements that were directly addressed by the theory (Macy and Willer, 2002) and relied on "situating" simulation by combining agent-based modeling (ABM) with GIS to include both time and space. The study found support for the theory's core proposition that shifts in routine activities away from home increase the incidence of street robbery. In addition, a spatial analysis demonstrated that the observed clustering in street robbery events is beyond the degree that would be expected based on the configuration of the streets.

The second study developed two new versions of the original model that implemented theoretically based routine activity spaces for individuals and then examined the effect of those activity spaces on the spatial distribution of robbery events (Groff, 2007c). In contrast to the Simple version where agents were either at home or "at risk" of participating in a street robbery, agents in the new versions have more nuanced schedules. In the Temporal version, agents have an assigned time schedule that dictates how much time they spent at activities. While in the Activity Space version, agents have both a temporal schedule (times to spend) and a spatial one (places to visit). The study found differences in the spatial distribution of street robbery as society spent more time away from home regardless of version. In addition, temporal and spatio-temporal constraints on agents' activities significantly changed the spatial distribution of street robbery events.

Using the same three versions of the basic model, this research examines whether the core premise of routine activity theory will continue to hold true as spatial and spatio-temporal constraints on routine activities are systematically manipulated. Like the previous studies this one proceeds in the tradition of Schelling (1971), Epstein and Axtell (1996), and many others where the goal of simulation is greater understanding rather than prediction. Accordingly, the point of this research is not to predict the pattern of street robbery events in Seattle, Washington, but rather to operationalize the assumptions of routine activity theory in an artificial society and then test whether the model outcomes match the predicted outcomes. The approach taken here emphasizes theory-testing but still in a theoretical world. In this way, the method represents an interim testing ground between the verbal formulation of the theory and the testing of theory with empirical data (Dowling, 1999; Eck, 2005). While this exercise does not result in a determination of whether a theory is true in the real world, it does provide a way to test the plausibility of the theory's assumptions.

The remainder of this paper is organized as follows. The next section offers a brief overview of simulation and agent-based models. Then a description of the model and its space–time extensions is offered. Theoretical underpinnings are only briefly described because they are thoroughly covered elsewhere (Groff, 2007a,c). Next, the research design for this study is described. The analysis of the results is explained and the paper ends with a discussion of the implications of these findings.

Simulation and agent-based models

Simulation models are developed from theory and involve a simplification of reality but their specification is in the form of a computer program (Ostrom, 1988; Gilbert and Terna, 1999). Once built, the computer program is run to obtain results which are then analyzed using statistical models. Simulation models rely on a bottom-up approach. In other words, a few simple, theoretically based rules are developed for the individual agents. The interactions of individuals in the model produce the macro-level patterns that *emerge*. The property of *emergence* refers to any unexpected consequences from the application of simple behaviors (Epstein and Axtell, 1996; Gilbert and Troitzsch, 1999). Individuals in simulation models are able to make dynamic decisions based on changing information (Bonabeau, 2002). Since routine activity theory posits both the micro-level factors necessary for a crime and the macro-level consequences of changes in the convergence of those factors, simulation modeling is particularly well suited to operationalizing it.

Agent-based models are a type of simulation model that consists of a collection of autonomous entities implemented within a software program. Entities in the model (i.e., agents) can represent individuals or a collection of individuals in the model (e.g., people, governments, neighborhoods, etc.). Each agent has a set of unique characteristics and behaviors. Typically, these agents are placed in an artificial world to interact, although there is a recent movement to use GIS to provide a "real" landscape (O'Sullivan and Haklay, 2000; Brown *et al.*, 2005; Groff, 2007b). Agent-based models allow heterogeneity among individuals that more closely approximates the variety found in life. In addition, they are better able to accommodate the non-linearity in relationships that is frequently evident in complex and dynamic interactions (Epstein and Axtell, 1996; Gilbert and Terna, 1999; Dibble, unpublished; Liu *et al.*, 2005).

Agent-based models can be implemented in the form of a computational laboratory. A computational laboratory is a set of software tools that enable the specification and execution of systematic experiments using simulation (Chen *et al.*, 1994; Slavin, 1996; Dibble, 2001; Parker *et al.*, 2001; Tesfatsion, 2001). The combination of heterogeneous agents and control enables the researcher to conduct a variety of experiments, using different conditions or applying various prevention scenarios, and then evaluate outcomes for minimal cost as compared to experiments undertaken in the real world. These characteristics directly address the shortcomings of earlier research testing routine activity and suggest ABM as an important component of a new, more flexible methodology.

The use of simulation models is not without its drawbacks. As models, they are constrained by the original assumptions and the rules on which they are based. This drawback is mitigated, but not eradicated, by the use of empirically based parameters whenever possible. Relatedly, the creation of an artificial society opens the research effort to a variety of issues regarding the generalizability and usability of findings. Even when the simulation is based on a real place, the society is still representative rather than empirical. In addition, as compared to mathematical models, simulation does not produce any measures of the robustness of a particular solution (Axtell, 2000; Lempert, 2002). Mathematical models produce such statistics as confidence intervals that communicate the surety with which results can be interpreted. Simulation results can approach this type of measure through an iterative process of varying input parameters and cataloguing the outcomes of those variations so that we can begin to say something about the robustness of a particular model. Despite these drawbacks, when the goal of ABM is directed toward explanation rather than prediction, the knowledge gained from using an iterative strategy to study artificial societies can serve to increase our understanding of how a process "works".

The employment of ABM in the social sciences has increased over the last 10 years (Gilbert and Doran, 1994; Gilbert and Terna, 1999; Gilbert and Troitzsch, 1999; Macy and Willer, 2002). This rising interest in ABM stems from its unique capabilities that range from description, to knowledge discovery, to hypothesis testing. Another intrinsic advantage is derived from the computer code written for the simulation. Formalized computer code provides concrete documentation for the assumptions of the model and enables transparency in the research enterprise that is necessary for replication and testing of results (Chattoe, 1996; Gilbert and Terna, 1999). These attributes are especially important when trying to discover the mechanisms through which observed macro-level patterns are formed.

Description of the street robbery model

Since this research applies an existing model of street robbery, a combined discussion of the theoretical basis and implementation for both the original model (Groff, 2007a,b) and the two additional versions (Groff, 2007c) is offered here. For a more thorough discussion of those topics please see the earlier papers.

Criminological foundations for the street robbery model

The original model of street robbery is primarily based on routine activity theory (Cohen and Felson, 1979) but relies on rational choice theory for the specifics of offender decision-making (Clarke and Cornish, 1985, 2001). This is necessary because routine activity theory pays little attention to the source of the offender's motivation and merely assumes a supply of motivated offenders.

As mentioned earlier, the central premise of Cohen and Felson's (1979) routine activity theory is that increases in crime are the result of a shift of routine activities away from home. As originally conceptualized, the 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. A fourth element, *routine activities,* influences when and where victims and offenders converge. According to the routine activity approach, convergence of individuals is the key dynamic element that enables illegal acts to occur during the course of everyday activities. Changes in social structure impact the frequency with which these elements converge by modifying the routine activity patterns of offenders, victims, and potential guardians. From this basic argument, the theorists go on to hypothesize that if the frequency with which these elements converge in space and time increases crime will also increase, even if the supply of offenders or targets remains constant within a city.

Figure 1 provides a conceptual view of the model (Groff, 2007c). Society consists of two types of people, civilians and police. Following routine activity theory, the civilians in the model can take on three different roles, offender, victim, or guardian. The role taken in any situation is a function of the characteristics of the civilians present and their attributes. Each civilian in the model has a unique set of characteristics that include criminal propensity, time to stay at home, wealth, and employment status.

Some civilian agents are assigned criminal propensity. These agents have decided to commit a crime and are now open to an opportunity to do so (Clarke and Cornish, 1985, 2001). Civilians with criminal propensity can potentially take on any role but those without criminal propensity can only be victims or guardians. Thus, patterns of offending and victimization are allowed to emerge from decisions made by individuals in particular contexts. In all other ways, civilians with criminal propensity are exactly the same as those without. All civilian agents are also assigned a time to spend at home that is static over a model run, and a wealth and employment status both of which are dynamic. Once convergence occurs, guardianship and suitability of target are considered by the offender when making the decision whether or not to commit a robbery.

Police agents represent formal guardians and their presence automatically prevents a crime from occurring. At the start of the simulation, police agents are randomly distributed across the nodes and they follow a "random walk" movement pattern in which they move one node at a time and only to an adjacent node.

Regardless of model version, the decision to offend is made as follows. At each model tick (i.e., each minute of the model year) all nodes with at least one agent present are evaluated. Active nodes meeting the following three criteria are evaluated further: (1) no police present; (2) at least two civilians present; and (3) at least one of the civilians must have criminal propensity. If there is only one offender at the node, that agent automatically becomes the active offender. Otherwise, the active offender is randomly selected from the list of agents with criminal propensity who are at the node. Offender agents who are not selected to be active are at risk of becoming victims. When an agent commits a robbery, one unit of wealth is taken from the victim and transferred to the offender. Once the active offender at each of the active nodes evaluates their situation, all agents move and the decision structure repeats.

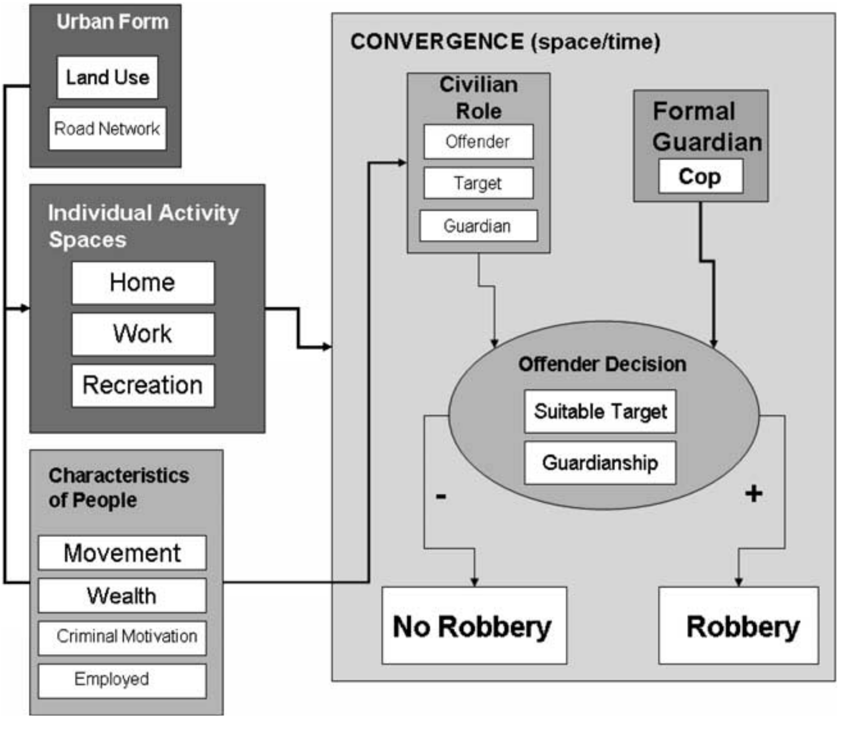

Figure 1. Conceptual model of street robbery for all versions.

Activity spaces in the model versions

The spatio-temporal aspects of human behavior (i.e., routine activities) that facilitate convergence is a critical element in routine activity theory and must be included in any attempt to explore the theory (Groff, 2007c). Previous studies have relied on time geography and related work to characterize routine activity spaces used in the model versions (Groff, 2007b,c) Consequently, three types of activity spaces are included in the model; each adds one element of complexity and is associated with a different version of the model: Simple, Temporal, and Activity Space (Table 1). All three versions are "situated" in Seattle, Washington because two-thirds of the city is bounded by water which minimizes edge effects and thus provides a good test case.

Using three versions of the same model provides a systematic way of testing the impact of time and time–space schedules on the incidence of street robbery.[1] Agents in the Simple version of the model travel randomly on the street network the entire time they are not at home. Temporal version agents travel randomly when not at home. However, each agent is assigned a unique time schedule to follow. The time schedule contains amounts of time to

[1] One drawback of the activity spaces in the model is that they are completely static while human behavior often has small daily changes. Unfortunately, software limitations prohibit dynamic activity spaces. See Groff (2007a,b) for a complete discussion.

Table 1 Implementation versions of the conceptual street robbery model

	Simple	*Temporal*	*Activity space*
Civilian movement (initial distribution)	Random (random)	Random (random)	Defined activity space (assigned)
Police movement (initial distribution)	Random (random)	Random (random)	Random (random)
Civilian characteristics			
Criminal propensity	Yes	Yes	Yes
Wealth	Yes	Yes	Yes
Activity space	No	Temporal only	Spatio-temporal
Multi-faceted risk status	No	Yes	Yes
Employment status	No	Yes	Yes

spend at work, at activities, and in transit. Each type of activity has a different level of risk for street robbery. While at home or at work the agent is not at risk of participating in a street robbery. Thus, the amount of time at home or at work reduces risk of street robbery, while time spent traveling or engaging in other activities increases it. This representation of risk is in keeping with the crime being studied. By definition, street robbery happens only on the street or in public places; not in a home or inside a workplace.[2]

In the Activity Space version, routine activity spaces are implemented as a set of nodes (places) and paths (list of places traversed when traveling from one node to another) (Groff, 2007c). As in life, each agent has a routine activity space that consists of a set of places that are visited each day. Specifically, each civilian agent is assigned four places representing a home, a main activity (e.g., work, school, etc.) and two other activities (e.g., recreation, social, and retail places). The places are assigned based on the distributions of population, jobs, and activities in Seattle (e.g., if 10 per cent of the population lives in a particular block group then 10 per cent of the agents are assigned to that block group) (Groff, 2007b,c). In this way, the size and form of activity spaces is influenced by the distribution of residential housing, jobs, schools, retail and services.[3] Each civilian agent has two potential activity spaces; one activity space is used while employed and the other while unemployed. The two activity spaces are identical except that the work location is dropped from the unemployed path and a new activity location is added.

Absolute risk of committing or being a victim of a street robbery is closely tied to the temporal and spatio-temporal aspects of activity spaces. Civilians in the Temporal and Activity Space models share the same temporal schedule for activities and travel and consequently those agents spend the same amount of time "at risk" for street robbery.

[2] The designation of "at risk" is simplified from real life. A person who is shopping in a retail store also cannot be a victim of street robbery but is considered "at risk" in the model. The main purpose of the designation is to vary the time a civilian agent is at risk based on their activities.

[3] The agent activities are attached to a series of street intersections rather than street addresses or street blocks. The use of street intersection reflects a software limitation. Repast cannot read network or geodatabase files from ArcGIS.

Employment status also affects risk in the Temporal and Activity Space versions of the model by changing the amount of time spent at the three activity nodes (but not the overall time spent away from home) and the amount of wealth that an agent receives. In the case of the Activity Space version, employment status also determines the spatial configuration of the agent's activities (i.e., the locations of the places that are visited). Those agents who are employed receive a regular, static infusion of wealth every 2 weeks over the model year but civilians who are unemployed do not get paid. Every month, 3 per cent of unemployed agents become employed and are replaced by a new random selection of employed agents who become unemployed. It is important to note that the employment status is assigned independently of the criminal propensity indicator; civilians with criminal propensity can be employed in the model, as they are in life.

Hypotheses

The earlier studies identified two questions related to the role of time and space in the production of crime events (Groff, 2007a,c). Does the amount of time spent away from home continue to impact the incidence of street robbery in the predicted direction regardless of the spatio-temporal structure of routine activities? What effect do temporal and spatio-temporal constraints on routine activities have on the incidence of street robbery events? To examine these questions, the current research revisits the earlier study's hypotheses and tests if they hold true when the structure of routine activities is varied:

H1: *As the average time spent by civilians on activities away from home increases, the aggregate number of street robberies will increase.*

H2: *The temporal and spatio-temporal schedules of civilians while away from home change the incidence of street robbery events.*

The first hypothesis tests the core assertion of routine activity theory when agents have temporal and spatio-temporal schedules. The earlier study's findings demonstrated the plausibility of this hypothesis when agents traveled randomly (Groff, 2007a). The second hypothesis examines the effect of adding temporal and then spatio-temporally defined activity spaces on the incidence of street robbery.

Research design

This section describes the overall methodology used to answer the research questions. First, the software environment is described. Next the input data are examined. The choice of street robbery is explained. Finally, the experiments that are conducted to test the effects of space and time on the frequency of street robbery events are discussed.

Software environment

All versions of the basic model share the same software environment, Agent Analyst (Groff, 2007a–c).[4] Agent Analyst combines two of the most popular packages for ABM and

[4] Agent Analyst is under development as a partnership between ESRI and Argonne National Laboratories, the parent companies of ArcGIS and Repast, respectively. Agent Analyst is free at www.institute.redlands.edu/agentanalyst. The website for Repast is http://repast.sourceforge.net/.

GIS. For ABM it relies on the Recursive Porous Agent Simulation Toolkit (Repast) product line and for GIS it uses ArcGIS. Once the Agent Analyst toolbox is added into an ArcGIS session, individual models can access shapefiles allowing: (1) individual agents to become spatially aware and (2) the visualization of agent movement and decision outcomes (e.g., locations of crimes).

Data

The tests described here use the same input data and parameters as the previous studies (i.e., the land use and street network of Seattle, Washington) to provide the basis for the model landscape and the agent activity spaces (Groff, 2007a–c). Four data sets describing conditions in Seattle are used to inform the activity spaces of agents in the model: (1) total population (U.S. Census Bureau, 2000); (2) total employment (U.S. Census Bureau, 2002); (3) total potential activities (ESRI, 2003); and (4) streets. Individual 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 at which a street robbery may occur. The model parameters are described in Table 2. Findings from the original model were robust to sensitivity tests (i.e., changes in both parameter values and random number seeds) (Groff, 2007a). The same sensitivity tests are conducted here: (1) five of the parameter values are increased and (2) the random number seed is changed four times. The model runs are repeated for each test and a one-way analysis of variance (ANOVA) is applied to evaluate the results.

Choice of street robbery

The crime of street robbery offers several advantages for this study: (1) it is an instrumental crime and thus more likely than expressive crimes to involve a rational decision process (Clarke and Cornish, 1985; Cornish and Clarke, 1986; Walsh, 1986); (2) street robbery is by definition restricted to the street or some other exposed area rather than in a residence or business and thus involves the public intersection of offender and target in space and time; (3) police presence is assumed to be more effective against street-level crime than crimes that take place indoors (e.g., domestic violence).[5]

Experiments

In keeping with the earlier studies, the same series of five experiments are conducted on each of the two new versions of the street robbery model. The societal time spent away from home is systematically raised in ten per cent increments across five different conditions (i.e., condition 1 = 30 percent, condition 2 = 40 percent, etc.). These experiments are used to test: (1) whether changes in routine activities (defined as time spent away from home) can

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[5] Marcus Felson pointed out that the model actually represents interactions more similar to those for a street robbery with a weapon. Robberies without a weapon tend to have more than one perpetrator and a model should include those co-offenders.

Table 2 Parameters in the model

Variable	*Rationale*
Society level	
Number of agents = 1,000	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 cops would be present at some of the convergences that occur across the 16,035 places in Seattle. The actual ratio is 1 to 472. Subsequent tests with two police did not change the main conclusions of the research.
Unemployment rate = 6%	The unemployment rate of 6% is based on the 2002 unemployment rate for Seattle (Bureau of Labor Statistics, 2003).
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). This value is a starting point. Subsequent tests using 5 and 90% criminal propensity did not alter the main conclusions of the research.
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 minutes (for the 30% condition) and a standard deviation of 10% of the mean (s.d.=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.
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 of a 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.

increase street robbery even if the numbers of motivated offenders remains constant; and (2) the impact of spatial and temporal constraints on the incidence of street robberies. These tests proceed in a systematic fashion, with each condition representing an increase in the societal average for time spent on routine activities away from the home. All of the percentages represent an average time spent away from home for the agent population as a whole; individual agents have different times spent away from home.

Analysis

Descriptive statistics such as mean, median, standard deviation, and range are employed to characterize the results of each of the experiments and to compare them. An ANOVA is used to determine if there is a significant difference among the street robbery rates for the five experimental conditions across the model versions (Axelrod, 2006). The response variable is number of robberies for each of the one thousand civilian agents.

Findings

This section summarizes the findings of the analyses just described. First descriptive model outcomes are expressed by examining both place- and societal-level attributes to characterize differences in the results from the model runs of the three versions across the five experimental conditions. Next, the results pertinent to each of the hypotheses are conveyed.

Descriptive analysis

Societal-level changes in the number of street robberies and the frequency of convergence of agents in space-time (i.e., opportunities for street robbery) for all three versions of the model are in line with what routine activity theory would expect; the values increase steadily with time spent away from home (Table 3). While the overall trends are consistent, significant differences in slope and volume exist by model version (Figure 2). The Simple model has the highest number of robberies and the steepest increases as time spent away from home increases. Both convergences and robberies increase at the same rate. The Temporal version has the fewest robberies and a similar slope as the Activity Space version. These results point to the importance of a time schedule in lowering the incidence of street robberies regardless of the time spent away from home. The addition of a spatially constrained schedule to the Temporal version increases the absolute number of street robberies. This outcome is most likely related to the rate of convergence (i.e., presence of motivated offender and suitable target at same place–time), which tends to be highest in the Activity Space version and lowest in the Temporal version. On a related note, the diverging lines for robberies and convergences in both the Temporal and Activity Space models indicate that as time spent away from home increases, a decreasing proportion of convergences result in a street robbery.

Results from this research also show that deterrence (i.e., number of times the presence of a police agent prevents a robbery from taking place) increases for all model versions as the societal time spent away from home increases and the relationships among the versions are identical to those for convergence. This supports Cohen and Felson's (1979) hypothesis that the frequency of convergence impacts the potential for deterrence. Whenever there are more convergences there are by definition more times a police agent can function as an agent of formal guardianship.

Table 3 Societal-level model outcomes

	Experimental condition (%)				
	30	*40*	*50*	*60*	*70*
Target time to spend away from home in minutes (hours)	432 (7.2)	576 (9.6)	720 (12)	864 (14.4)	1008 (16.8)
Actual time spent away from home	436.9 (S) 427.8 (T) 427.7 (AS)	580.2 (S) 572.5 (T) 572.3 (AS)	723.5 (S) 717.0 (T) 716.9 (AS)	866.8 (S) 861.6 (T) 861.5 (AS)	1010.1 (S) 1006.2 (T) 1006.2 (AS)
Total robberies	54,637 (S) 12,807 (T) 32,326 (AS)	76,032 (S) 13,671 (T) 34,628 (AS)	95,219 (S) 15,183 (T) 38,331 (AS)	118,085 (S) 16,196 (T) 41,266 (AS)	139,007 (S) 17,181 (T) 46,085 (AS)
Total convergences	1,454,341 (S) 736,787 (T) 1,889,899 (AS)	2,050,761 (S) 1,013,814 (T) 2,663,961 (AS)	2,631,149 (S) 1,285,568 (T) 3,446,132 (AS)	3,238,760 (S) 1,579,963 (T) 4,260,133 (AS)	3,835,299 (S) 1,880,647 (T) 5,018,754 (AS)
Total robberies deterred by police	1,532 (S) 325 (T) 1,286 (AS)	2,148 (S) 414 (T) 1,417 (AS)	2,693 (S) 416 (T) 1,484 (AS)	3,430 (S) 454 (T) 1,670 (AS)	4,040 (S) 450 (T) 1,979 (AS)
Percentage of civilians who were robbed	77.7 (S) 74.5 (T) 74.0 (AS)	77.6 (S) 73.2 (T) 72.8 (AS)	76.4 (S) 74.6 (T) 71.8 (AS)	75.1 (S) 72.5 (T) 72.5 (AS)	76.2 (S) 71.5 (T) 73.5 (AS)
Percentage of civilians who were repeat victims of street robbery	65.2 (S) 64.6 (T) 64.4 (AS)	65.2 (S) 64.1 (T) 63.1 (AS)	65.5 (S) 63.9 (T) 62.6 (AS)	65.1 (S) 63.2 (T) 62.9 (AS)	65.7 (S) 62.6 (T) 63.4 (AS)
Number of civilians with criminal propensity who committed a street robbery	200 (S) 199 (T) 200 (AS)	200 (S) 200 (T) 200 (AS)	200 (S) 200 (T) 199 (AS)	200 (S) 200 (T) 198 (AS)	200 (S) 200 (T) 197 (AS)

S, simple; T, temporal; AS, activity space.

Together these findings illustrate the separate impact of a temporal schedule and a defined activity space on the frequency of convergences across the three models. Agents who travel randomly but have a temporal schedule experience the fewest number of convergences because they are traveling randomly and the time they are “at risk” is less than the agents in the Simple version. When a spatial element is added (i.e., agents have defined activity spaces), it increases the frequency of convergence because agent’s homes, jobs, and activities are clustered as opposed to randomly allocated across Seattle as in the other versions. An increasing rate of convergence translates into more street robberies for agents in the Activity Space version.

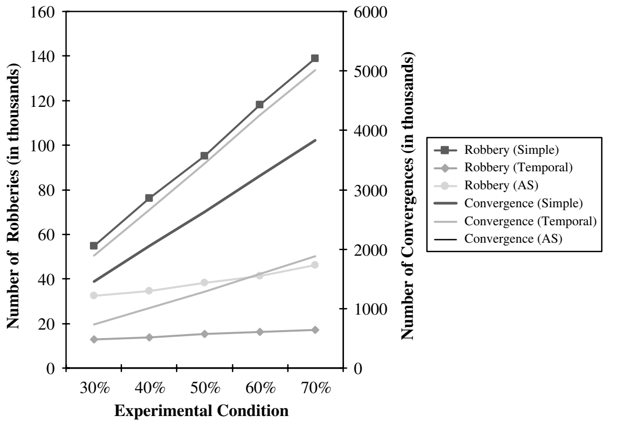

Figure 2. Comparison of robbery incidents and convergences.

Hypothesis test results

The first hypothesis tests the core assumption of RAT; *as the average time spent by civilians on activities away from home increases, the aggregate rate of robbery will increase*. A one-way ANOVA is applied to the means of the five experimental conditions to determine if the average number of robberies across all the civilian agents increases as the time spent away from home increases. Separate tests are conducted for the Temporal and Activity Space versions of the model. The results of the ANOVA indicate significant differences only for the Temporal version (Table 4). Overall, the only version that does not support routine activity theory is the one that includes space.[6]

Additional tests using Tamhane's T2 are employed to identify which groups differed significantly (Table 5).[7] Comparing each group, in turn, to the other four groups reveals that there are differences between the conditions in the Simple and Temporal versions.[8] While all but two comparisons for the Simple version were significant, only three of the

[6] The large sample size has a twin effect producing both a powerful design capable of detecting even small effects and making finding statistical significant relationships more likely. The non-significant finding for the Activity Space version may stem from the large standard deviation found in each of the conditions. A variety of additional analyses confirm the finding of non-significance for the Activity Space model. Specifically, analyses conducted with the same response variable under a univariate generalized linear model (GLM), and additional tests using both a one-way ANOVA and univariate GLM but with a logged response variable, produce consistent findings.

[7] Tamhane's T2 is used because it does not assume equal variances. A test for homoscedasticity showed the variances are not equal across the five experimental conditions. 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).

[8] Tamhane's T2 is only applied to those versions in which there were significant differences for the version as a whole.

Table 4 ANOVA for street robbery events across versions and experimental conditions

	Proportion of time spent away from home				
	Condition 1 (30%)	*Condition 2 (40%)*	*Condition 3 (50%)*	*Condition 4 (60%)*	*Condition 5 (70%)*
Number of civilians	*N*=1,000	*N*=1,000	*N*=1,000	*N*=1,000	*N*=1,000
*Simple model****					
Mean (s.d.)	54.64 (101.99)	76.03 (144.15)	95.22 (182.35)	118.09 (228.14)	139.01 (270.06)
*Temporal model****					
Mean (s.d.)	12.81 (17.54)	13.67 (19.35)	15.18 (22.42)	16.20 (24.34)	17.18 (26.64)
Activity space model					
Mean (s.d.)	32.33 (87.69)	34.63 (103.26)	38.33 (129.42)	41.27 (148.5)	46.09 (174.90)

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

between-group differences are significant for the Temporal version; between the 30 per cent and both the 60 and 70 per cent conditions as well as between the 40 per cent and the 70 per cent condition. Thus, one effect of a temporal activity schedule is to reduce the number of significant differences between the experimental conditions.

The second hypothesis is that *the temporal and spatio-temporal schedules of civilians while away from home change the incidence of robbery events*. This hypothesis explores whether the versions of the model produce significantly different numbers of street robberies for each of the experimental conditions (e.g., whether the number of robberies under the 30 per cent time away condition for the Simple version was significantly different than under the Temporal or the Activity Space versions). The results of the ANOVA indicate there are significant differences between the rates of street robbery for all three versions of the model. A *post hoc* analysis reveals there are significant differences among all five experimental conditions (Table 6). In other words, regardless of the amount of time spent away from home, including the temporal and spatial components of activity spaces resulted in significantly different robbery rates. These results support the separate importance of both time and space when modeling routine activities.

Sensitivity test results

Similar to results for the original model, the new model versions are robust to changes in parameters and random number seeds (Groff, 2007a). The absolute number of robberies increased or decreased depending on the parameter being varied. However, findings related to routine activity theory's core proposition remain consistent across all the tests except two, lending additional support for robustness of the model even as parameters are varied. First, one of the tests varying the random number seed did produce a significant result for the Activity Space version. Otherwise, the results of the model are shown to be

Table 5 *Post hoc* tests of mean differences by experimental condition (seed=100)

(I) Randomization condition	*(J) Randomization condition*	*Mean difference (I–J)*	*Standard error*	*Significance*
30% Time away	40% Time away			
	(S)[a]	−21.39	5.584	0.001
	(T)	−0.86	0.826	0.970
	50% Time away			
	(S)[a]	−40.58	6.607	0.000
	(T)	−2.38	0.900	0.081
	60% Time away			
	(S)[a]	−63.45	7.903	0.000
	(T)[a]	−3.39	0.949	0.004
	70% Time away			
	(S)[a]	−84.37	9.129	0.000
	(T)[a]	−4.37	1.009	0.000
40% Time away	50% time away			
	(S)	−19.19	7.351	0.088
	(T)	−0.51	0.936	0.676
	60% Time away			
	(S)[a]	−42.05	8.534	0.000
	(T)	−2.53	0.983	0.098
	70% Time away			
	(S)[a]	−62.98	9.681	0.000
	(T)[a]	−3.51	1.041	0.008
50% Time away	60% Time away			
	(S)	−22.87	9.236	0.126
	(T)	−1.01	1.046	0.983
	70% Time away			
	(S)[a]	−43.79	10.305	0.000
	(T)	−2.00	1.101	0.515
60% Time away	70% Time away			
	(S)	−20.92	11.180	0.470
	(T)	−0.98	1.141	0.993

S, simple; T, temporal.
[a]Significant differences were found between experimental conditions *I* and *J* at $P<0.05$.

robust to changes in the random number seed.[9] Second, increasing the time an agent with criminal propensity has to wait to commit another street robbery made the ANOVA for the Temporal version non-significant and pointed to the importance of timing in the decision to offend. These were the only changes in the model outcomes from manipulating the parameters.

[9] The numeric results are available upon request from the author.

Table 6 *Post hoc* tests of mean differences between same condition in different model versions (Seed=100)

(I) Version	*(J) Version*	*Mean difference (I–J)*	*Standard error*	*Significance*
Simple	Temporal			
	30% Time Away[a]	41.83	3.272	0.000
	40% Time away[a]	62.36	4.599	0.000
	50% Time away[a]	80.84	5.810	0.000
	60% Time away[a]	101.89	7.255	0.000
	70% Time away[a]	121.83	8.582	0.000
	Activity Space			
	30% Time Away[a]	22.31	4.253	0.000
	40% Time away[a]	41.40	5.607	0.000
	50% Time away[a]	56.89	7.071	0.000
	60% Time away[a]	76.82	8.608	0.000
	70% Time away[a]	92.92	10.175	0.000
Temporal	Activity space			
	30% Time Away[a]	−19.52	2.828	0.000
	40% Time away[a]	−20.96	3.322	0.000
	50% Time away[a]	−23.15	4.154	0.000
	60% Time away[a]	−25.07	4.758	0.000
	70% Time away[a]	−28.90	5.594	0.000

[a]Significant differences were found between model versions *I* and *J* at $P<0.05$.

Discussion

This research extends previous research that found support for the theory's main premise that the shift of routine activities away from home increases rates of street robbery (Groff, 2007a) but left unexamined the effect of the temporal and spatio-temporal aspects of routine activities on the incidence of street robbery events. The research tests the core premise of routine activity theory that shifting routine activities away from home increases street robbery and explores the impact of progressively more complex temporally and spatio-temporally explicit activity spaces on the incidence of street robbery.

Two major findings emerge from these efforts. First, support for routine activity theory's core proposition depends on the type of schedule constraints placed on the agents. When agents have no constraints on their travel or when they have only temporal constraints (i.e., the Simple and Temporal versions), the number of street robberies increases as the agents spend more time away from home. However, when the agents are assigned spatio-temporally defined activity spaces, the incidence of street robbery still increases but the differences among the experimental conditions are not statistically significant. Therefore, the findings provide support for routine activity theory's core proposition but not when the agent's activity spaces are spatially constrained. This finding also provides evidence of the importance of the spatial component of routine activity in structuring where and with whom convergences occur.

The finding of non-significance for the Activity Space version has theoretical implications. It demonstrates that spatial constraints largely, but not completely, counteract the influence of increasing time spent away from home. Although crime continues to increase with time spent away from home, the differences between the experimental conditions are no longer large enough to be significant. Thus it is the spatio-temporal etiology of routine activity, and not just the gross amount of time spent away from home, that underpins macro-level robbery rates.

The implementation of activity spaces in the model is one potential source of explanation for the lack of significant findings for the Activity Space version. The maximum of only two potential activity spaces (i.e., when employed and when unemployed) constrains the spatial extent of agent travel to an unrealistic degree. Consequently, during any model run specific agents can only converge with the relatively few other agents whose activity spaces intersect their own. While activity spaces are somewhat static, it is the degree to which activity spaces are constrained that is the issue. In the model, the repeated interaction of the same agents quickly causes the offender agents to gain more wealth than the civilian agents, so that when only two civilians converge and the offender has more wealth no crime occurs. As a result, increasing convergences do not translate into higher numbers of robbery. While this phenomenon is present in all three versions of the model, it is most pronounced in the Activity Space version. Three potential strategies that may ameliorate this phenomenon are to: (1) make the wealth distribution for citizens reflect criminal propensity by assigning offenders lower wealth; (2) increase the number of civilian agent activity spaces available for agents; and (3) boost the number of civilian agents in the model.

Second, temporal and spatio-temporal constraints have a differential influence on the incidence of street robbery. As compared to the Simple version, in which agents travel randomly the entire time, the addition of temporal schedules for civilian agents reduces the incidence of street robbery by about 77 per cent and changes the distribution of street robbery events. This result provides evidence in support of Ratcliffe's (2006) hypothesis that temporal constraints are a major source of observed patterns of opportunity-based crime. When spatially defined activity spaces are added to the model and the temporal schedule for each agent is held constant, the separate and even larger impact of space is clearly demonstrated. Spatio-temporally constrained schedules significantly increase the incidence of street robbery as compared to temporally constrained ones and radically change the distribution of street robbery events. The clustering in the spatial distribution of robberies is higher than the other versions and more linear in nature due to concentration along the major travel routes among homes, jobs, and activities.

These findings regarding differences by type of schedule constraints are consistent across all five experimental conditions. In other words, regardless of time spent away from home, the type of constraints on agent's activity spaces (i.e., simple, temporal, or spatio-temporal) produce significantly different numbers and patterns of street robbery. Thus, the impact of temporal and spatio-temporal constraints on activity is robust with regard to time spent away from home.

There are several potential explanations for these findings. The changes in incidence could be related to the amount of time the agents are "at risk". The addition of a temporal schedule reduces both the time that civilian agents are "at risk" of being victimized and the time that civilians with criminal propensity have to offend. In this way, temporal schedules constrain the activities of both offenders and non-offenders and directly influence the number of convergences. Differences in time "at risk" do not explain the increase in street robberies between the Temporal and Activity Space versions because the temporal schedule is held constant between the two.

The explanation for differences between the Activity Space version of the model and the others lies in the clustered nature of human activity that is reflected therein. The homes of civilian agents are concentrated in certain areas, they travel to jobs that are clustered in other areas and they participate in activities that have yet another, but still clustered, distribution. The road network acts to amplify this result in that agents traveling to the same area tend to be routed along the same major roads. In this way, the implementation of spatio-temporal routine activity spaces following time geographic principles acts to increase overlap in activity spaces which in turn, increases the frequency of convergence. One interesting side effect of this increased concentration is that police agents who are randomly assigned to patrol in those high concentration areas are able to deter more crimes than when civilian agents are only temporally constrained but randomly distributed (as in the Temporal version of the model). This finding has implications for achieving a better understanding of the relationship between police patrol strategies and crime.

Implications for policy and practice

This research demonstrates an alternative method for modeling criminal behavior at the individual level and exploring the basic assumptions of routine activity theory. Although the basic model (and its extensions) continues to be simple, its implementation accomplishes several essential functions. First, this effort demonstrates the potential contribution and establishes a foundation for further, more complex explorations of criminal behavior. The agents developed for this research have the core behaviors that are essential to the creation of richer representations. Second, the theoretical aspects of routine activities are multi-layered. This model implements the coarsest level. Subsequent models could incorporate finer details using this model as a platform. Third, the application of the model provides a set of findings that can be evaluated and discussed to determine necessary changes and serve as a catalyst for further research. Finally and maybe most importantly, the model provides a forum for exploring the impact of policy decisions. This is a particularly important advantage in the social sciences when policy makers must often choose between competing strategies with little or no evidence.

By building additional analytical capability into this base model, there are a variety of policy questions related to crime prevention, policing strategies, and response to terrorist incidents that could be studied. For instance, computational laboratories could be used to test the veracity of theoretical assumptions in advance of empirical research. This strategy has the potential to be far more cost-effective because new policies can be "tested" within the simulation and only those that show promise funded for field research.

In the area of crime prevention, policies suggested by Crime Prevention through Environmental Design (CPTED) (Jeffery, 1971; Newman, 1972) and opportunity theories can be studied intensively. The physical design and access control strategies suggested by CPTED are often very expensive (Reppetto, 1976). Simulation could potentially save money by helping to identify the strategies with the highest potential for success on the ground. The quantitative output of the simulations can be used in preliminary cost–benefit analyses to evaluate new approaches.

Opportunity theories have hypothesized about the elements necessary for a crime to occur as well as the physical and social environments. In a computational laboratory, each one of these components can be analyzed while the others are held constant.[10] In this way, the often confounding effects

[10] The other components are not actually held constant but rather the same random number algorithm is used for each experiment so that each run is the "same" as the last.

of variables can be separated. For instance, the decision to offend can be studied intensively. Instead of having criminal propensity as a presence/absence trait, criminality could be assigned randomly and in various strengths. Criminal tendency could then be used as a variable in a more complex equation describing the decision to offend in a particular situation.

Agents could "learn" from the relative success of previous decisions and use that information in future decisions. For instance, agents could have the ability to "recognize" other agents with whom they come in contact at a node. Each time two agents come in contact with one another, the concurrence could be stored for future reference. This information would be called upon when an agent is making the decision to offend. Disaggregating the factors involved in the decision to offend is necessary to gain a better understanding of each individual factor and how they interact.

Another important facet of opportunity is the issue of guardianship. Questions concerning the role of place managers (Eck, 1995) and intimate handlers (Felson, 1986) as guardians could be tested in a computational laboratory. In fact, the entire phenomena of guardianship could be dissected in such a laboratory because of the ability to hold factors constant. A researcher could change the weightings of agents representing guardianship (e.g., police officers, known agents, place managers, etc.) to determine the effect on the decision to offend.

In addition to examining the agents' interactions with one another, their interaction with the environment could also be studied. One intriguing aspect is to study the effect of urban form on the physical configuration of routine activities undertaken by the agents. Theory holds that criminals, as well as other individuals, become familiar with areas and their associated opportunities for crime via the travel routes they use in their own routine activities (P. Brantingham and P. Brantingham, 1981a, b; P.J. Brantingham and P.L. Brantingham, 1984; P.L. Brantingham and P.J. Brantingham, 1993). This assumption could be tested in a computational laboratory. Another area of research concerns the journey to crime. A computational laboratory enables agents to be assigned behavioral rules and then allow patterns of behavior to emerge. In this way, research could allow the comfort zone of an offender to emerge from the simulation. Comparing the functional distributions from the simulations with those from empirical research could test the veracity of the patterns observed.

Related to police patrol strategies, the distribution of agents and/or cops across the landscape could be changed and the effect on macro-level crime patterns observed. For example, a simple experiment that changes the initial geographic distribution of agents (e.g., random vs. clustered vs. uniform) would provide interesting information about the effect of changes in population distribution on emerging crime patterns. These types of models could also be used to test the effectiveness of different patrol patterns on crime reduction (e.g., hot spot policing). For example, a researcher could use the results of the previous simulation (and the same random number seed) to assign cops to small areas with high crime and see how the pattern/rate of crime changes. Spatial statistics could be used to compare resulting patterns and more rigorously test the significance of the results. The optimum number of police officers for a particular jurisdiction could be explored by comparing the crime levels at varying force sizes.[11] Diffusion is another area related to police effectiveness that could be examined in new depth with computational laboratories.

[11] An anonymous reviewer of the original funding proposal to the National Institute of Justice made the suggestion that experiments could be conducted to find the optimal ratio of police officers to citizens using simulation.

The scope of the computational laboratory for theoretical testing and exploration is very broad. This research provides one foundation for additional, more richly specified models to be developed. More advanced models have the potential to produce concrete, public policy relevant findings to address the situational elements of crime since opportunity theories by definition concentrate on aspects of the crime event that can be changed far more quickly and easily than ones involving the root causes of criminal motivation.

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