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EDITOR'S NOTE

Welcome to the third volume of *Crime Patterns and Analysis*. Once again, this issue contains some insightful and relevant research conducted by members of ECCA. This volume also offers something we have not had in the past – two issues. Following publication of this first issue of volume three will be publication of a special issue highlighting the work that is being conducted at Simon Fraser University. My hope is that this becomes a regular second issue of each volume, where schools that have an environmental criminology focus highlight some of their research. As always, if you have any questions or suggestions, just email me. I look forward to seeing you all in Australia.

Jeffery T. Walker
Editor

Situational Crime Prevention and Co-Offending*

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The crime prevention literature often contrasts "social prevention" and "situational prevention." Social prevention focuses on reforming individuals through social policies. Situational prevention seeks instead to reduce crime by altering the settings or conditions in which we carry out daily routines, and avoids trying to change offender dispositions. Yet offender dispositions are not their only "social" feature. Much crime, especially at young ages, is "co-offending" carried out in small groups. In addition, offenders at diverse ages socialize in settings that lead to illegal acts in nearby times and places. Such settings are amenable to situational measures. Interestingly, situational crime prevention can alter the size, composition, timing, location, and informal supervision of small group activities and routines. This widens the range of crime reduction possibilities, while undermining the assertion that situational prevention is "non-social."

INTRODUCTION

The crime prevention literature often contrasts "social prevention" and "situational prevention" (e.g., Rosenbaum, Lurigio and Davis 1998). In common parlance, social prevention focuses on reforming individuals through social policies, often including changes in education, rehabilitation, and youth activities designed to improve character. Situational crime prevention, however, takes individual dispositions towards crime as given. It seeks instead to change the everyday settings, products, and procedures that make crime rewarding and safe for the offender, and easy to carry out (Clarke 1997, 2005).

One could easily conclude that situational prevention is non-social, and some critics indeed dismiss it as "administrative criminology," further conveying the notion that situational prevention is "non-social," or even "anti-social" (see Clarke (2005) for a discussion of this and

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other criticisms of situational prevention). In reality, situational prevention and its kindred theories – including crime pattern theory, the routine activity approach, crime geography, and rational choice theory – display a keen awareness of human social characteristics, including human responsiveness to environmental cues (see Wortley and Mazzerole 2008).

A more interesting critique would apply simultaneously to situational prevention and its social prevention rivals. Both general approaches to crime prevention focus on individuals as the actor in the crime system. Social prevention seeks to reform individuals, thereby reducing their criminality. In contrast, situational prevention seeks to alter decisions made by individuals. Despite that contrast, one can criticize both social and situational approaches for not being social enough. This criticism is based on a single fact: that so much crime is carried out by small groups of offenders, not by individuals (see the next section). Thus, neither individual dispositions nor individual decisions tell us enough about crime. At adolescent ages, when crime participation ascends, co-offending is especially important. Co-offenses,[1] as defined by Reiss (1988), are committed with the simultaneous presence of at least two offenders. This contrasts with solo-offending, for which illicit cooperation is either absent or non-simultaneous. Consider a bank robber who plans the crime with someone else but acts alone in the robbery itself. The latter act is treated as a solo offense in Reiss's definition, even though it is part of a sequence with a social dimension and has an accomplice from a legal viewpoint. Thus, one should not assume that a "solo offense" is a "non-social offense."

Clear (1996) criticizes traditional crime theories as "atomistic," namely, focusing too much on individual action and individual reform. As it is commonly known, situational approaches to crime and crime prevention also tend to be atomistic. Yet situational prevention is flexible enough to take small group offending into greater account. This may be thought of as part of Wortley's (2008) situational precipitators concept: the presence of peers before the criminal event (through peer pressure and group dynamics) has a significant influence on the generation of crime and, consequently, its prevention. Sometimes peers before an event continue to work together in the criminal act itself, making it a co-offense.

CO-OFFENDING IS IMPORTANT FOR CRIME AND ITS PREVENTION

The literature shows that crime is substantially a matter of co-offending.[2] In adolescent ages, about half of crime incidents occur in groups, usually of two or three offenders. Allowing for multiple counting when multiple offenders are present,[3] approximately two-thirds of youth crime participations are in groups (Andresen and Felson 2010; Felson 2003; Reiss 1988; Reiss and Farrington 1991). This number is subject to measurement discussion, but the point is that we cannot look at crime only as a feature of individuals. Moreover, many solo offenders are involved with others just before or after their offense (Tremblay 1993). This does not deny individual decision making or individual variations, but puts individuality into a larger context.

Co-offending poses a significant number of practical requirements. A group must assemble for such offenses to occur, and such assemblage is not automatic. Nor is an assembled

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[1] These types of offences are also called accomplice crimes or group offenses. We avoid the word "accomplice" because, in legal terms, it might include non-simultaneous cooperation in crime.

[2] Some recent research lessens or even denies the importance of co-offending (Carrington 2002; Stolzenberg and D'Alessio 2008); but as shown below our data support the importance of co-offending.

[3] Thus a single offense with two offenders counts as two participations, while an offense with three offenders counts as three participations.

group necessarily located in a convenient setting for carrying out crime. Indeed, co-offending cannot occur without situational features; thus, it depends on time and space, as well as circumstances and routines.

Co-offending helps us understand why routine activities, crime pattern theory, situational prevention, crime geography, and rational choice theory converse with one another. Everyday life brings offenders together with one another under particular criminogenic circumstances. For both individual actors and small groups of co-offenders, assemblage involves several processes, including (but not limited to) routines and convergences, proximity to crime opportunities, and foraging for crime targets. Most often, these assemblages are the temporary formation of a group for crime opportunities that dissolve upon completion of the criminal task (Brantingham and Brantingham 2008). Practical crime policy interferes with some of the above or any other processes, products, or procedures if such interference breaks up crime opportunities, however indirectly. Thus, situational interference with co-offending is part and parcel of situational prevention. Indeed, we can think of situational prevention as a set of methods for

- reducing crime opportunities,
- reducing offender convergences (possibly by disrupting networks of youth), and
- interfering with hangouts that set the stage for co-offending.

The size, composition, timing, and location of small group activities affect nearby crime, regardless of whether youths plan for the crime, and regardless of whether the crime is itself defined as co-offending or solo-offending. The process of co-offending is related to solo-offending as well because offenders often dispose of stolen goods or involve others before or after a solo crime (Tremblay 1993), most co-offenders also solo-offend (Reiss and Farrington 1991), and most solo-offenders also co-offend, sometimes in the same crime sequence.

From a situational viewpoint, consider that today's population is roughly the same at 1:30 pm and at 3:30 pm. But the group configurations at these two times can be entirely different. Youths who earlier were in class supervised by a teacher are later in small groups or alone on the way home from school. Thus, offenders and targets emerge as daily patterns quickly shift. These shifts in group patterns, sizes, and circumstances are central for understanding how crime occurs and how it can be thwarted.

RE-ENTER THE INDIVIDUAL

So far, we have emphasized situational aspects of co-offending. That is, we have discussed how the size, composition, timing, and location of small group activities affect nearby crime. We do not mean to imply, however, that co-offending situations obliterate individual actors and decision-makers in the crime process. First, individuals often choose to commit crimes with others for practical reasons – to better carry out the crime. For example, it might be easier or safer to rob somebody with a co-offender. Each offender has made choices. Second, group dynamics affect individuals in the crime-making process. The more youths present, the more crime ideas, the more targets to be considered, the more dares.

Admittedly, it is difficult for us to conceptualize a small group as an actor. Yet small group dynamics are a significant aspect of social psychological theory and research, and individuals often act differently together than they do separately. Indeed, considering group aspects does not constitute a denial of individuals as crime actors. Rather, it considers, or recognizes, the interdependent nature of decision-making such as game-theoretic approaches to understanding the decision to co-offend (McCarthy et al. 1998). The central point is that co-offending processes, including assemblage processes and the decision-making process previously discussed, enrich our understanding of how crime occurs. This enriched understanding widens the situational prevention measures that could reduce crime to include consideration for co-offending processes.

YOUTH CONVERGENCE SETTINGS[4]

Youth convergence settings have been reviewed in Scott's (2001) pamphlet on disorderly youths. Scott did not emphasize crimes at nearby times and places, but rather crime and disorder in public youth hangouts. We adapt some of his situational questions to our current paper by asking three questions and filling in several sub-questions:

- *Where*, specifically, do the youth gather?
  - Near entrances to businesses or other buildings?
  - Near stairways, escalators or other high-traffic areas?
- *Why* do the youth gather where they do?
  - What accounts for the location's attractiveness?
  - Are there comfortable places to sit or lean?
- *How* can they evade supervision?
  - Can they conceal an illegal act?
  - Does the manager of the place tolerate disorderly behavior?
  - Is the manager involved in illicit conduct?

Scott (2001) relates that only limited success is gained by a pure coercive approach, viewing youth as offenders whose conduct must be controlled and prohibited. He recommends an accommodation approach, balancing the needs and preferences of youths and the complainants. He suggests creating legitimate places and activities for youths to minimize the trouble they may cause. In some cases, he suggests avoiding locating businesses that create youth hangouts, or modifying some public places to render them less comfortable, convenient, or attractive as youth hangouts. Scott (2001) also suggests modifying some settings to increase informal social controls and deny anonymity, as well as enforcing truancy and curfew laws.

Felson (2003) put forth the concept of offender convergence settings to understand how we may disrupt the process of finding suitable co-offenders. Invoking Barker's (1963) theory of behavior settings, Felson (2003) states that to find one another, likely co-offenders must be able to converge in time and space without outside interference, and have enough time to prepare for criminal cooperation. As people age through youth, they often shift their social life to more private and supervised convergence settings, such as the home and the workplace. This produces a natural depletion of potential co-offenders. As such, a crime partner regeneration process is

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[4] We must also consider the importance of "electronic convergences" with youth using telecommunications and computer technology. Though our focus is in regard to physical convergences in this research note, we provide a brief discussion of this issue below.

necessary for a suitable number of co-offenders to become available.[5] To disrupt this crime-partner regeneration process, Felson (2003) suggests modifying or removing particular behavioral settings so those searching for co-offenders have trouble doing so or lack adequate time to coordinate subsequent criminal activity. Thus, fewer offender convergence settings will exist and criminal cooperation will decline. The task for scholars and practitioners is to identify offender convergence settings, along with any environmental or situational modifications to remove them or at least make them less criminogenic. In the spirit of situational prevention, appropriate crime reduction policies minimize the need for arrests while maximizing the impact of very low cost changes.

EMPIRICAL CONFIRMATION: THE IMPORTANCE OF CO-OFFENDING

The essential point of this paper is to emphasize situational efforts to shrink offender convergence settings. That importance depends on confirming the magnitude of co-offending. This confirmation is particularly important because some recent but exceptional research finds that co-offending may not be as prevalent as previously thought (Carrington 2002; Stolzenberg and D'Alessio 2008). This section confirms, with Canadian data in British Columbia, the magnitude of co-offending, and hence justifies giving it policy attention.

The Royal Canadian Mounted Police (RCMP), Police Information Retrieval System (PIRS) data in British Columbia represents 174 of the 186 police jurisdictions in the province and 67 percent of the population. We extracted from this data system approximately 5 million negative police contact events from 01 August 2002 to 31 July 2006. This analysis considers four major offenses: aggravated assault, robbery, burglary, and theft. Considering the importance of age in the explanation of crime (Hirschi and Gottfredson 1983), we focus on those between the ages of 12 and 29, the prime offending ages.

The PIRS database contains information for approximately 5 million negative contacts with the police involving approximately 9 million individuals (offenders, victims, complainants, and witnesses) over the four available years. These data have a number of advantages in assessing the nature of co-offending, some of which were also present for the two previous analyses of co-offending that used large-scale, incident-based data. Although we are not the first to use a large-scale data set to analyze co-offending, this is the largest data set yet applied to the problem. Connected to each of the 5 million incidents is a list of involved individuals, stating their age at the time of the incident and why they were included. The current analysis uses only a subset of 25,876 incidents yet a very large data file was necessary to produce that N, given the subsetting process. Our Base N's per offense range from 975 for robbery to 16,292 for theft.

Although these data represent 174 different police jurisdictions, they are tabulated from one police agency or reporting body. Unlike the NIBRS database that combines data from thousands of enforcement agencies, the RCMP data minimize inconsistencies in reporting of criminal incidents. Finally, we were able to calculate all statistics using averages across the years covered by the PIRS database, ironing out the unusual features of any given year.

From this database, co-offending is calculated by combining three categories – suspect, chargeable, and charged.[6] Together, these categories approximate the arrest categories in NIBRS,

[5] This is not to deny that some workplaces provide settings for offender convergences, or that some families are engaged jointly in crime. But these criminogenic potentials are weaker than in non-family and non-work settings.
[6] A suspect is someone whom the RCMP believe committed the crime, but they do not (at the time of entry) have supporting evidence to pursue a charge; charged is for a person whom the RCMP believe committed the crime and

providing a basis for comparing U.S. and Canadian findings. With the addition of suspects, these data are more inclusive than Carrington (2002). As such, based on Carrington's (2002) other Canadian results, we should be biasing our results to decrease the impact of co-offending.

Table 1. Percent of participations that are co-offending, four major offenses, by single year of age, 12 through 29, British Columbia, Canada, August 1, 2002 through July 31, 2006

	Percent Co-offending	Base N
Robbery	54	975
Burglary	54	4513
Aggravated Assault	43	4096
Theft	37	16, 292

Source: The Royal Canadian Mounted Police (RCMP), Police Information Retrieval System, also known as RCMP-PIRS data. This table is based on approximately 5 million negative police contact events, 750 000 are index offenses. Such events include suspects, those charged, and those deemed chargeable the RCMP.

As shown in Table 1, co-offending is a significant portion in each of the four major offense categories. Moreover, for robbery and burglary, over half of crime participations involve co-offending. These co-offending percentages range from 37 to 54 per cent, with the percentages of co-offending for youth (12 – 29 years of age) being greater than 50 percent for robbery and burglary. Clearly, interfering with offender group processes deserves serious consideration as a set of crime reduction techniques. This can be accomplished through at least four mechanisms:

1. Reducing the number of offender convergence settings,
2. Making crime targets less accessible to these convergence settings,
3. Increasing supervision of these settings,
4. Reducing the presence or dominance of such settings during high risk times of day or days of week.

All of these techniques make it more difficult for co-offenders to converge, helping to reduce co-offending and perhaps solo-offending that occurs very soon after the group converges. Each of these four mechanisms are amenable to situational analysis and perhaps situational prevention at low cost, while avoiding high levels of arrest.

Figure 1 shows that disrupting convergence settings will have a differential impact on different crime categories. The magnitude of co-offending is particularly high for youth involved in robbery and residential burglary. Theft is predominantly a co-offense in the early teen years, but quite rapidly becomes a solo-offense in the later teen years. Finally, though of a lesser magnitude and most often below 50 percent, even aggravated assault has a significant portion of its participations being co-offenses. This implies that it is worthwhile to disrupt co-offending and any offender convergence settings that give rise to it. This leads us to note that the situational crime prevention perspective is relevant to co-offending analysis and counteraction.

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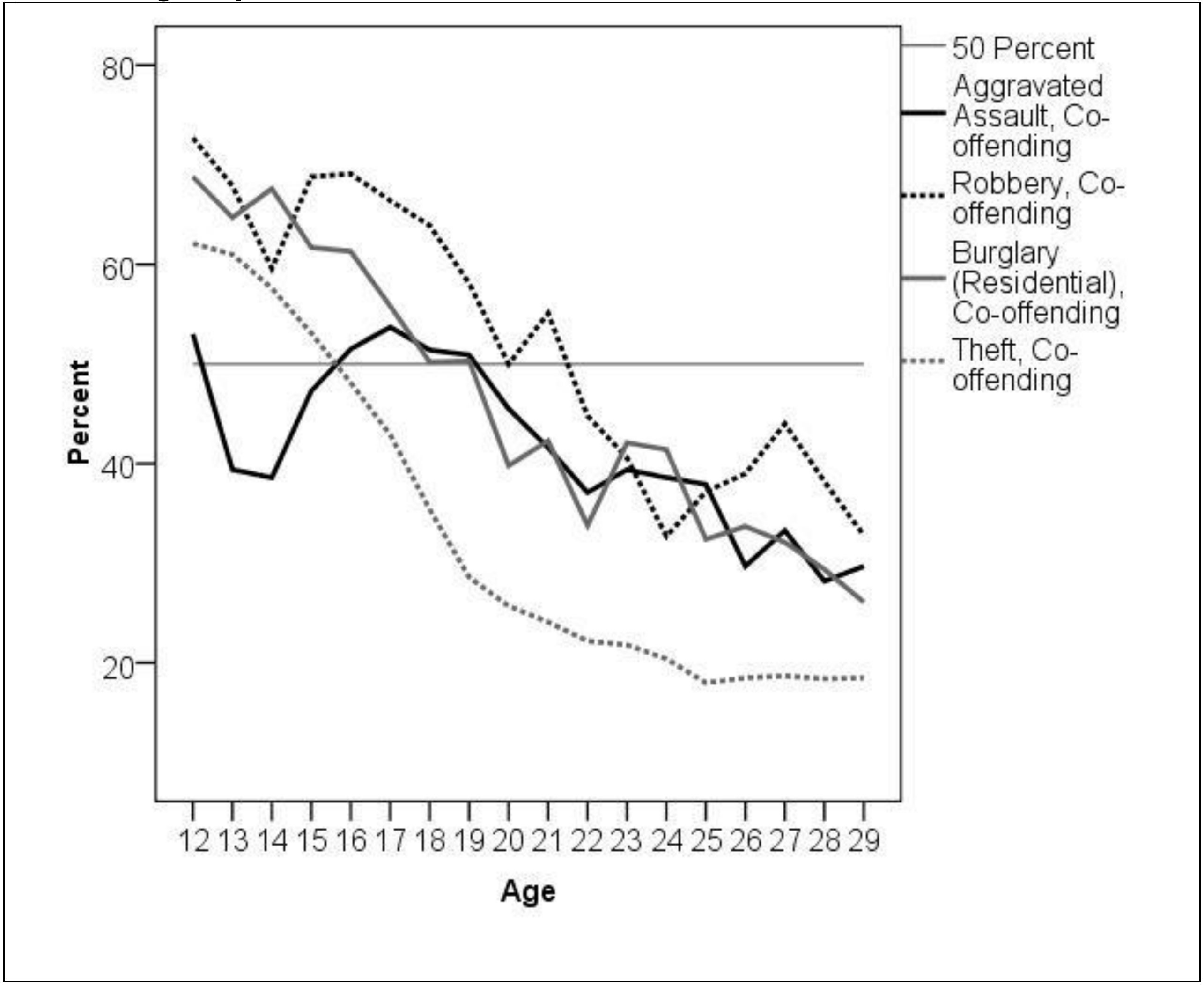
for which there is supporting evidence; chargeable is for a person whom the RCMP believe committed the crime and for which there is supporting evidence, but who is not charged for a variety of reasons, such as being under the age of criminal responsibility.

Figure 1. Percent of participations that are co-offending (aggravated assault, robbery, burglary, theft), by single year of age, 12 through 29, British Columbia, Canada, August 1, 2002 through July 31, 2006



Source. RCMP Police Information Reporting System (PIRS).

RE-THINKING CERTAIN SITUATIONAL CRIME PREVENTION MEASURES WITHIN A CO-OFFENDING FRAMEWORK

Certain crime prevention measures, commonly discussed in individual terms, might actually make more sense within a co-offending framework. A first example is truancy reduction – normally seen as a means to prevent individuals from falling prey to crime as offenders or as victims (See Garry (1996) for a review of truancy research). However, truancy also allows youths to meet away from adult supervision. Truants are likely to discover or create convergence settings from which illegal actions emerge at nearby times and places. Although it is possible for truant youths to commit crimes alone, it is more likely that their crimes will be carried out in small groups, and that their convergences will help that happen. Accordingly, truancy reduction might be most effective if it focuses upon controlling settings where truants converge prior to carrying out their offenses. Focusing upon a small number of truant convergence settings could be more effective than arresting truants one by one.

A second police problem commonly thought of in individual terms is "social cruising."[7] We refer here to youths walking or driving around in public places to meet one another. The public often objects to cruising for its direct consequences, namely, that it generates immediate noise, traffic, and takeover of public space. Social cruising also has indirect consequences, by assembling youths who might then become involved in crime. More precisely, cruising can help youths find suitable co-offenders. Although the public might not be directly aware of these indirect consequences, they may have at least a sense this is happening, fueling their objections to groups of youths hanging out at night.

Local police agencies in Arlington, Texas, and Huntington, West Virginia, have sought to control social cruising by diverting youths towards less disruptive settings where they can meet without creating as many collateral problems (Glensor and Peak 2004). In Arlington, city officials reserved a large parking lot for teenagers to socialize in the evenings with gentle police presence (Bell 1989). This policy increased community security, not only directly but perhaps indirectly, by channeling and supervising youth convergences and thus diminishing their ability to stage co-offenses. Related work by Scott (2001) offers additional methods by which youth convergences can be managed to prevent crime. The general point is that situational measures to manage social convergences of youths can reduce crime.

A third example has to do with runaway youths. Although police and parents commonly view juvenile runaways as individual cases, in practical terms runaways often converge in settings where they commit crimes, both alone and together. Again, the situational control of the runaway problem offers a means to reduce co-offending in nearby times and places by impairing the discovery of suitable co-offenders (Dedel 2006).

Fourth, several projects to reclaim and manage urban parks in effect serve to prevent offenders from hanging out there. Hilborn (2009) documents several such efforts. His appendix B includes some 20 problem-oriented policing projects with that in mind.

A final example has to do with football violence. It is easy to view football hooligans as individual bad apples, but increasing evidence tells us hooliganism is a group phenomenon (Madensen and Eck 2008). A sports event not only converges legitimate fans, but it also draws together violent co-offenders, some of whom meet before the match to plan their activities.[8] Many of the situational techniques to reduce football hooliganism do so by impairing this convergence process.

FUTURE QUESTIONS ABOUT ELECTRONIC IMPACTS ON CO-OFFENDING

Some people have suggested to us that modern technology has enhanced simultaneous electronic linkages among youths, altering their social processes and thus influencing co-offending. One no longer has to find a telephone to reach others, so social life can occur remotely at almost any time of day or night.

[7] The word "cruising" is sometimes used with reference to men walking or driving around in search of prostitutes. We do not include that in the current analysis.

[8] This paper neglects examples of how bars and taverns are managed and licensed to control dubious convergences and nearby crime. That topic is too rich for visiting within the confines of this paper.

A full discussion of this topic would require an entire book and quite a bit of additional research. However, this short section at least provides a basis for future discussion and inquiry. We might begin by dividing fixed time into four types of allocation:

a. Time spent in face-to-face social interaction,
b. Time spent in simultaneous electronic social interaction,
c. Obligatory time (e.g., work and school), and
d. Other time allocations.

The empirical question is how increases in simultaneous electronic interaction, category (b), influences the other categories. The question is complicated by the fact that electronic usage is often combined with time spent in other activities; thus, obligatory time includes side activities, such as students in class or employees at work who are also text messaging friends. More relevant for now is whether this additional social life is subtracted from category (a), producing less face-to-face time. If so, then offender convergence settings may become less relevant. In addition, co-offenders might set up their crimes via category (b) rather than (a).

On the other hand, it is possible that electronic contact serves primarily to set up social life rather than replace it. If that is the case, category (a) does not decline in size, but it may alter in location or group composition. If the basic social impulse remains fundamental to human life, and face-to-face social life is at the core of that impulse, then category (a) will not shrink and youth convergence settings will remain significant. Moreover, contacts among those who have not previously been introduced, or who do not know one another well enough for electronic intrusion, will continue to depend on physical convergences in suitable settings.

CONCLUSIONS

Using the RCMP-PIRS data in British Columbia for four major offenses we are able to confirm that co-offending is indeed important for crime. In fact, for these (and other) offense categories, co-offending is the dominant form of offending for prime offending ages. This raises the issue that benefits from altering offender convergence settings could be cost-effective, and that situational efforts to do so could become important. The prevalence of co-offending justifies further inquiry into offender convergence settings and what to do about them.

A long history of criticism of situational prevention is found in the literature. Critics have long claimed that situational crime prevention is too limited. Over time, situational prevention research and theory has, step by step, widened its application and undermined claims of its limited power. In linking situational prevention to co-offending, we have further demonstrated its potential. Situational measures to reduce or constrain offender convergence settings can undermine the formation of co-offending groups, or impair their access to crime targets.[9] More generally, situational attention to offender convergence settings can impair efficient foraging for crime targets. As this happens, it will no longer make sense to dismiss situational prevention as nonsocial.

[9] This paper neglects the discussion of civil liberties issues in situational prevention. Those issues are discussed specifically with regard to convergence settings in Felson (2003).

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DELIQUENTS ON THE MOVE: EXAMINING SUBGROUP TRAVEL VARIABILITY

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Efforts to model variation in offender travel habits may benefit from the identification of robust factors accounting for subgroup patterns. Using information about activity nodes frequented by 2,563 delinquent youths residing in Southern California, this study examined subgroup variation in distances traveled to hangout locations. Curve estimates generally concur with prior research; most distributions exhibited a segmented, nonlinear curve joining logarithmic and negative exponential functions. Significant variation was found for subgroups classified by the urban structure of the residential city and travel method used when out with friends. Theoretical and policy implications are raised by the diminished importance of notable demographic factors and crime type in light of the significant effects of community and behavioral variables.

INTRODUCTION

Increasingly, a geographic orientation focused on the nexus between the offense location and its proximity to the criminal's "haven" is adopted to explain crime patterns (Kent et al. 2006; Rossmo 2000). Distance decay functions, which describe and model the distribution in travel length, reflect a decrease in the likelihood and number of offenses committed as the distance from the home base increases (e.g., Canter and Hammond 2006; Levine 2009; Rossmo 2000). This pattern is not unique to criminal behavior; all travel-related activity tends to exhibit higher frequencies of short distances anchored by home locations (e.g., Haynes 1974; Wheeler and Stutz 1971; McDonald 2007).

To better understand travel variation, previous studies sought to identify homogenous population subgroups with distinctive travel habits by comparing the relative effects of each potential covariate (e.g., Buchanan and Barnett 2006; Giuliano and Dargay 2006; Schlossberg et al. 2006; Schwanen and Mokhtarian 2005; Wheeler 1972). While this line of inquiry is fairly advanced in transportation research, few studies of offender travel have included a range of different types of determinants (i.e., individual characteristics, behavioral elements, culture, and community or contextual issues). Yet, despite this methodological limitation, substantial evidence exists to suggest that the typical distance traveled by an offender varies by crime type, access to transportation, age, and to a lesser extent, modus operandi and the nature of the intended target (e.g., Capone and Nichols 1976; LeBeau 1987; Phillips 1980; Wiles and Costello 2000).

To advance the understanding of offender mobility, studies may benefit from continuing to investigate covariates that may represent population subgroups exhibiting differential distance decay distributions among offenders. Expanding the search for suitable covariates is critical as the failure to appropriately parse offenders may: underemphasize the importance of certain determinants; obscure or even distort travel distributions; and generally, neglects community-level factors found to be associated with travel decisions generally (Bichler et al. in press; Rengert et al. 1999; Smith et al. 2008; Townsley and Sidebottom in press; Van Koppen and de Keijser 1997). For instance, notable variation by age and offense type is widely supported; however, few have directly compared the relevance of these factors against other covariates (e.g., gang involvement, travel method, and community juxtaposition). Discovering whether there is notable subgroup travel variation among a large, diverse sample of delinquent youth may contribute to the understanding of crime patterns, offer evidence upon which to build multilevel models, and provide strategic direction toward effective crime prevention.

ESTIMATING DISTANCE DECAY

Theoretical arguments favor the existence of a steep distance decay pattern in the distribution of distances offenders travel to crime sites. Central places such as home, work, or school are key to anchoring travel patterns for many reasons (for a discussion of how central place theory explains crime patterns, see Brantingham and Brantingham 2008). Studies of travel habits (commute to school or work and leisure activities) find that transportation barriers, costs, and accessibility interact with an expansion tendency (to explore new resources) to generate a trip density pattern suggestive of a home range effect (Haynes 1974). With these general travel behaviors in mind, it follows that offenders are equally unlikely to travel far to fulfill their criminal purposes.

Offenders' travel decisions are contingent on the awareness of opportunities that are developed through regular, non-criminal behavior (see Cohen and Felson 1979; Felson 2008). Familiar locations located near home are likely to require the least effort – measured by the expenditure of time, energy and funds – and maximum gain (Van Koppen and de Keijser 1997). Further, daily non-criminal activity may also provide reasonable estimates of risk (see Cornish and Clarke 2008). While there is theoretical consensus that delinquents prefer to stay relatively close to their home, notable variation in observed travel patterns continues to accumulate, fueling efforts to identify stable population subgroups exhibiting distinctive travel patterns.

Variations in Distance Decay Functions

Previous efforts to model travel distributions found variability in the rate and critical distance at which decay occurs (see Table 1). Transportation research examining commuting behavior (to school or work) and recreational activity typically find that travel distributions are best fit by a negative exponential function; although notable methodological limitations may overemphasize the consistency of these findings (for a review of this issue see Haynes 1974). Among offenders, simple models typically involve inverse linear (Pal 2007), logarithmic (Canter and Hammond 2006), and negative exponential functions (e.g., Capone and Nichols 1976; Kent et al. 2006; Lu 2003; Pal 2007). Explanations for this variation suggest that a steep decay reflects a reluctance to travel far from home to commit a crime; whereas, slower decays may indicate that offenders are only marginally influenced by their home location. In the latter case, a larger area may be needed to find suitable targets, the offender's general activity patterns might be more dispersed for non-crime reasons, or offenders may act strategically to lessen the chances for apprehension (Lundrigan and Canter 2001; Levine 2009).

Table 1. Sample of Distance Decay Functions

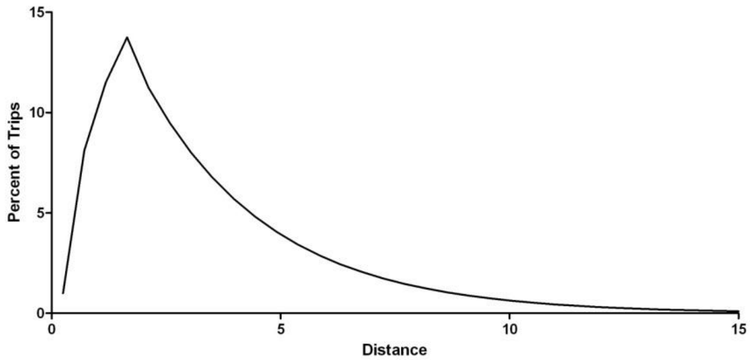
Model	General Equation
SIMPLE	
Inverse Linear	$Y = a - b^{*} d_{ij}$
Logarithmic	$Y_1 = a_1 - \beta_1 * \ln(d_{ij})$
Negative Exponential	$Y = a_1 + (\beta_1 / d_{ij})$
SEGMENTED*	
Logarithmic Increase Joined to a Negative Exponential Decrease	$Y_1 = a_1 + \beta_1 * \ln(d_{ij})$ $YatX_i = \beta_1 * X_i + a_1$ $Y_2 = a_2 * \exp(\beta_2 * d_{ij})$ $Y = IF(X < X_i, Y_1, Y_2)$
Linear Increase Joined with a Negative Exponential Decrease	$Y_1 = a_1 + \beta_1(d_{ij})$ $YatX_i = \beta_1 * X_i + a_1$ $Y_2 = (a_2 - p) * \exp(-\beta_2 * d_{ij}) + p$ $Y = IF(X < X_i, Y_1, Y_2)$ Where, p= plateau value.

Note: Segmented models are joined at a peak distance denoted by X_i; where, X_i = distance of joint point (d_{ij} value peak in distribution) and Y is the predicted distance traveled.

Segmented non-linear models (a.k.a. truncated models[1]) are frequently used to describe offender travel distributions that exhibit a buffer effect. Segmented models join functions at a peak distance (see Figure 1), and are used to describe how offenders avoid areas within the immediate vicinity of an anchor point (the buffer is presumed to be around the home), yet they tend to select targets near home. Trip distance decays substantively beyond a critical distance, with longer crime commutes being extremely infrequent (Kent et al. 2006; Santtila et al. 2003; Levine 2009). While studies have found varying decay rates, the preponderance of evidence supports applying a logarithmic function joined with a negative exponential function to model offender leisure activity (Bichler et al. in press), as well as journey to crime (Levine 2009; Kent et al. 2006). Notably, peak offending distances vary by crime type. For instance, Levine (2009) reports a range of .3 miles for homicide to 5.75 miles for bank robbery. Even within a single crime type, such as automobile theft, peak travel can range— for instance, Lu (2003) reports a range of 1.5 to 4.5 miles. If mean distances are used to indicate likely peaks, these are a bit more stable, with most falling within one mile or less (e.g., Phillips 1980; Rhodes and Conly 1981; Snook 2004), or between 2 and 2.5 miles (e.g., Chamard 2007; Wiles and Costello 2000). Of note, these distance decay findings have been called into question by methodological concerns.

[1] These models have been referred to as truncated models because curvilinear analysis of travel distributions often involves applying power functions. These analyses are not able to process distance intervals with zero cases; thus, researchers often truncate (shorten) the distribution to pool the extreme right tails present in studies of travel patterns. Hence, these models have acquired the common label of "truncated models".

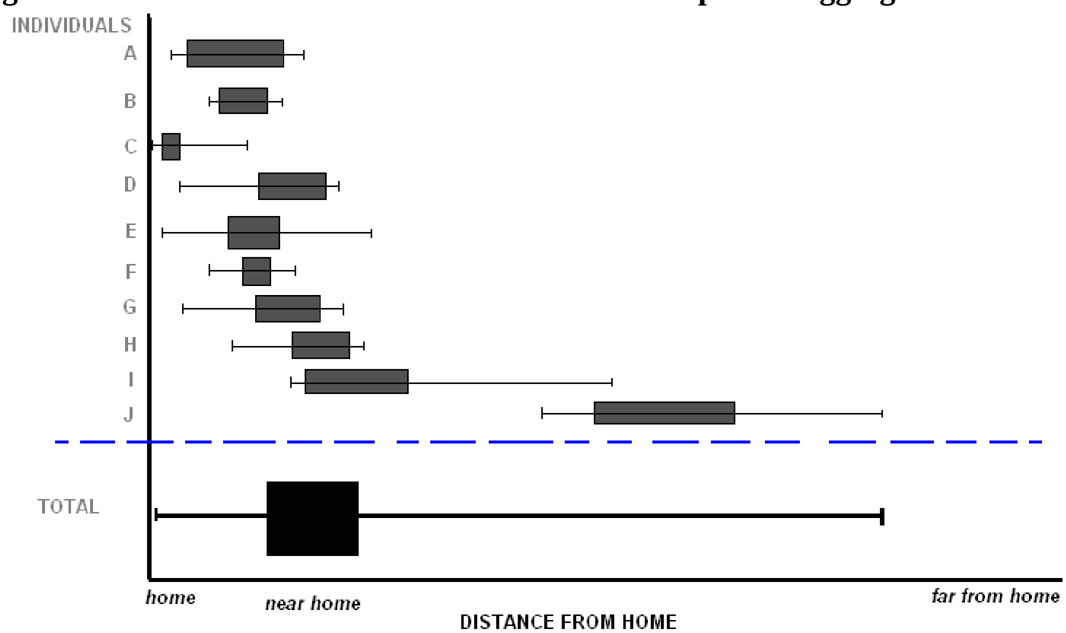
Figure 1. Distance Decay Function



Methodological Issues

Among the most prevalent concerns about distance decay studies is the use of individual versus aggregated data, with some researchers claiming that drawing conclusions about individual behavior from aggregated data results in fallacious inferences (e.g., Costanzo et al. 1986; Haynes 1974; Smith et al. 2008). Van Koppen and de Keijser (1997) argue that the distances traveled by offenders differ according to their operational range despite any similarities to one another, with no offenders being equal in their spatial patterns. They argue that distance decay emerges from collapsing individual patterns (see Figure 2). These results were produced by simulated behaviors, however; [2] and analyses of observed travel patterns are less conclusive.

Figure 2. Box Plots of Individual Offender Crime Trips and Aggregate Crime Trips



[2] By creating a simulated sample of 1,000 offenders, each of which committed 20 offenses ranging in distance, they found an aggregated level of distance decay despite a lack of decay when considering offenders individually. As a result, they claim aggregated results may be an inaccurate reflection of individual journeys to crime.

Arguing that aggregate decay is a summary of individual patterns, Rengert et al. (1999) found distance decay among offenders both at the individual and aggregate level for a sample of burglars in Philadelphia and Wilmington. The presence of a range of individual and aggregate patterns leads some to reconsider what factors constitute useful covariates of travel patterns. For example, some offenders do not begin their target search from their home (i.e., co-offenders may assemble at a unique location). In this instance, co-offenders represent a subgroup of offenders and should be examined separately. Subgroups may exhibit different patterns that aggregated, account for the decay phenomena (Haynes 1974; Smith et al. 2008).

SUBGROUP VARIATION

Review of the limited, recent scholarship addressing individual offender travel behavior reveals that behavioral factors (i.e., general mobility as measured by stable access to private motor vehicles and offending types) and community-level considerations (i.e., juxtaposition of residential city within the region) may exhibit stronger subgroup variation than offender demographic characteristics. Macro-level shifts in general mobility, interacting with regional community development, may partially account for these findings, and raises questions about the utility of previously noted correlates of crime commutes.

Demographic Characteristics

Demographic characteristics are heavily used in transportation research to account for differences in observed travel behavior or decision making. Also, general urban mobility studies find that demographic factors such as age and race also contribute to one's decision to travel longer distances (Beckman and Goulias 2008; Stutz 1973; Wheeler and Stutz 1971). The only variable consistently shown to be associated with offender travel patterns is age. Admittedly, only a few studies have directly examined multiple demographic factors, such as gender, race, and ethnicity in regard to offender mobility: however, there is little support that demographic characteristics are indicative of offender travel variation (Tita and Griffiths 2005; Westerberg et al. 2007; Wiles and Costello 2000).

Moreover, recent studies have begun to revisit the correlation between age and crime trip distance (e.g., Bernasco and Block 2009; Smith et al. 2008; Tita and Griffiths 2005; Wiles and Costello 2000). For instance, Westerberg, Grant, and Bond (2007) found that once juveniles reach the legal driving age, they become much more mobile and are able to travel as far as adults when committing a criminal act; in other words, the discrepancies in travel distance appear to normalize when juveniles reach the legal driving age. It is plausible that early findings of strong correlates between the distance traveled and demographic characteristics were confounded by an underlying association between the demographics considered and vehicle accessibility.

Behavioral Factors

Vehicle Accessibility. Vehicle accessibility is a long established correlate to the length of crime commutes (Felson and Poulson 2003; Johnson et al. 2007; Ratcliffe 2002); offenders with some form of vehicle access travel farther to commit a criminal offense than those who utilize another means of transportation (see Snook 2004; Van Koppen and de Jansen 1998; Wiles and Costello 2000). Additionally, access to a private means of transportation (as well as a source of income) seems to have a strong, positive correlation with higher levels of delinquency (Anderson and Hughes 2009). Access to cars enables older youth to spend a greater amount of discretionary time away from home, in environments with insufficient adult supervision, providing opportunities to engage in delinquent acts (Allard 2008; Felson and Gottfredson 1984; Osgood and Anderson 2004; Osgood et al. 1996; Robertson 1999; Warr 2005). It follows that vehicle accessibility, directly through ownership (or parental permission) or indirectly through peers (friends with vehicles), is a critical differential.

Offending Seriousness. Unique travel patterns have been associated with the type and severity of offending. For example, offenders who commit property crimes tend to travel farther than those who commit violent crimes (e.g., LeBeau 1987; Phillips 1980; Rossmo 2000; Westerberg et al. 2007; Wiles and Costello 2000). Some evidence suggests that the potential earnings may lead to longer commutes (e.g., Capone and Nichols 1976; Morselli and Royer 2008; Rengert 1989; Wiles and Costello 2000). Fritzon (2001) found that arsonists with emotional motives traveled much shorter distances than those influenced by external factors. Also, prolific or habitual offenders tend to travel farther than those who commit fewer offenses (Johnson et al. 2007; Morselli and Royer 2008; Westerberg et al. 2007).

Involvement with Delinquent Peers. While the presence of a co-offender has been linked to differences in travel distance, what constitutes a viable criminal group that may influence crime trip length remains unclear. Snook (2004) found that offenders are more likely to travel farther to commit a criminal act when accompanied by other offenders than when acting alone. While this study did not directly assess whether co-offenders belonged to the same criminal group, it is notable that the presence of delinquent others extends travel distance. Gang membership alone has not been found to be correlated with travel patterns or distances (Tita and Ridgeway 2007); however, known territories may have some influence on the travel patterns of gang members aware of the jurisdictional boundaries (Bernasco and Block 2009).

Community-level Factors

Travel patterns may shift over time as changes in routine behavior (Wiles and Costello 2000) interact with community growth and development trends (Felson 1987). If the distribution of facilities routinely accessed by offenders are reflected in the distances traveled to crime sites, (see crime pattern theory, Brantingham and Brantingham 2008), then community development and changes in transportation methods or accessibility should influence observed travel distances. For instance, the growth of shopping and entertainment complexes built at the nexus of transportation corridors will likely shift routine behavior away from the central business district (Felson 1987). It is reasonable to suggest that this type of community development would substantively lengthen crime commutes and call into question the applicability of early journey-to-crime research to current activity patterns (Bichler et al. 2010; Rengert and Wasilchick 1985).

There is a global trend toward regionalization, with urban areas showing high levels of inter-city connectivity reflected in commuting patterns (e.g., ESPON 2003; Halbert 2007; Lee 2007; Lee et al. 2009). For example, residential and employment dispersion patterns produce long commuting distances within Southern California (e.g., Buchanan and Barnett 2005; Gordon and Richardson 1996a, 1996b). Commuting patterns are also changing among suburbanites, as inadequate public transportation, as well as time and spatial constraints, increase automobile travel (Crompton 2006). Youth behavior is also influenced by these macro-level trends.

Driving children to school has become common due to scheduling and widespread changes in school selection, vehicle accessibility, open enrollment policies, and the amalgamation of smaller schools into large regional centers (McDonald 2008; Schlossberg et al. 2006; U.S. Department of Transportation 2008). Since schools are key facilities anchoring juvenile delinquency (e.g., Gottfredson et al. 2001; Gottfredson and Soulè 2005; Soulè et al. 2008; Ratcliffe 2006), it is probable that forming friendships with youths from different communities and having access to vehicles alters the overall distance traveled, as well as the distance traveled to engage in delinquent behavior.

Longer crime commutes are likely as these routine activities are exposing offenders to more attractive opportunities outside of the home community. The link between risky facilities (Eck et al. 2007) and crime attraction (Brantingham and Brantingham 1995) is supported by the spatio-temporal crime concentration (Ratcliffe 2004) found at specific facilities (e.g., Groff et al. 2008; Weisburd et al. 2009) and land use mixes (Kinney et al. 2008) that draw youth from different neighborhoods (Bichler et al. 2010; Chamard 2007). This resulted in some calling for a regional approach to crime pattern analysis (La Vigne and Wartell 2001) and a closer inspection of community and school level influences on juvenile delinquency (Welsh et al. 1999).

Few studies have explicitly examined the link between city-level characteristics (urban structure) and offender travel patterns (Rengert 1980, 1981; Wiles and Costello 2000). Bichler, Christie-Merrall, and Sechrest (in press) compared distance traveled to a deviance location with the path length from home to usual hangouts and found that the crime trip fell between local hangout places and convergence settings (i.e., malls and movie theaters). The distances traveled to popular hangouts (i.e., malls) were considerably farther than expected, and could be accounted for by the inter-city flow of youth within regions. Examining which macro-level indicators of urban structure were more closely associated with crime levels, Bichler and colleagues (2010) found that, while measures of the inter-city hierarchy (spatial structure) exhibited significant, robust associations with crime levels, the social organization (inter-city flow) of youth was also a significant factor. In another study, Bichler, Malm and Enriquez (2009) discovered that a small number of facilities (most were malls and movie theaters) within each region drew youth from a wide range of schools throughout the area. Given the importance of such facilities in accounting for juvenile delinquency (Felson 1987), these authors concluded that greater attention must be paid to better understanding which magnetic facilities draw youth out of their home cities. By examining offender travel behavior in relation to such facilities, a richer, contextualized understanding of travel activity will begin to accrue.

METHODS

The aim of the current study is to compare the fit of distance decay functions across subgroups to identify factors of multivariate models of the travel patterns common to juvenile delinquents. Based on the literature reviewed above, it is anticipated that behavioral covariates (such as vehicle accessibility) will outperform demographic variables. Further, subgroups based on community-level differences should differentiate travel variation patterns better than behavioral factors. By assessing the performance of these subgroups, a foundation may be developed for generating multilevel models to better predict offender crime commutes.

Information used for this study were developed from the Youth Mobility Data (see Bichler et al. in press) gathered during an evaluation of a county-wide juvenile diversion program. The sample includes youth, ranging in age from 12 to 17, that reside in a large county in Southern California. All youth were under the supervision of probation officers due to their involvement in delinquent or criminal activity. Of the 3,871 juveniles surveyed about their travel habits between July 2001 and September 2006, complete geographic information was available for 2,563 individuals. No sample bias was introduced by the attrition of cases.

Local Information and Distance Calculations

Youth were asked about hangouts during structured surveys, administered by their assigned probation officer during their intake into a diversion program. These open-ended questions allowed youth to self-nominate places where they spend time on a regular basis. Specifically, youth were asked to name and provide address information (such as cross streets) for the following: primary hangout (where the youth is likely to be if not at home or school), preferred fast food location when out with friends, video rental location, preferred movie theater, as well as the store they would go to if they were going to buy clothing.[3] School and home addresses were extracted from probation records (case files).

To calculate the travel distance, the median distance of all travel to activity nodes was generated for each subject. A median distance was used to avoid the methodological limitations posed by aggregating trips (see Van Koppen and de Keijser 1997; Smith et al. 2008; Rengert et al. 1999). The frequency of travel was not considered; one distance measure was used for each type of location, so the median score was not influenced by the number of times a person visited each activity node. This produces a median distance for locations rather than a median of all travel.[4] The Network Analyst extension of ARCView® 3.2[5] was used to calculate the distance from each youth's home to their self-nominated primary hangouts (activity nodes) along the street center line (updated Census 2000 street file).[6]

Subgroups

Offender Demographics. Many of the subjects were Hispanic (58.9%); males comprised about 62.6% of the youth surveyed. Rather than use actual age, youth were categorized into three groupings: elementary aged youth (6.5% of the sample were 10 to 12 years old), middle school aged youth (57.5% were 13 to 15 years old), and high school aged youth (36.0% were 16 years old and above).

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[3] Probation officers received extensive training on how to query for location information. It was determined that juvenile probation officers located within the residential city would be in a better position to survey youth during the intake process as they would be the most familiar with the way youth refer to places and the general youth hangout activity for their area. To support the data cleaning process, youth were asked to estimate the distance of each location from their home in time and estimated mileage. This information was used during data cleaning and georeferencing to ensure that the correct location was identified (i.e., while there might be three fast food outlets with the same name within a city, each will be on a different major road). With information about the likely distance of the facility from home, it is possible to identify the correct address information needed for georeferencing.

[4] The home address was assumed to be the starting point for each route. Path distance was calculated using the closest facility function. To be included in this study, each youth must have information for at least 4 hangout locations.

[5] Address matching preferences set at 75 for spelling sensitivity, minimum match score, and minimum score (Bichler and Balchak 2007). The match rate was above 95%.

[6] The use of street center lines without an offset may have introduced measurement error (Ratcliffe 2001) for malls, and similarly large properties. To account for the potential measurement error, differences in median distances must exceed a quarter mile threshold to be considered substantively important.

Behavioral. Three behavioral subgroup typologies were used: general mobility, offending behavior, and involvement with delinquent peers. General mobility subgroups involved a typology based on travel method used to reach destinations while in the company of friends. Juveniles were divided into two groups: using their own sweat power (28% of youth walk, skateboard, or bicycle to activity nodes) or depending on vehicles (64.2% used their own car, friend's car, or family car)[7]. Juveniles were also separated into one of two groups based on the severity of their deviant behavior. About 37% committed minor acts of delinquency (e.g., truancy, alcohol abuse, and school disciplinary issues). Most (62.5%) committed offenses that would otherwise constitute criminal behavior (e.g., carrying a weapon, drugs possession, and assault and battery). Involvement with cliques of delinquent peers was measured by having a confirmed gang affiliation (11.4%). Probation officers consulted teachers, counselors, parents, friends and other individuals to confirm gang affiliation.

Table 2. Description of Median Travel Distances of Juveniles by Subgroups

	DESCRIPTIVE STATISTICS					***DISTRIBUTION SUMMARY***		
SUBGROUP	**N**	**1ST Q**	**MED.**	**3RD Q**	**MAX DIS.**	**PEAK BIN VALUE**	**CUM % AT PEAK**	**% LOST FROM TRUNCATION**
DEMOGRAPHIC								
COHORT								
ELEMENTARY	143	1.59	2.38	4.22	2.24	2.25	39.16	0.00
MIDDLE SCHOOL	1,263	1.58	2.70	4.63	79.74	1.75	37.60	0.16
HIGH SCHOOL	792	1.77	3.08	5.37	31.69	1.75	30.43	0.13
GENDER								
FEMALE	937	1.72	2.93	5.01	36.57	1.75	33.72	0.11
MALE	1,571	1.62	2.82	4.72	79.74	1.75	36.16	0.13
ETHNICITY								
HISPANIC	1,092	1.56	2.85	4.78	31.69	1.75	36.63	0.09
NON-HISPANIC	762	1.84	3.00	5.00	79.74	1.75	32.55	0.26
BEHAVIORAL								
TRAVEL METHOD								
SWEAT	630	1.27	2.02	3.61	24.25	1.75	49.52	0.00
VEHICLE	1,443	1.85	3.20	5.29	36.57	1.75	29.18	0.14
LEVEL OF								
DEVIANCE	725	1.66	2.78	4.73	36.57	1.75	36.70	0.14
MINOR	1,829	1.65	2.92	5.00	79.74	1.75	34.40	0.11
SERIOUS								
GANG AFFILATION								
NOT INVOLVED	2,037	1.67	2.86	4.89	36.57	1.75	34.36	0.10
AFFILIATED	262	1.72	2.88	5.13	23.77	1.75	37.02	0.00
COMMUNITY-LEVEL								
CITY OF RESIDENCE								
CORE	531	1.77	2.80	4.00	36.57	1.75	33.90	0.19
PERIPHERY	1,678	2.65	5.00	7.94	79.74	1.75	38.56	0.00
ISOLATE	353	1.56	2.65	4.62	20.76	1.25	14.73	0.57

Note: The distances reported are in miles from home. Calculations are based on path distance along the street centerline. Rather than diary information, one median distance was reported for each person. First and third quartiles are included in the table.

[7] Youth who reported using multimodal means (7.8% used public transportation or a combination of methods) were not included in the analysis.

C*ommunity-level.* To capture the hierarchical arrangement of cities within functional urban areas, commerce and recreational amenities ranks[8] and topographic information (e.g., city adjacency) of the area[9] were used to classify the residential city (for a more detailed explanation see Bichler et al. 2010). Approximately, 20.7% of the sample resided in core cities, 65.8% resided in peripheral cities, and 13.8% of the youth resided in isolated communities.

Analytic Strategy

Although little is known about the variability in juvenile travel patterns, three equations found to fit the travel behavior of adult offenders were used. The first equation involved an inverse function of the path distance between the origin and destination (d_{ij}):

$$Y = a_1 + (\beta_1 / d_{ij}) \qquad \text{(EQ 1)}$$

Two segmented regression models were also used. One model used linear and negative exponential regression functions joined at the maximum or peak distance:

$$\begin{aligned} Y_1 &= a_1 + \beta_1(d_{ij}) \\ YatX_i &= \beta_1 * X_i + a_1 \\ Y_2 &= (a_2 - p) * \exp(-\beta_2 * d_{ij}) + p \\ Y &= IF(d_{ij} < X_i, Y_1, Y_2) \end{aligned} \qquad \text{(EQ 2)}$$

Where, p= plateau value and, X_i = distance of joint point (X value peak in distribution). A second model used a logarithmic function to fit the first segment and a negative exponential function to fit the second segment:

$$\begin{aligned} Y_1 &= a_1 + \beta_1 * \ln(d_{ij}) \\ YatX_i &= \beta_1 * X_i + a_1 \\ Y_2 &= a_2 * \exp(\beta_2 * d_{ij}) \\ Y &= IF(d_{ij} < X_i, Y_1, Y_2) \end{aligned} \qquad \text{(EQ 3)}$$

Where, X_i = distance of joint point (X value peak in distribution).

Distributions of percentages were generated for half mile intervals with bin values set to the mid-point to better represent the distribution (Kent 2003; Pal 2007). All segmented models were joined at the maximum distance (peak bin interval).

Although it is common practice to assess the goodness of fit with the R^2 value, important outliers may exist; thus, the D'Agostino and Pearson Omnibus K^2 test and residual plots were used to examine the normality of residuals for each distribution (Poitras 2006; Öztuna 2006). Significant D'Agostino and Pearson Omnibus K^2 tests indicate that even though the predicted

[8] A commerce and amenities score was derived by summing the number of on- and off-site liquor sales outlets, shopping malls, fast food outlets, movie theaters, schools and parks in each city. The score was standardized by square mileage and used to rank each city.
[9] Topographical information was recorded in a city-to-city proximity matrix based on highway accessibility, adjacency (to other cities), and isolation due to physical barriers (i.e., mountains or uninhabited desert regions).

values may be near to the observed data, not all points fall within 95% confidence intervals. Residual plots can be used to assess whether the heterogeneous variance identified through the K^2 tests are indicative of ill patterned fit.

RESULTS

Offender Demographics

All subgroups differentiated by demographic characteristics fit a segmented model joining logarithmic and exponential decay functions (R^2 ranged from .95 to .99) and notable outliers were present in each distribution. With one noted exception, functions were joined at a bin interval of 1.75 miles (indicating a peak in travel habits terminating between 1.5 and 2 miles from home). Only gender failed to present substantive differences (see Table 3).

Age Cohort. Comparing non-linear regression models illustrates the similarities between the elementary and middle school cohorts in the steepness of the initial slope values and the divergence of the high school cohort. Decay exponents differ also, with the middle school cohort exhibiting the most dramatic declines. Thus, the travel patterns among middle school aged youth might be anchored more strongly by home than other cohorts.

Ethnicity. Variation by ethnic group appeared to be localized to the initial slope of the segmented regression model. Hispanic youth were more apt to have median travel terminating within 2 miles from home; whereas, as indicated by the flatter initial slope, a greater range in travel patterns were found among non-Hispanic youth. Aside from differences in the intercept, decay parameters were similar.

Behavioral Factors

All subgroups differentiated by behavioral groups fit a segmented model joining logarithmic and exponential decay functions (R^2 ranged from .92 to .99) at a bin interval of 1.75 miles and notable outliers were present in each distribution. No substantive differences were found between groups differentiated by gang membership.

Travel Method. While the goodness of fit statistics and residual diagnostics were similar between both forms of travel, the parameter estimates differed notably. The distribution of median travel distance for those who exerted physical effort to navigate their environment while out with friends exhibited a steep initial logarithmic curve joined to a sharp decay. Conversely, juveniles who traveled by vehicle were more varied, as indicated with a flatter distribution and a more gradual decay. This means there is a wider array of behavioral patterns among individuals who regularly travel by vehicle to hang out with their friends.

*Offending Behavior. S*light differences in the initial slope were observed with regard to youth grouped by levels of deviance. A greater proportion of youth involved in criminal behavior were characterized as traveling within a home buffer of 2 miles, compared to youth involved in minor delinquency. Though differences were found between the initial slopes, the decay rate for each subgroup was comparable.

Table 3. Coefficient of Determination, Residual Diagnostics, and Parameter Estimates for the Best Fitting Curve Estimates for Individual Travel

SUBGROUP CLASSIFICATION	MODEL	GOODNESS OF FIT			RESIDUAL DIAGNOSTICS		PARAMETER ESTIMATES (STANDARD ERRORS)			
		R^2	SUM OF SQUARES (Sy.x)	$df_1(df_2)$	OMNIBUS K^2	NO. OF OUTLIERS	INTERCEPT_1	B_1	INTERCEPT_2	B_2
DEMOGRAPHIC										
COHORT										
ELEMENTARY	Segmented (EQ3)	.949	40.11 (.85)	4(56)	27.37	9	10.88 (.38)	7.05 (.49)	16.74 (2.93)	-.32 (.04)
MIDDLE SCHOOL	Segmented (EQ3)	.981	12.40 (.47)	4(56)	39.63	4	10.96 (.33)	6.96 (.41)	26.67 (1.29)	-.39 (.02)
HIGH SCHOOL	Segmented (EQ3)	.975	12.79 (.48)	4(56)	27.25	5	9.06 (.34)	5.77 (.41)	19.62 (.91)	-.31 (.01)
GENDER										
FEMALE	Segmented (EQ3)	.981	10.75 (.44)	4(56)	16.59	9	9.83 (.31)	6.65 (.38)	23.30 (1.01)	-.35 (.01)
MALE	Segmented (EQ3)	.986	8.28 (.38)	4(56)	43.67	5	10.73 (.27)	6.84 (.33)	24.73 (.97)	-.37 (.01)
ETHNICITY										
HISPANIC	Segmented (EQ3)	.976	14.32 (.51)	4(56)	15.92	10	11.43 (.36)	7.23 (.43)	21.82 (1.12)	-.34 (.02)
NON-HISPANIC	Segmented (EQ3)	.965	21.33 (.62)	4(56)	52.75	11	8.24 (.44)	5.37 (.53)	26.49 (1.56)	-.37 (.02)
BEHAVIORAL										
TRAVEL METHOD										
SWEAT	Segmented (EQ3)	.973	24.05 (.66)	4(56)	26.62	8	15.30 (.47)	9.33 (.56)	43.08 (3.59)	-.58 (.03)
VEHICLE	Segmented (EQ3)	.980	10.85 (.44)	4(56)	28.61	10	8.30 (.31)	6.12 (.38)	21.66 (.90)	-.32 (.01)
LEVEL OF DEVIANCE										
MINOR	Segmented (EQ3)	.960	25.32(.67)	4(56)	25.24	7	10.09 (.48)	6.02 (.58)	25.62 (1.74)	-.38 (.02)
SERIOUS	Segmented (EQ3)	.990	6.59 (.34)	4(56)	31.42	4	10.43 (.24)	7.06 (.30)	23.47 (.82)	-.36 (.01)
GANG AFFILIATION										
NOT INVOLVED	Segmented (EQ3)	.991	5.09 (.30)	4(56)	26.95	11	10.18 (.22)	6.88 (.26)	24.86 (.75)	-.37 (.01)
AFFILIATED	Segmented (EQ3)	.915	50.94(.95)	4(56)	38.16	11	10.04 (.68)	6.55 (.82)	24.10 (2.39)	-.37 (.03)
COMMUNITY-LEVEL										
RESIDENTIAL CITY										
CORE	Segmented (EQ2) Linear and Exp. Decay	.976	18.85 (.59)	5(55)	43.56	10	-2.24 (.71)	11.11 (.82)	33.78 1.87)	P = -.07 (.10); K = .42(.02)
PERIPHERY	Segmented (EQ3) Logarithmic & Neg. Exponential	.981	12.16 (.47)	4(56)	35.07	5	11.31 (.33)	7.19 (.40)	28.03 1.37)	-.40 (.02)
ISOLATE	Inverse (EQ1)	.840	49.94 (.93)	2(58)	17.94	9	7.92 (.49)	-.14 (.01)	NA	NA

Note: Travel distributions were truncated at 30 miles. All estimates and diagnostic tests are highly significant at the $p<.001$ level. All segmented models were joined at interval 1.75 miles (peak distance 1.5 to 2 miles) except for the elementary school cohort; the elementary cohort model was joined at 2.50 miles.

Community-level Factors

The most variation was found when examining the residential city. Each travel distribution was fit with a different model. Travel among youth residing in core cities followed a segmented linear exponential decay model (EQ2), joined at 1.75 miles (see Figure 3a). While the data fits the curve (R^2= .976), the D'Agostino and Pearson Omnibus K^2 (43.56) indicates the lack of normalcy in residuals linked to the presence of outliers. A segmented logarithmic negative exponential decay model (EQ3), joined at 1.75 miles was fitted to the travel of youth from periphery cities. Once again, a good fit (R^2=.981) was found, as was a lack of normalcy in residuals (K^2=35.07) and the presence of outliers beyond the 95 percent confidence level (see Figure 3b). An inverse function best fit the travel behavior of youth based in isolated cities (EQ1); but this was the poorest performing model (R^2 = .840). This is illustrated in Figure 3c.

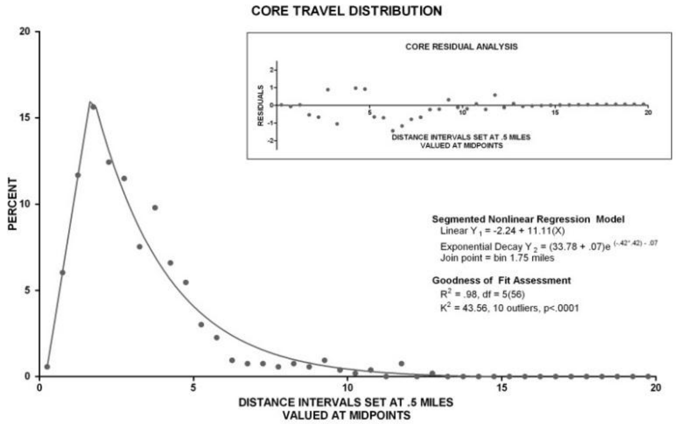
DISCUSSION

Identifying subgroups of offenders with unique travel habits would benefit efforts to model travel behavior. Moreover, periodically reconsidering established covariates of offender travel distance is important as societal changes in general commuting behavior are likely to be evident in crime trips and would influence the continued applicability of early research (Rossmo 2000; Wiles and Costello 2000). The results of this study indicate that individual offenders vary in their typical travel habits, with subgroup variation existing in the manner hypothesized; thus, support is found for the continued inquiry into identifying the relationship between travel patterns and useful subgroups (Smith et al. 2008; Townsley and Sidebottom in press). Although age and ethnicity present some value in understanding subgroup variation, their effects are significantly eclipsed by the nature of an offender's residential or home city and their preferred method of travel. While the rate of change differed between groups, a segmented regression joining logarithmic and negative exponential functions at a peak distance interval of 1.75 miles fit most subgroups. One critical exception warrants attention: the median travel distance for youth classed by the regional hierarchical position of their residential city was regressed with significantly different functions. Several implications follow from these findings.

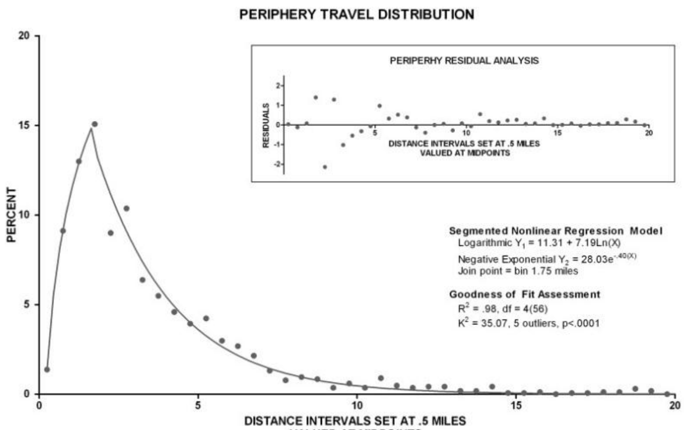
Conventional Subgroups

The steepness of the travel buffer present around an offender's home varies somewhat by age cohort, ethnicity, and the level of deviance, with a greater proportion of younger (elementary and middle school aged) and Hispanic youth remaining closer to home. This indicates that some demographic factors may still be associated with travel variation, though their importance is substantially constrained compared to other factors. Moreover, it is unclear whether age and ethnicity are important or whether this is a spurious effect. For instance, while the relatively minor variation observed among age cohorts supports previous studies (Bernasco and Block 2009; Tita and Griffiths 2005), it is plausible that age cohorts merely reflect differential motor vehicle access. As students reach high school age, they are more likely to make use of private transportation – either their own or one of their peer's (Allard 2008; Westerberg et al. 2007). Of note, previous studies indicated that higher parental income is associated with more consistent access to private transportation (Anderson and Hughes 2009); such consistency of access is likely to result in longer median travel distance. Income may interact with land use to produce longer median travel distances as youth from wealthier families may reside in neighborhoods with larger average lot sizes, located farther from commercial zoning. Finally, residential clustering by ethnicity may be reflected in the travel patterns observed.

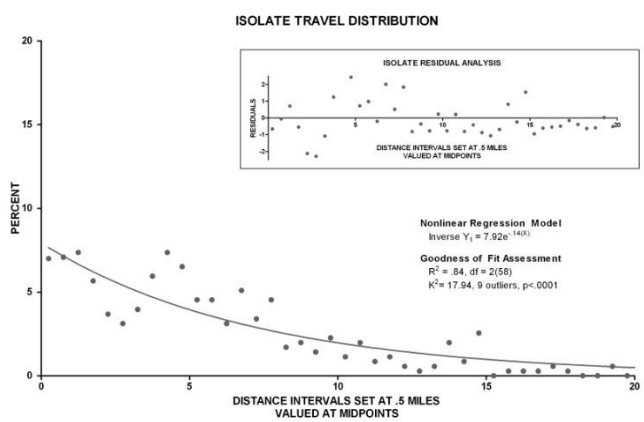
Figure 3. Comparison of Distance Decay Curves by Community of Residence



(a). Median Travel for Youth Residing in Core Cities



(b) Median Travel for Youth Residing in Peripheral Cities



(c) Median Travel Distance for Youth Residing in Isolated Cities

Studies examining where youth go to hang out with friends find that many travel to private facilities such as the home of a friend or relative (Botcher 2001; Robertson 1999). While the reasons for selecting these locations have not been examined in depth, it is plausible the absence of supervision is a critical factor. Moreover, some evidence suggests that youth residing in single parent households may find ample time to engage in delinquent behavior at home while their guardian is at work (e.g., Anderson 2002; Bottcher 2001; Gottfredson et al. 2001). For instance, during an interview with a delinquent youth, Robertson (1999) found a direct link between marital status and supervision levels:

> *When I was twelve years old, my Mom divorced my stepdad. From that time, that's when I really started getting into trouble. […] At nights when my Mom was working in the bar, I was alone or I was at home partying. I'd make sure I had everything put away by 2:00am in the morning when she came home (p. 344).*

Thus, marital status and preference for hanging out at private locations may be associated with shorter distances to crime sites. Subsequent studies should investigate whether subgroups designated by levels of parental supervision, marital status, and family income exhibit significant variation.

Subgroups Derived by Behavior

All behavioral subgroups performed as expected.[10] Juveniles who used a vehicle for transportation traveled farther than those who exerted physical effort. Such a relationship has been observed in other studies as well (e.g., Felson and Poulson 2003; Johnson et al. 2007; Ratcliffe 2002; Snook 2004; Van Koppen and de Jansen 1998; Wiles and Costello 2000). Travel method, rather than age, is the more critical factor accounting for subgroup variation in overall travel habits of delinquents. In this study, vehicle accessibility was measured by the method of travel typically used when hanging out with friends. Interestingly, even within these mobility subgroups, a range of travel lengths were found. Given the importance of this factor, a more precise measure of vehicle accessibility may generate additional insight; specifically, youths may be grouped by ownership of their own vehicle, riding around in a friend's car, or using a family vehicle. It is likely that using a family vehicle may be associated with greater parental control, such as restrictions on the distance a youth could travel or the time they need to return home. Alternatively, youth driving their own car may have greater freedom, and thus, a wider range. Additionally, it should be noted that a general lack of public transportation existed in the study area. Data obtained from an area with readily available forms of public transportation may yield differing results and should be examined in future studies.

Subgroup travel variation by offense seriousness is supported by early research suggesting that violence and other serious offending was generally located closer to home than other activities (e.g., Phillips 1980; Wiles and Costello 2000). Recent studies show that chronic or habitual offenders tend to travel farther than others (LeBeau 1987; Morselli and Royer 2008; Rossmo 2000; Westerberg et al. 2007). In this study, the difference between subgroups was slight. Methodological differences between this and prior research may account for this

[10] The inability of gang involvement to significantly influence juvenile travel patterns supports the findings of prior studies (Bernasco and Block 2009; Tita and Ridgeway 2007). Juvenile travel patterns are generally not affected by gang boundaries.

observation. For instance, offense seriousness was classed into one of two categories. Collapsing all serious offending may have substantively altered the findings. A more detailed analysis of each category of offending would help to identify behaviors that could be reasonably classed together; this may generate findings more aligned with prior research (i.e., Levine 2009).

Community-level Factor

The most dramatic subgroup differences were found when youth were parsed into classes based on the character of their home city. Previously, it was determined that offender mobility findings may be constrained by the scale of the analyses (Costanzo et al. 1986); and, while much attention has been placed on determining the extent of ecological fallacy affecting journey distance, few have questioned the impact that jurisdictional boundaries may have on measures of the typical distance traveled (exceptions include Bichler et al. in press; Wiles and Costello 2000). Finding that urban structure has some relation to travel habits is supported in the literature (e.g., Bichler et al. 2010; Brantingham and Brantingham 2008; Capone and Nichols 1976; Kinney et al. 2008; Rengert 1981) and studies of general activity patterns (e.g., ESPON 2003; Gordon and Richardson 1996a, 1996b; Lee 2007; Lee et al. 2009). This may be explained by target density and anonymity.

Some facilities (i.e., shopping complexes) and cities (core cities with high levels of amenities drawing youth from surrounding communities) may offer a sufficient level of target concentration or density. This density may have a magnetic effect. Juveniles residing in a periphery or isolated cities, with lower levels of anonymity and fewer potential targets, may be enticed to travel out of their home jurisdiction toward core communities. Alternatively, youth residing close to such land use would travel shorter distances to reach these target rich areas.

When considered in tandem with the growing accessibility of motor vehicles, restricting crime commutes to activity occurring within a municipal boundary would severely limit crime patterns. Adopting a facilities orientation (Eck et al. 2007; Rossmo 2000) with a regional dataset of offender behavior (La Vigne and Wartell 2001) may produce greater clarity regarding offender travel habits (Bichler et al. 2010). Given the policy implications tied to geographic patterns of offender behavior, it is critical that these findings are confirmed by subsequent research that does not face the same limitations endemic to the present study.

Caveats and Limitations

This study differs from prior research in its use of a median travel distance for each offender (rather than aggregating trips), using a sample drawn from across one of the largest counties in the United States, and not parsing the sample by functional urban areas. Moreover, the youth surveyed were on probation as opposed to being arrested for a specific crime. This constitutes a significant departure from prior research that is generally restricted to cleared cases associated with known offenders. In addition, only bivariate analyses were conducted. Despite these limitations, the findings presented here provide a useful foray into developing a broader understanding of the travel habits of juvenile delinquents.

The first issue of concern is the variation in coefficients for the initial segments of travel distributions. While all demographic and behavioral subgroups fit the logarithmic and exponential decay model and decay segments were relatively similar (with the noted exception shown between travel methods), the initial segment varied widely. Moreover, the peak distance was considerably more stable and closer to home than expected as compared to prior findings (e.g., Levine 2009; Lu 2003). One possible explanation for this finding is that the travel was measured by median travel to places, not the median trip distance as typically used elsewhere. In other words, this study captured the typical distance from home that the offender travels instead of diary information (i.e., where the trip to school would be counted 5 times, the place they hangout after school Tuesdays and Thursdays would be counted twice, and so on). This was necessary to pursue a place-oriented approach and avoid methodological problems raised by aggregating data. Using multiple trip distances would have produced individual distributions that may have underestimated the general range of offenders' activity space, as places closest to home are likely to be visited more frequently. Using a place-oriented median distance may offer a more appropriate benchmark against which to compare these findings. For instance, Levine (2009) compared crime trip behavior where similar land use or types of places were classed together (i.e., bank robbery). There, the degree of variation among peak distances varied dramatically. If a subsequent study examined general offender travel to different types of places (private versus commercial) similar peaks may be revealed.

Second, much of the sample resides in suburban cities drawn from a large county (7,000 square miles) located in Southern California; this county is comprised of several different regional circulatory systems (see Bichler et al. 2010). As reflected in the demographic characteristics of the sample, there is a large, growing Hispanic community in this area. Moreover, the region is primarily suburban in nature. Taken together, these factors may limit the generalizability of the study conclusions because using such a diverse region makes it difficult to compare this study to others limited to city boundaries.

With this said, the size and composition of the study area may be one of its most important features. The travel distances captured may represent actual land use patterns as opposed to jurisdictional limits of local law enforcement data systems. In doing so, these findings may better reflect actual travel when compared to studies of offender behavior clipped by jurisdictional boundaries. As this is one of the first data sources to involve such a wide geographic coverage, it is not possible to truly assess the comparative fit of these findings with prior research. At this point, it is unlikely given the size of the area and the widespread reliance on private vehicles that these findings are applicable to the major urban centers, such as New York or London.

A third consideration is that comparison was not made between different functional areas. Aggregating data across metropolitan areas (clusters of cities) would mask real differences in circulatory systems that may account for the distributions found. Regional studies find evidence that intercity dynamics are contributing to the development of polarized deconcentration (specialized urban centers in different cities catering to the region) and activity dispersion through functional regional areas (e.g., Gordon and Richardson 1996a, 1996b; Halbert 2007; Lee 2007). Urban development patterns show a trend toward locating large leisure and recreation facilities (i.e., regional malls) on the edges of communities. Large facilities pull youth from residential cities to edge areas; often these are non-incorporated areas located between urban centers. This serves to increase the criminogenic capacity of the property because anonymity is maximized and targets are prevalent (Brantingham and Brantingham 1995; Eck et al. 2007; Felson 1987; Kinney et al. 2008). Without detailed information of the general intercity flow of specific areas, it is difficult to classify urban agglomerations. It is possible that examining all peripheral cities in this study distorted the unique differences between peripheral cities located in different types of urban agglomerations (i.e., a monocentric region versus a polycentric region with several core cities pulling people in different directions). A more precise examination of urban structure is needed to tease out unique travel patterns.

This study used information from offenders on probation (self-nominated behavior) instead of locations identified by cleared offenses. Drawing from previously untapped data sources (Robinson 1936) and using self-nominated behavior (e.g., Short and Nye 1958; Wallerstein and Wyle 1947) has been shown to illuminate previously undiscovered offending patterns. Gathering information from youth on probation stands to broaden the net of behavior captured as compared to prior studies and, thus, may address a criticism of journey-to-crime scholarship (Bichler et al. in press). Until replicated in other regions, however, it is not possible to determine whether the findings presented here are suggestive of stable patterns or if they merely reflect unique travel patterns endemic to Southern California.

The present study is also limited by its reliance on bivariate effects. Multivariate analysis of these subgroups rooted at varying levels (individual, neighborhood or community) requires a mixed (hierarchical) model to permit the assessment of nesting effects that may have non-linear associations (Raudenbush and Bryk 2002; Singer and Willett 2003). Such an analytic strategy would permit the investigation of interaction effects that are likely to exist between age, access to motor vehicles, and income. Moreover, the use of multilevel modeling would facilitate a more rigorous inquiry into subgroups identified at community or regional levels. Given that non-linear, segmented models were best apt to describe travel variation, it is possible that hierarchical linear models (HLM) may not be suitable; however, research is needed to uncover the nature of the multivariate interactions between subgroups and travel distance, and as such, HLM may provide a useful starting point.

CONCLUSION

Offender travel patterns should be frequently reexamined since macro-level shifts may generate important changes. In this study, subgroups classified by community-level factors exhibited the most dramatic variation. While this may be surprising to some, this finding is supported by regional studies (e.g., Gordon and Richardson 1996b; Halbert 2007; Lee 2007) and current criminological theory explaining crime patterns (Brantingham and Brantingham 2008; Felson 1987; Kinney et al. 2008; Rossmo 2000). Near universal access to transportation and the larger, more widely dispersed network mobility brings, may negate the importance covariates identified through previous research (e.g. Wiles and Costello 2000; Bichler et al. 2010). Further, the increased fluidity of movement through highway infrastructure development, in conjunction with changing community growth and land use patterns, may have significantly altered offender travel behavior, thus questioning the utility of the geographic patterns established by early findings. Based on the results of this study, future research should integrate individual factors, behavioral considerations and community-level indicators in a mixed model format to account for cross-level interaction effects. Nesting models would be best suited to uncover such effects (Townsley and Sidebottom in press).

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DO PHYSICAL BARRIERS AFFECT URBAN CRIME TRIPS?

THE EFFECTS OF A HIGHWAY, A RAILROAD, A PARK OR A CANAL ON THE FLOW OF CRIME IN THE HAGUE[1]

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One way the intensity of criminal traffic between areas has been examined is through gravitational models (e.g. Smith, 1976; Kleemans, 1996; Ratcliffe, 2003; Reynald, Averdijk, Elffers and Bernasco, 2008; Elffers, Reynald, Averdijk, Bernasco and Block, 2008). This is an approach that envisages the origin area as "producing crime trips," the destination area as "attracting crime trips," and takes into account that in between origin and destination areas the would-be criminals may encounter friction. The term gravitational model exploits the parallel with gravitation models in physics, in which the attraction force between two solid bodies, such at the earth and the moon, is modelled proportional to the mass of both bodies and inverse to the distance between them. This is also the case in crime trip models. Here, the distance between origin and destination areas is one of the main friction variables, where the greater the distance the less likely a crime trip will happen. However, more friction variables than just geographical distance may play a role. De Poot, Luykx, Elffers and Dudink (2005) and Reynald and colleagues (2008) showed that social barriers between origin and destination neighbourhoods had such an effect in The Hague (the Netherlands). In that research, the more those areas differed in terms of ethnic composition and level of wealth, the more friction had to be overcome. Inspired by Stouffer (1940, 1960), Elffers and collegues (2008) investigated, again in The Hague, to examine the availability of intervening opportunities that might be acting as a friction variable over and above distance. They found this to not be the case. Greenberg, Rohe, and Williams (1982), Greenberg and Rohe (1984), Ratcliffe (2001, 2003) and Clare, Fernandez, and Morgan (2009) investigated to what extent physical barriers act as friction variable. Physical barriers are obstacles between origin and destination areas, blocking a direct, easy trip, and presenting some difficulty to either cross or circumvent. Examples of this type of barrier are rivers, fences, and main roads crossing the origin-destination line (Rengert, 2004). Van der Wouden (1999) also described railroad lines as physical barriers. Physical barriers require a person undertake more effort to get to a destination. Crossing a barrier like a railroad line, a highway, or a river, at least in a vehicle, is only possible at locations where bridges or tunnels are present, thereby presumably increasing the travel distance.

[1] This article is based on the master thesis (University of Leiden) of the first author (Peeters, 2007).

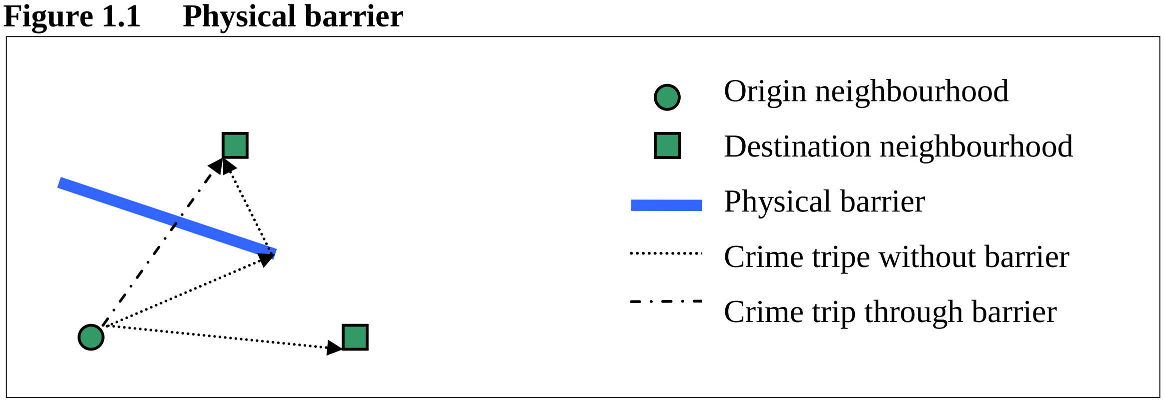
These studies often produce conflicting results with respect to the influence of physical barriers. For example, Greenberg, Rohe and Williams (1982) and Greenberg and Rohe (1984) found positive effects of highways and railroad lines in Atlanta, United States on travel to crime; while Ratcliffe (2003) found no effect of vegetation and major roads in Canberra, Australia. Clare, Fernandez, and Morgan (2009) found positive effects of main roads and of the river estuary in Perth, Australia. The present research takes up this issue again, and examines the influence of highways, the railroad lines, parks, and canals as physical barriers in the city of The Hague, the Netherlands.

Physical Barriers within Location Choice Theory

The intensity of crime trips between areas (i.e. the number of trips per unit of time) is an aggregation of target choices made by individual offenders. In the rational choice tradition, Bernasco and Nieuwbeerta (2005) explained the target choice of an individual offender as being governed by a comparison of the attraction level of all potential target areas. This comparison is made in terms of the aggregated value of all targets available for an offender, discounted by the distance to be covered to reach that target area.

The influence of physical barriers in this model may be examined by modifying the effect of distance. Usually, we have no direct information on actual distance covered by an individual offender to a chosen target; and the analyses in the literature cited use approximated distance between the origin and target (often as the distance between the centroids of origin area to destination area). By doing so, researchers implicitly use this distance as an approximation to the actually covered distance. Incorporating whether an offender encounters a physical barrier may improve on this approximation because the existence of a barrier forces the potential offender to circumvent it, hence covering a larger distance than otherwise would have been the case. Alternatively, the offender may have to use a more cumbersome method of passing the barrier (which is then a permeable barrier in the sense of Rengert, 2004), e.g. by using a ferry, climbing a fence, or wait for a traffic sign to show green, which all amount to increasing travel time. We will use the term "facing a barrier" for the two phenomena together: circumventing a barrier or passing through it. In figure 1.1, without a barrier, the upper target would have been closer to the origin than the right hand target (hence, ceteris paribus, being preferable). When the offender has to circumvent the barrier, the upper target becomes less attractive, as the distance to be covered increases.

Figure 1.1 Physical barrier



Of course, the mere indication that a barrier is present is a crude approximation to the additional distance to be covered or to the time it would take. While it may, in principle, be possible to measure the effect of a barrier on time and distance of an actual crime trip in an individual case, this will in practice seldom be feasible; and would require much more detailed data on available roads from origin to destination than usually will be available. We expect, however, that certain types of barriers do present more difficulties to would-be offenders than others. For example, in the Dutch context, an inner city highway will present more difficulties than a canal, as the number of points where one may cross that highway will in general be less than where one can pass a canal. This explanation is not only valid for criminal activity, but will hold for any activity a person from an origin area may consider in choosing a destination area, of course with a different set of attraction indicators. This observation shows that, within the framework of routine activity theory (Cohen and Felson, 1979), we may expect effects of physical barriers. When such a barrier is present, routine activity theory expects less non-criminal traffic from origin to destination, and hence, less crime as well.

Methodology

Research Questions and Hypotheses

By examining data on the intensity of crime trips, it is possible to investigate whether the number of crime trips that include a barrier is significantly different from the number of crime trips that do not cross a barrier. Within a gravitational model of crime trip intensity that has distance as its main friction indicator, we expect that offenders, ceteris paribus, travel less to areas where they have to face a barrier than to neighbourhoods not requiring them to encounter a barrier. As such, the main research question of this article is:

> *Do physical barriers influence the journey-to-crime of offenders, controlling for distance?*

Knowing that distance is a dominant explanatory factor in gravitational models (Elffers et al., 2008; Reynald et al., 2008), we hypothesize that:

> *Physical barriers only have a small amount of additional value next to travel distance.*

As argued above, not all types of barriers are expected to have equal influence, according to the ease with which they may be circumvented. This leads to the next hypothesis:

> *Different types of physical barriers display a different strength of influence on the journey-to-crime of offenders.*

Within the context of the Dutch environment, we expect an urban highway to be a less permeable barrier than a railroad line, a park, or a canal because there are fewer opportunities to cross it.

Finally, the expectation is that having to circumvent a physical barrier will have more influence when the unhampered distance between origin and destination is shorter. This leads to the third hypothesis:

> *Barriers have a larger influence on intensity of crime trips when the trips have shorter travel distances.*

When an offender has to travel only a short distance, the additional travel distance that emerges from facing the barrier is relatively large. The same amount of extra distance is relatively small when the neighbourhoods are far apart and the travel distance is long (Clare et al., 2009).

Data

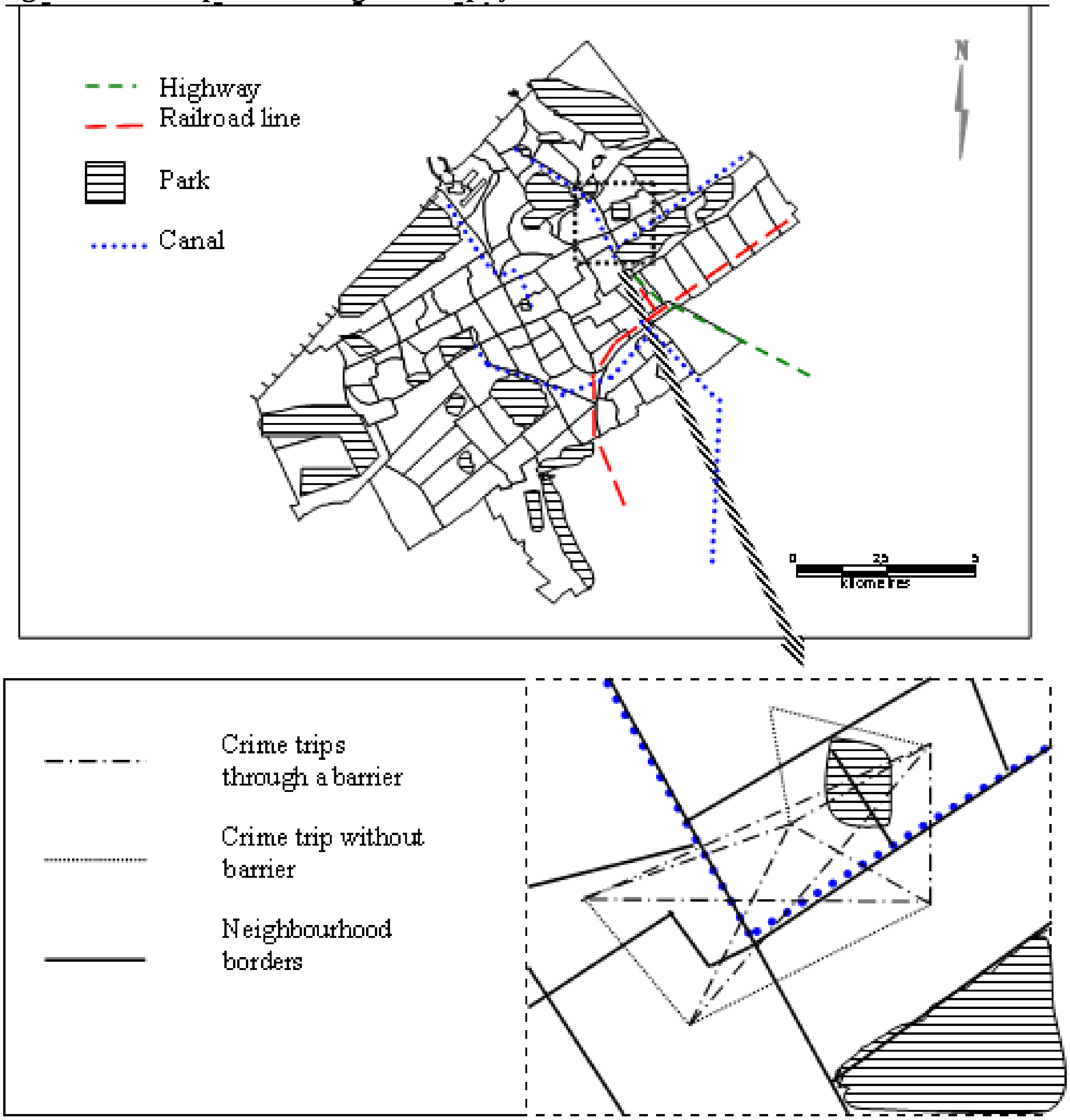
To test whether physical barriers have an influence on crime trips, information about the origin and destination of crime trips is required. Crime data used here is provided by the regional police force Haaglanden,[2] and is identical to the data used in the research of Reynald and colleagues (2008) on the influence of social barriers. The data is from police records of crimes in the city of The Hague from 1996 till 2004. The data contains 62,871 solved offences committed in The Hague by offenders who lived in The Hague at the time of the offence. We can only use solved crime data, otherwise the origin location of the criminal is unknown. Aggregating the data gives us the total flow of criminal traffic in and between neighbourhoods. Origin-destination trip intensity is defined as the number of crime trips between two neighbourhoods in the time frame considered.

The Hague, Figure 2.1, is a city at the North Sea coast of The Netherlands, with approximately 440,000 inhabitants. The city's current boundaries include the former coastal villages of Scheveningen, Loosduinen, and Kijkduin. The city comprises 94 neighbourhoods, the boundaries being defined by the The Hague municipality on the basis of historical and infrastructural characteristics. For this research, these neighbourhoods are linked to each other to examine the influence of the barriers. This leads to 94 x 94 = 8836 ordered origin-destination combinations. This includes the 94 links where origin and destination neighbourhood are identical. These cases are crime trips where the offender commits a crime in his or her own neighbourhood, which will be referred to as internal crime trips. Since every offender needs to travel to a location where the opportunity to commit a crime is present, every offence can be influenced by physical barriers; therefore, we include all types of offences recorded by the police in the analysis.[3]

[2] We are grateful to the Regional Police Force Haaglanden for providing access to these data under a covenant with NSCR.

[3] Property offences (37 percent), traffic (23 percent), violent (17 percent), public order (7 percent), vandalism (5 percent), drug related (4 percent) and other offences (7 percent).

Figure 2.1 Map of The Hague with physical barriers



It should be noted that The Hague is a rather small city (ca. 20 x 15 km), and the barriers considered are certainly not insurmountable. The railway line has a number of underpasses, the highway, as well as most of the canals, have a number of viaducts or bridges to cross them, and most of the parks are well kept urban parks with a net of foot paths crossing them. Compared to previous studies (eg. Clare et al., 2009, who studied a very large river as a barrier), barriers in this study are of moderate size, hence we should expect only a small influence of their presence.

Model and operationalisation

For investigating the influence of physical barriers, a gravitational model is used, which models the intensity of crime trips between origin area *o* and destination area *d* in terms of a *push* factor, a *pull* factor, and a *friction* factor.

$$\text{intensity}_{od} \sim \text{push}_o^{\alpha} \cdot \text{pull}_d^{\beta} / \text{friction}_{od}^{\gamma}$$

for some exponents α, β, γ.

Following Reynald and colleagues (2008) and Elffers and colleagues (2008), the push variable is operationalized as the total number of crime trips that originate from the origin neighbourhood to a destination neighbourhood (outflow). The pull variable is operationalized as the total number of crime trips to the destination neighbourhood, originating from whatever neighbourhood (inflow). By taking logs, we linearize such a model (see Smith, 1976).

Friction variables come in two varieties. First is the distance, as is customary in all journey-to-crime studies (we use Euclidian distance between centroids of neighbourhoods). The second is the indicator(s) for the presence of a certain type of physical barrier, i.e. $\text{barrier}_{od}^{(i)} = 1$ if a barrier of type i crosses the line between the centroids of o and d, and $\text{barrier}_{od}^{(i)} = 0$ if that is not the case (for i=any barrier, highway, railroad, park, canal). These barrier indicators were scored manually from a detailed version of map 2.1 . Here, notice that

$$\text{barrier}_{od}^{(\text{any barrier})} = 1 - (1-\text{barrier}_{od}^{(\text{highway})}) \cdot (1-\text{barrier}_{od}^{(\text{railroad})}) \cdot (1-\text{barrier}_{od}^{(\text{park})}) \cdot (1-\text{barrier}_{od}^{(\text{canal}))})$$

When the origin neighbourhood equals the destination neighbourhood (*o=d*), the distance_{od} is taken to be half the square root of the neighbourhood surface, which approximates the distance between two random points in the neighbourhood (Ghosh, 1951). By definition, we set $\text{barrier}_{od}^{(i)} = 0$ when o=d, as our data are too crude to distinguish intra area trips in categories that pass or do not pass an intraneighbourhood barrier.

Figure 2.1 shows the location of barriers of the four types (urban highway, railroad line, parks, and canals) as present in The Hague. Notice that urban highway and railroad barriers are rather scarce, while canals and especially parks are quite common. Furthermore, some barriers are located on the borders of the city and the barriers seem to be somewhat clustered.

Analysis

The effects of physical barriers are examined by estimating a regression model for the log of crime trip intensity. The base model, the standard gravitational model, is compared with the base model including physical barrier indicator(s). The physical barrier indicators are added to the model to test whether the physical barrier has an influence on the journey-to-crime when controlling for push, pull, and geographical distance factors. This leads to the following model:

Model with barrier of type i (i = ‘any barrier’, highway, railroad, park, canal)

$$\ln(\#\text{crime trips}_{od}) = \beta_0 + \beta_1 \cdot \ln(\text{inflow}_d) + \beta_2 \cdot \ln(\text{outflow}_o) + \beta_3 \cdot \text{distance}_{od} + \beta_4^{(i)} \cdot \text{barrier}_{od}^{(i)}$$

We also examine whether the influence of physical barrier indicators is different for short and long distance by estimating the model separately for subsets of crime links with small and large o-d-distances.

The research questions then translate into the questions (for i = any barrier, highway, railroad, park, canal)

- are the $\beta_4^{(i)} = 0$ and if not, are these coefficients small (i.e. is explained variance with and without incorporating $\beta_4^{(i)}$ comparable)?
- are the $\beta_4^{(i)}$ different for different i ?
- are the $\beta_4^{(i)}$ larger in a subset of *o-d*-pairs that have small distances only?

Results

Descriptives

The occurrence of barriers is different for the various type of barriers. Canal and park barriers are present as a barrier between 61% of the neighbourhood pairs (i.e. the set of all o-d-links). A railroad is present between 20% of the neighbourhood pairs, followed by a highway which is present as a barrier between 11% of the neighbourhood pairs. In total, a barrier is present in 83% of the links between the neighbourhood pairs.

Correlation analysis between the separate barrier indicators shows a correlation of 0.42 between highway and railroad barriers (over the set of all o-d-links), which is a consequence of them only being present together at the south-east side of the city. This fact should be regarded when interpreting results of those barriers: they largely co-vary in the present dataset. Parks and canal barrier indicators are also rather substantially correlated (0.30). Distance is, as expected, rather highly correlated with the presence of a barrier (0.45 with parks, 0.43 with canals, 0.25 with highway, 0.16 with railroad). Correlation between barriers and push and pull factors is less prominent (all coefficients < 0.10). Descriptives of explanatory variables of the base model are given in table 3.0.

Table 3.0 Descriptives of explanatory variables in the model

	Minimum	Median	Mean	Maximum
Inflow	3.76	6.13	6.02	8.61
Outflow	-2.30	1.39	5.64	7.99
Distance	0.18	3.76	3.96	11.53
Total crime	-2.30	0.69	0.25	6.07

for the definition of variables, see main text

Regression analyses

Table 3.1 shows the results of the analysis for the presence of any barrier (highway, railroad, canal, park, or several of them). When the physical barrier indicator is inserted in the model over and above the push and pull factors and geographical distance, the influence of distance decreases slightly, as could be expected, given their substantive correlation. The barrier indicator takes over a small part of the influence of distance, and in the expected direction (the presence of a barrier mitigates criminal traffic); but the explained variance of the model remains the same as when only push, pull, and distance are included. This means there is no additional influence of the barrier indicator beyond that of distance, though the barrier seems to take over some of the influence of the distance.

Table 3.1 Influence of 'any physical barrier' indicator on the number of crime trips (standardized regression coefficients β)

	Base model	Base model plus 'any' physical barrier term
PUSH AND PULL FACTORS		
Inflow	0.32	0.32
Outflow	0.58	0.58
FRICTION FACTORS		
Geographical distance	-0.29	-0.26
Physical barrier ('any barrier')	-	-0.07
R^2	0.59	0.59
ΔR^2 (compared to the model without barrier term)	-	**0.00**
N	8836	8836

Note 1: all coefficients significant (< .001 two-sided)
Note 2: estimated standard errors of the β estimates are all smaller than 0.01 in both models
Note 3: no collinearity problems occur, all variance inflation factors are smaller than 2

Table 3.2 shows the strengths of various barrier effects in four different models in which the individual barrier indicators are added separately to the base model. In this way, it is possible to see which barrier indicator has the highest influence on crime trips. The results show that the barrier with the highest regression coefficient is the canal barrier, followed by the park and the railroad line. The influence of the highway is not significantly different from zero. Most interesting, however, is that models with barrier indicators do not explain more variance than the base model. It seems that introducing barrier variables only mitigates the influence of distance, which is seen as a reason to look in more depth into the effect of barriers on small and larger distances in the next section.

Table 3.2 Influence of individual physical barrier indicators on the number of crime trips (standardized regression coefficients β)

	Base model	Canal barrier	Railroad barrier	Park barrier	Highway barrier
PUSH AND PULL FACTORS					
Inflow	0.32	0.32	0.32	0.32	0.32
Outflow	0.58	0.58	0.58	0.58	0.58
FRICTION FACTORS					
Geographic distance	-0.29	-0.27	-0.28	-0.28	-0.28
Individual barrier indicator	-	**-0.05**	**-0.02**	**-0.03**	**ns**
R^2	0.59	0.59	0.59	0.59	0.59
ΔR^2 (compared to the model without a barrier term)	-	**0.00**	**0.00**	**0.00**	**0.00**
N	8836	8836	8836	8836	8836

Note 1: all coefficients significant ($p < .001$ two-sided)
Note 2: estimated standard errors of the β estimates are all smaller than 0.01 in all models
Note 3: no collinearity problems occur, all variance inflation factors are smaller than 2

"Any Barrier" Effect for Shorter and Longer Distances

The next analysis investigates the hypothesis that physical barriers have a stronger impact on short distances than on longer distances. Introduction of an interaction term in the regression equations did not result in considerable differences compared to the previous tables. This is unexpected, seeing that the main effect β-estimates for distance change in table 3.1 and 3.2 when the barrier indicators are incorporated. It may be the case that linear interaction terms do not pick up the relevant variance. For that reason, we also examined interaction by a different method. We selected only those origin-destination links that had a distance smaller than a given constant. We analysed four different cases[4]: very small distances only (< 500 m, N = 107), small distances only (< 1000 m, N = 452), smallest quartile of all distances only (< 2430 m, N = 2202), and smallest half of all distances only (< 3760 m, N = 4424). Of course, later subsets contain the earlier ones. We expect that when two neighbourhoods are far apart, crime flow will be close to zero due to the large distance, irrespective of a physical barrier, hence physical barriers will have a stronger influence (additional to distance) for the subsets with shorter distances only.

Table 3.3 shows the results for the any barrier indicator. It displays a very small amount of extra variance explained by the physical barrier indicator within the very short distance subset, but no effect for the larger distances subsets, compared to the base model. However, this small effect is an intricate composition of taking over (interaction) effects from the other regressors (inflow, outflow and distance itself) – some of them going up, others down – and the barrier coefficient itself is not significantly different from zero. The analyses also show that the models provide a better explained variance in short distances subsets than in the longer distances subsets.

Table 3.3 **Influence of a physical barrier on the number of crime trips when adjusted distances are selected (standardized regression coefficients β)**

	Distance 0 – 0.5 km (1% of all distances)		Distance 0 – 1 km (5% of all distances)		Distance 0 - 2.43 km (25% of all distances)		Distance 0 – 3.76 km (50% of all distances)	
	No barriers	With barriers	No barriers	With barriers	No barriers	With barriers	No barriers	With barriers
PUSH AND PULL FACTORS								
Inflow	0.24	0.29	0.27	0.29	0.32	0.33	0.31	0.31
Outflow	0.62	0.59	0.64	0.64	0.62	0.63	0.63	0.63
FRICTION FACTORS								
Geographic distance	-0.26	-0.24	-0.30	-0.30	-0.30	-0.29	-0.31	-0.31
Any physical barrier	-	**ns**	-	**ns**	-	**ns**	-	**ns**
R^2	0.76	0.77	0.74	0.74	0.69	0.69	0.64	0.64
ΔR^2 (compared to the model without barrier terms)	-	0.01	-	0.00	-	0.00	-	0.00
N	107	107	452	452	2202	2202	4424	4424

Note 1: all remaining coefficients significant (p < .001 two-sided)
Note 2: estimated standard errors of the β estimates are all smaller than 0.01 in all models
Note 3: no collinearity problems occur, all variance inflation factors are smaller than 2

[4] Peeters (2007) also investigates cases where very short distances are left out, e.g. the links in which o and d are identical, as well as cases where very weak crime links (less than 100 criminal trips between o and d) are left out. These analyses do not produce different results.

We the repeated the previous analysis for the separate barrier variables, adding all individual barrier indicators to the base model together. Table 3.4 shows that the various barriers have different influences on short and longer distances subsets. Additional explained variance of the barrier indicators at the 500 meters subset is a substantial 4% where the railroad and canal barrier have substantial coefficients. Push and pull regression coefficient do increase in the two shorter distance subsets, indicating interaction of these influences with the presence or absence of barriers. In the longer distances subsets, the additional explained variance of the barriers decreases to a 1%. Only the canal barrier is significant in all analyses.

Table 3.4 Influence of various physical barriers on the number of crime trips when adjusted distances are selected (standardized regression coefficients β)

	Distance 0 – 0.5 km (1%)		Distance 0 – 1 km (5%)		Distance 0 - 2.43 km (25%)		Distance 0 – 3.76 km (50%)	
	no barrier	barrier	no barrier	barrier	no barrier	barrier	no barrier	barrier
PUSH AND PULL FACTORS								
Inflow	0.24	0.30	0.27	0.30	0.32	0.33	0.31	0.31
Outflow	0.62	0.64	0.64	0.64	0.62	0.63	0.63	0.63
FRICTION FACTORS								
Geographic distance	-0.26	-0.22	-0.30	-0.29	-0.30	-0.28	-0.31	-0.30
Canal	-	**-0.16**	**-**	**-0.08**	**-**	**-0.05**	**-**	**-0.05**
Park	-	**ns**	**-**	**ns**	**-**	**ns**	**-**	**ns**
Railroad line	-	**-0.19**	**-**	**-0.11**	**-**	**ns**	**-**	**ns**
Highway	-	**ns**	**-**	**ns**	**-**	**-0.08**	**-**	**-0.05**
R^2	0.76	0.80	0.74	0.75	0.69	0.70	0.64	0.65
ΔR^2 (compared to the model without barrier terms)	-	0.04	-	0.01	-	0.01	-	0.01
N	107	107	452	452	2202	2202	4424	4424

Note 1: all remaining coefficients significant (p < .001 two-sided)
Note 2: estimated standard errors of the β estimates are all smaller than 0.01 in all models
Note 3: no collinearity problems occur, all variance inflation factors are smaller than 2

Discussion

To examine the influence of physical barriers on the intensity of crime trips between origin and destination neighbourhoods in The Hague, the Netherlands, we estimated gravitational models. Each of the models produced only a small or even absent influence of various barriers on crime trip intensity. Our results are therefore more in line with Ratcliffe (2001) than with Clare and colleagues (2009) and the studies of Greenberg and colleagues (1982, 1984). Small size influences are not unexpected in our study area due to the relative high permeability of the The Hague barriers when compared to the Perth-study of Clare and colleagues (2009), and are also in line with the relative small effects found by Reynald and colleagues (2008) in their study on the influence of social barriers in The Hague.

Barriers of various types have been shown here to have different strength of influence; but the small amount of the total influence makes this result not very helpful. However, the effect as such may be interpreted as an incentive to apply the same method in a city where both formidable barriers and rather permeable barriers are present, such as in Amsterdam. This city has a large river right through the city, with few crossing facilities on the one hand, and a variety of parks, canals, railroads, and highways on the other. This effect makes it understandable that Clare and colleagues (2009) found much stronger effects in Perth with its rather impermeable river barrier. Moreover, as we observed, the distribution of barriers over the study area in The Hague is rather skewed (railroad and highway barriers rather highly concentrated), which may have influenced their impact overall. Future research should try to find a study area in which barriers are rather uniformly distributed over the area.

There is an indication that barriers are slightly more important on short distances, but this has to be qualified. An interesting result here is the regularly observed interaction between barrier effects and the traditional elements in gravity models (especially the pull factor and geographical distance factor) when analyzing origin-destination pairs on short distance only. Introducing a barrier indicator in the model gives, for those short distance cases, a significant barrier effect; while at the same time the effect of inflow, outflow, or distance factors increases or decreases. This result indicates that the influence of barriers is not invariant over a geographical area, and their impact may be different on strong crime links than on weak one. Moreover, we observe that the strength of separate barrier effects is largest on short distances (with strong crime links generally). We may interpret this result as a need for a better understanding of crime links on a micro scale. Looking into crime origins and destinations on a less crude scale than we have done here in terms of neighbourhood centroids may be worthwhile, therefore. It may be advisable to replicate the research with actual coordinates of origin and destination of individual crime trips. Such an improvement, which is within reach in principle with present day GIS methodology, would also make it possible to zoom in on intra origin area crime trips and whether they did have to face a barrier or not. Of course, a better operationalization of barriers in terms of additional distance having to be covered for a given crime would be possible then as well (at least for barriers to be circumvented; for permeable barriers that are passed through, this solution would not work).

Notice that our models work with a rather crude operationalization of the push and pull factors, which are the total outflow and inflow of crime (Elffers et al., 2008). In a sense, we thus have conditioned on overall observed attraction and production of offenders. It could be advisable to introduce more content-oriented submodels for the attraction of an area (such as those of Bernasco and Nieuwbeerta, 2005) as well as for production of motivated offenders in an origin area (in terms of demographics and other socio-economic factors).

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SIMULATING THE DYNAMICAL INTERACTION OF OFFENDERS, TARGETS AND GUARDIANS

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Routine Activity Modelling

Within the routine activity paradigm (Cohen & Felson, 1979; Felson, 2008), it is argued that crime takes place when a motivated offender finds a suitable target, while capable guardians are lacking. The beauty of this theory lies in its clarity and simplicity on a sufficiently abstract level (Elffers, 2004). Its simplicity dissipates, however, when moving from an abstract level to questions of underlying processes such as what governs whether a motivated offender will find an attractive target. The answer is dependent on the movement of offenders and the whereabouts of targets. For instance, the likelihood of such meetings will be dependent on the distribution of targets' attraction levels, their positions in space, whether they move or not, and whether their attraction levels are constant over time or not, and if not, what is governing their change. Likewise, the occurrence of a meeting between offenders and targets will be influenced by the movement pattern of motivated offenders, may be dependent on their knowledge of target availability or on other business of the offenders, on their preferences for certain attraction levels, and on whether these characteristics are influenced by having successfully or unsuccessfully attacked a target previously. Targets may have a movement pattern based both on their perception of criminal risk as well as of parameters governing their non-crime related behavior (e.g., the route they take to go to work), which will also be influenced by experiencing crime. The third routine activity factor, availability of capable guardians, has to be taken into account as well. For example, whether there are formal guardians, such as police officers and security personnel, or are informal or natural guardians, such as inhabitants and passers-by. The temporal and spatial dynamics of such offender, target and guardian processes is paramount for the occurrence of crime within a routine activity context. This becomes problematic in real life situations, as it seems rather optimistic that all of these processes can be specified, estimated, and analyzed. Measurement problems as well as analytical problems will be formidable.

A way to deal with such a complex case is simplifying the problem by holding constant as many parameters in the processes as is feasible. For example, research could

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compare pick pocketing rates in two neighborhoods close to each other, each with comparable population composition, but where one having houses with small windows is deemed to have low natural guardianship levels while the other neighborhood having buildings with large windows considered having a better guardianship structure. Assuming that offender routine patterns and target routine patterns are alike in both neighborhoods, comparing them is a fit method to investigate the effect of natural guardianship.

A second method is experimenting, for example by varying police surveillance intensity (as one of the guardianship parameters) over time periods in a given neighborhood. This research approach is, of course, also only feasible when other parameters are held constant. Dynamic aspects of the routine-activity-models are particularly problematic to this kind of research because the designs attempt to exploit the "ceteris paribus" of all other parameters than the one under scrutiny, and hence implies an incentive on static processes, thus defying investigation of dynamics.

In the current paper, however, we examine dynamic routine activity processes by means of (agent-based) simulation methods (David & Sichman, 2009) in which some routine activity processes are built into an artificial society of offenders, targets, and guardians. We then investigate what happens if offenders, targets, or guardians react to a situation by increasing or decreasing parameters of their preferences and by choosing the direction in which they move as a function of what is happening around them.

Simulation as an Analytical Tool

Simulation is used in the present research as an analytical tool that makes it possible to investigate events in an environment, given a set of rules, whose mutual interactions are too complex to analyze with traditional methods (see, e.g., Brantingham & Brantingham, 2004). Simulation is, in such an application, not an empirical but a theoretical method that uses computer generated instances of realizations of processes. It is meant for those cases where complexity outstrips the capability of theoretical or mathematical analysis. Simulation departs from a given theory (here routine activity theory) and examines the dynamic interplay of various processes as specified by that theory at a local level. As such, simulation is not testing the theory from which it departs, but, on the contrary, it is exploring it, bringing forward global level implications of the local level assumptions of the theory that were not straightforward and clear before. The resulting outcomes of a set of simulation runs should then be studied and are meant to generate a deeper insight in the process that, implicitly, has been specified by the simulation model. Observing and analyzing a number of simulation runs of the dynamic development of resulting crime processes may enhance the understanding of the dynamics of routine activity in a given context. This usually takes the form of an input-output analysis where, specific parameters of the process to be simulated are input and the outcomes observed. Applications of simulation as a tool for understanding can be found in various criminological fields. For example, Van Baal (2004) used it to study perceptual deterrence; Bosse, Gerritsen & Treur (2007, 2008) used it to study psychological processes that trigger violent behavior; and Bosse, Gerritsen, Klein & Weerman (2009) used it to study social learning of delinquent behavior in adolescents.

Developing a useful simulation model is not an easy task because simulation generates a great deal of output from which the researcher must make sense, either by insight or through systematic statistical analysis of the input-output connections. It is therefore wise for researchers to start with simple simulation models. Experience shows that interpreting and understanding input – output relations is quite a task even in simple models. A stepwise approach starts with a simple simulation model that can be made more complex after interpreting the output of the simpler case.

It seems worthwhile to stress explicitly that simulation models in the above sense are not yet meant as theories of reality. We know beforehand they are gross simplifications of reality, but this is also a unique strength. By rigorous simplification, researchers optimize the conditions for understanding the complex interplay between various parts and rules in the model. Only after having understood a relatively simple model thoroughly, may researchers go further and build complex models of reality, using as building blocks what was learned from the simple simulations. This modest view on simulation research rules out testing model results against empirical data, which is not an issue as we already know the models do not fit reality.

Other uses of the term "simulation research" and other visions on the effectiveness of simulation may be found in the literature (see, for example, Liu & Eck, 2008) and may be useful for their own purposes as well. Many researchers even propose their simulation models as fair approximations of reality. Some first successful attempts in this direction can be found in Brantingham et al., (2005), Groff (2005, 2008), Hayslett-McCall et al. (2008), Liu et al., (2005), and Melo et al. (2005). Nevertheless, it is our conviction that, at least concerning the dynamics of routine activity models, that stage has not been reached completely (see Elffers & Van Baal, 2008; for an attempt to analyze the dynamic structure of a model within a real life environment, see Malleson & Brantingham 2008).

A Simple Routine Activity Model, Global Description

In the present project, we examine a small society of immobile targets (*houses that can be targeted for burglary*), located in geographical space (*town*), with standard characteristics of *neighboring relations* and *distance to each other*, and having a certain distribution of attraction levels over space (*spatial autocorrelation of wealth*). The targets have a time dependent *reputation*, which is high when a property has been burglarized in the recent past and erodes again when nothing untoward is happening for some time. Through that society, a number of motivated burglars move around. They take one step every period (*day*), and have a preference of moving to more attractive targets.

They are rather short-sighted, however, and can see only targets one step away from their previous position. They chose a move with a certain probability proportional to attraction levels of targets in sight. Offenders (burglars) have a characteristic of *choosiness* such that every offender has a certain minimal attraction threshold that differs from other offenders. When arriving at a target, an offender intends to burgle it if and only if it is worthwhile, which is the case if the attraction level of the prospective target surpasses the minimal attraction threshold of that offender. This decision making process is similar to the ideas put forth by Brantingham & Brantingham (1993), who stated that offenders match the situations they observe against their crime templates (i.e., perceptions of which targets are appropriate). A target that is eligible for burgling to one offender may be passed over by another offender.

The last element in the model is the guardians, also moving around through the town. Guardians in this model are what has been called formal guardians, that is agents having an official guardian task (such as police officers or security personnel), as opposed to informal guardians, who may be present on the spot for other reasons (inhabitants, passers-by) and then nevertheless can preclude crime from happening (Felson & Cohen, 1980; Reynald, 2009). Guardians, like offenders, walk around one step at a time, and see only targets one step away. Guardians either have *no preferences*, i.e. they move around randomly (random policing), or have a preference for moving to targets with high reputations (vulnerable targets). The probability of moving to a target is proportional to the reputation being visible from the present position. This is hot spot preferences or hot spot policing. Such strategies are compatible with the often observed behavior of burglars called the *(near) repeat phenomenon* (Johnson & Bowers, 2004; Ratcliffe & Rengert, 2008; Townsley, Homel & Chaseling, 2003), where offenders prefer to strike targets they previously victimized (or those in near proximity thereof, although this second phenomenon is not addressed by our definition of reputation).

A guardian present at a target completely precludes a burglary taking place. So if an offender intending to burgle a house meets a guardian at the spot, the offender will not act. Of course, burglars who judged a target as not worthwhile will not be affected by guardians; they go on behaving themselves at that moment.

Research Questions

Within the framework of the model, we intend to investigate the effectiveness in crime prevention of various guardianship policies. This is the output variable, operationalized as 1 – crime rate, where the crime rate is the observed number of crimes per spatio-temporal unit in various circumstances, as specified by the spatial attraction patterns of the targets, the number of offenders and guardians, and the distribution of the attraction thresholds of the offenders (which are all input variables).

Guardian policies to be investigated here are random policing, hot spot policing, area (or beat) hot spot policing. The last of those policies is a hot spot policing scheme but with mutually exclusive zones allotted to the guardians, zones that they may not leave.

Circumstances varied in the model include the number of guardians and distribution of target attraction values. Concerning the former, we are interested in the extent to which the effectiveness in crime prevention is influenced by the amount of guardians present in the model. To this end, the number of guardians was varied between only 2 guardians and almost one guardian at every location. The other circumstance varied over the different simulations is the distribution of target attraction values. This choice was based on the hypothesis that differences in geographical makeup between areas may result in different burglary patterns (e.g., the burglary patterns in an area where all expensive houses are clustered will be different from those in an area where all expensive houses are spread), see, for example Rengert & Wasilchick, 1985. Other parameters of the model were the number of offenders present in the simulation and the distribution of threshold values of the offenders (i.e., the individual attractiveness levels of the offenders that a certain target should surpass to be judged sufficiently attractive to burglarize). However, these two parameters are kept constant over the different simulation runs.

Simulation Model

In this section, the simulation model is discussed in greater detail. The main component of the model is a virtual environment, a world that is represented mathematically by a matrix of m*n elements (and can be visualized as a grid of m*n adjacent locations). Thus, each location has maximally 4 neighbors (in case of central locations) and minimally 2 neighbors (in case of corner locations). This is illustrated in Figure 1, where each intersection represents a location and the dashed lines represent connections between locations. In addition, each location (or house) has a *level of attractiveness* attached represented by a natural number between 1 and 10. This number is assumed to represent the attractiveness of that particular location to burglars (a high number may stand for an expensive house without surveillance cameras). Finally, to enable the guardians to prevent near repeat burglary, each location has a *reputation* attached represented by a real number ≥ 1 and is assumed to represent the reputation of that location with respect to burglary (a high number stands for a house where many burglaries have taken place). Initially, the reputation of each location is set to the value 1. Reputation increases by 1 after a burglary takes place at that location and decreases by 0.5 when no burglary takes place.

Within a given simulation run, the world is populated by artificial *agents* (David & Sichman, 2009). Two types of agents are distinguished: *offenders* (i.e., potential burglars) and *guardians*. Each offender has an individual *burglary threshold*, represented by a natural number between 0 and 10, which represents the threshold above which the agent considers a house sufficiently attractive to burgle it (a high number denotes a person that will only select very attractive targets). Offenders travel through the environment by moving to locations with a probability that is proportional to their attractiveness. To be able to compare different surveillance strategies, the guardians exist in three different types:

- *type 1 guardians* follow a random strategy: they move randomly through the environment
- *type 2 guardians* follow a hot spot strategy: they select adjacent locations with a probability that is proportional to the reputations of those locations
- *type 3 guardians* follow an area hot spot strategy: they select adjacent locations with a probability that is proportional to their reputation, but only within their individually assigned surveillance area. This means that each guardian of type 3 has a number of locations assigned (an area), which it is not allowed to leave.

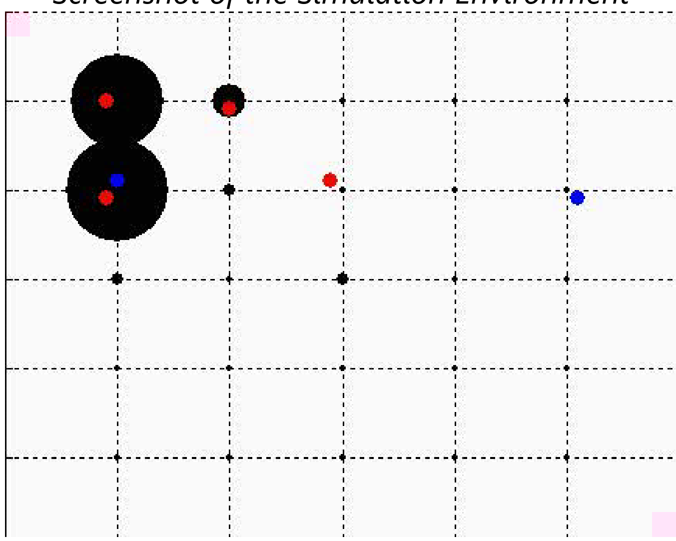
To generate a simulation run, the following algorithm is performed (denoted in pseudo-code):

1. *Initialize the simulation (either randomly or according to some setting defined by the user) according to the following steps:*
   a. *Determine the size of the world.*
   b. *For all locations, set the initial reputation to 1 and assign attractiveness levels.*
   c. *Determine the amount of agents of the different types.*
   d. *Assign burglary thresholds to all offenders.*
   e. *Assign personal areas to all Type 3 guardians.*
   f. *Place all agents at their start locations.*
2. *For each time step until the end of the simulation, repeat the following cycle:*
   a. *For each location, if it contains at least 1 motivated offender (the individual burglary threshold is lower than the attractiveness of the location) and no guardians of any type, then count a burglary for that location.*
   b. *Increase the reputation of each location that is burglarized by 1.*
   c. *Decrease the reputation of each location that is not burglarized by 0.5.*
   d. *For each offender, move to one of the adjacent locations (including the current location) with a probability that is proportional to its attractiveness. For example, suppose an offender is at a (corner) location A with two neighbors, B and C, and that the attractiveness of A, B, and C is 3, 5, and 7, respectively. Then, the probability that the agent will stay at location A is 3/(3+5+7) = 0.2. Similarly, the probability that it will go to location B is 0.33, and the probability that it will go to C is 0.47.*
   e. *For each Type 1 guardian, move randomly to one of the adjacent locations (including the current location). For example, if a guardian is at a central location, it may go north, south, west, or east, or stay at its current location, each with a probability of 0.2.*
   f. *For each Type 2 guardian, move to one of the adjacent locations (including the current location) with a probability that is proportional to its reputation. For example, suppose a guardian is at a (corner) location A with two neighbors, B and C, and that the reputations of A, B, and C are 4.5, 7.5, and 2.0, respectively. Then, the probability that the agent will stay at location A is 4.5/(4.5+7.5+2.0) = 0.32. Similarly, the probability that it will go to location B is 0.54, and the probability that it will go to C is 0.14.*

g. *For each Type 3 guardian, move to one of the adjacent locations (including the current location) <u>within its own area</u> with a probability that is proportional to its reputation.*

As can be seen in this pseudo-code, in principle it is possible to have guardians of different types in the same simulation; however, in the simulations discussed in this paper, this is not the case (only one type of guardian is placed in each simulation run).

Figure 1
Screenshot of the Simulation Environment



During a simulation, various types of relevant information are stored, such as the total number of burglaries, the amount of times offenders encounter guardians (prevention rate), and the amount of times 2 or more guardians are present at the same location (idleness rate). Since the model contains probabilistic elements, multiple runs will provide different results; therefore, to obtain reliable results, the model is run many times to generate a large number of simulated traces (developments of all dynamic parameters over time), of which the average is then taken.

The simulation model was implemented in Matlab. To provide the user more insight into the spatial dynamics of a simulation run, the implementation offers the possibility to visualize each simulation run in terms of an animation (which can be stored as an .mpg-file). In Figure 1, a screenshot of such an animation is shown. Here, each intersection represents a location in a city. In the example addressed here, there are 25 locations in total that are connected through edges (according to a grid or 'block' structure). Furthermore, there are 4 offenders (represented by the red dots) and 2 guardians (the blue dots). The black dots represent the reputation of a particular location: the bigger the dot, the higher the burglary reputation of that location. As an illustration, a number of animations (for different guardian strategies) can be found at: http://www.cs.vu.nl/~wai/crimesim/.

Input Parameters That Are Varied Over Different Runs

A large number of simulations were generated under different settings (input parameters). First, we used different settings for the distribution of the attraction values of the targets. In this way, four types of worlds were created (see Figure 2). In the first world type, all targets had the same attraction value (equal world). In the second world type, the attraction values were distributed without structure over the community (distributed world). Actually, in the present set of simulations, we manually distributed values between 1 and 10 in an unsystematic way over the society. In the third world type, the values were distributed according to a concentric ring structure (ring world), with the highest attraction value in the south-west corner of the world and attraction values decreasing linearly with the number of concentric rings. This can be compared to a city where the most expensive houses are located close to each other and the less attractive the houses are located further away from that wealthy centre. In the fourth world type, there were two distinct areas in which the expensive houses were located (segregated world), separated from each other by houses that were less attractive.

Figure 2

Types of Simulation Worlds

For each world, simulations were run with different numbers of guardians (i.e., 2, 3, 4, 5, 6, 10, 15 and 20 guardians), which were either all of Type 1 (random strategy), Type 2 (hot spot strategy), or Type 3 (area hot spot strategy). In each simulation, 4 offenders were present, with *burglary thresholds* 4, 5, 6, and 7. For each setting, 1000 simulations were run (of 200 time steps each), for a total of 96000 simulations (4 worlds * 8 amounts of guardians * 3 guardian types * 1000 simulations). The most interesting results are discussed below.

Simulation Results

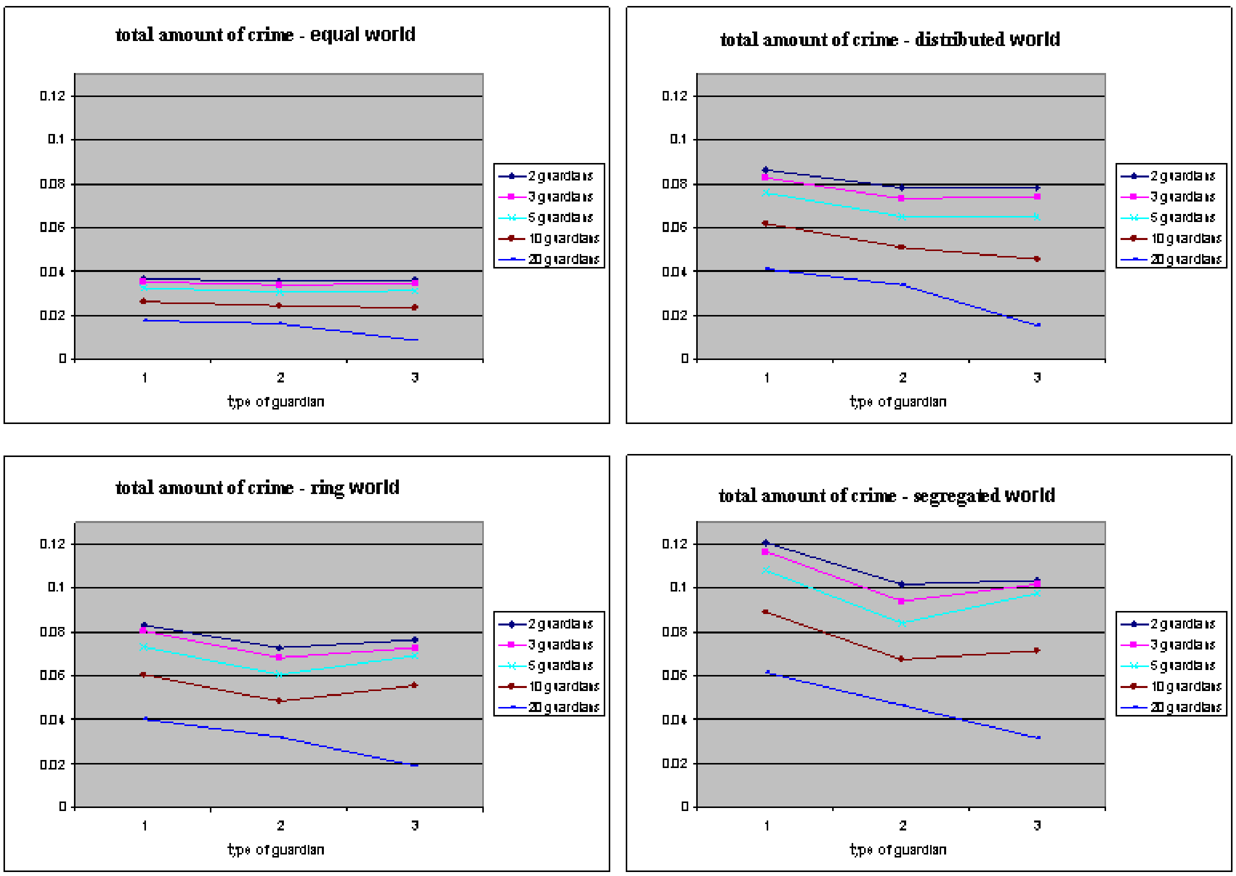
In this section, the results of the simulations are discussed with respect to total crime rates, crime hot spot rate, guardian hot spot rate, guardian efficiency, and the effect of larger geographical areas.

Total Amount of Crime

In Figure 3, the average crime rate is shown for the different worlds. In these graphs, the horizontal axis shows the different types of strategies, and the vertical axis shows the average amount of crimes per location per time point. Note that the results for 4, 6, and 15 guardians have been left out to improve readability. The different strategies seem to have the same effect in the segregated, ring, and distributed society. In these societies, both hot spot policing and area hot spot surveillance work better than random patrolling. Furthermore, hot spot patrolling is better than area hot spot surveillance until the number of guardians exceeds 5. Only in the equal society does the type of guardian have little influence. Overall, when there are more than 5 guardians, the guardians that patrol in an area hot spot manner are more effective than the other types of guardians.

Figure 3

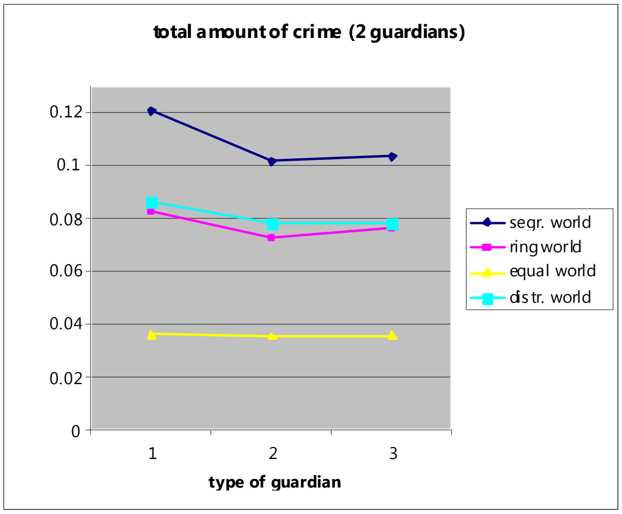
Total Crime Rate - Comparing Different Numbers of Guardians within One World.

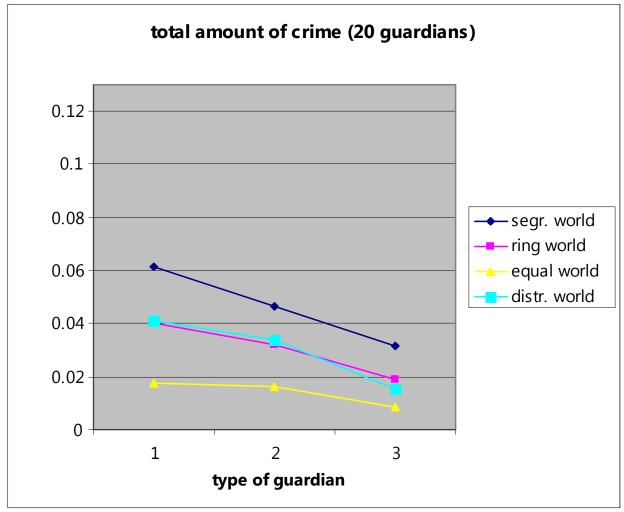


When the crime rates are compared in the different worlds (see Figure 4), they are the highest in the segregated community. In the ring and distributed society, the crime rates are about the same, and the equal society is the world with the lowest crime rate.

Figure 4

Total Crime Rate - Comparing Different Worlds for One Number of Guardians.





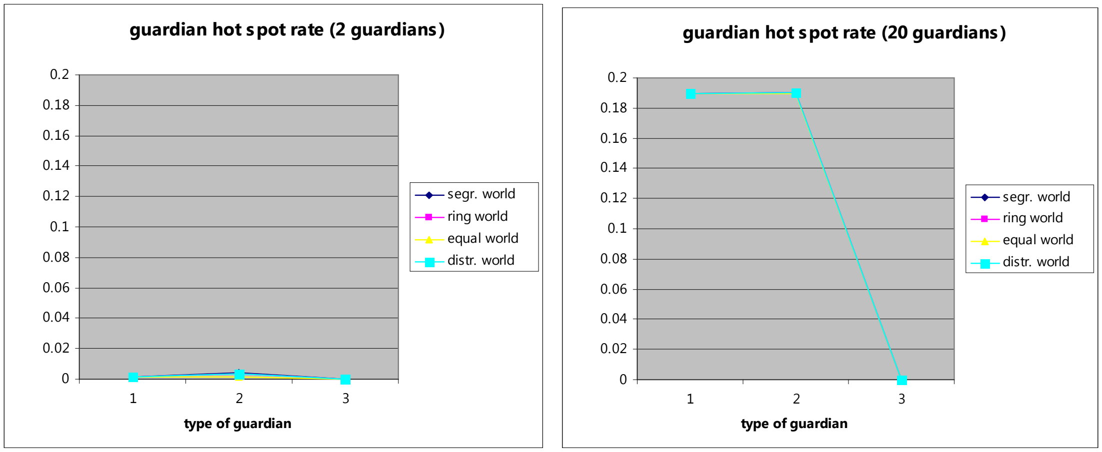
Crime Hot Spot Rate

For each location, we also counted the amount of times that it was populated by two or more motivated offenders per time point. Encounters between motivated offenders are independent of the amount and the type of guardians (since offenders move around in a random manner), therefore we do not show the results graphically as a function of the types of guardians. The motivated offenders encounter each other most often in the segregated world (0.017 times per location, per time point). The ring society is second (0.0095 times), the distributed society is third (0.0075). The offenders have the least encounters in the equal society (0). There were no encounters between motivated offenders in the equal society because, in this society, there was only one offender of which the burglary threshold was lower than the attractiveness of the houses.

Guardian Hot Spot Rate

Next, we investigated the average amount of times per location that each location was populated by two or more guardians per time unit. The results (for the case of two guardians and the case of twenty guardians) are displayed in Figure 5. Our main finding is that guardians using a hot spot strategy have more encounters than guardians that move randomly. Guardians that have an area hot spot strategy never meet each other because they are restricted to certain areas. Although this cannot be seen in the figures (since all points overlap), the guardians encounter each other most often in the segregated world. The ring society is second, the distributed society third, and the guardians have the least encounters in the equal society. However, these differences are very small.

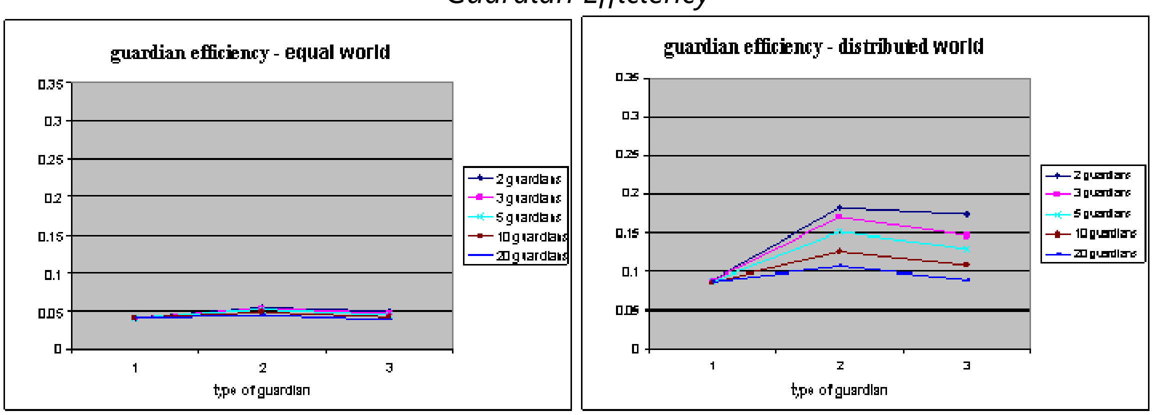
Figure 5
Guardian Hot Spot Rate.

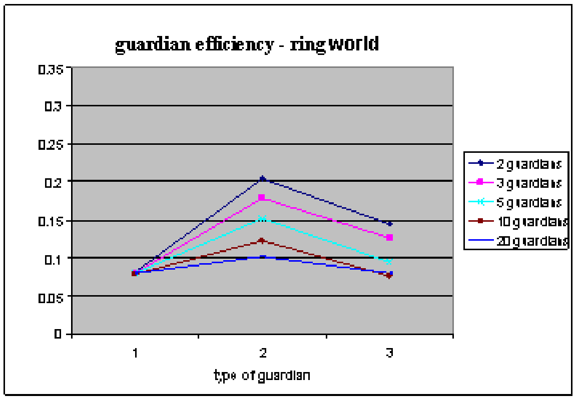


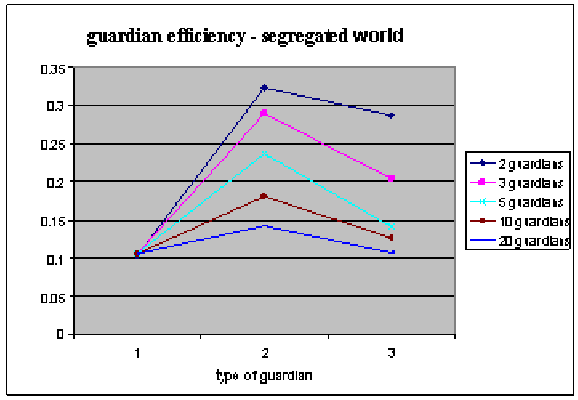
Guardian Efficiency

Guardian efficiency is the average amount of times that a guardian meets at least one offender per time point. The results of this are shown, for the different worlds, in Figure 6. In the

Figure 6
Guardian Efficiency







segregated, ring and distributed world, hot spot patrolling is more efficient than random patrolling area hot spot patrolling. Random patrolling and area hot spot patrolling are just as efficient in these worlds, at least for large amounts of guardians.; however, when there are fewer than 10 guardians, area hot spot patrolling is more efficient than random patrolling. In the equal society, hot spot patrolling is slightly more efficient than random patrolling and area hot spot patrolling. Random surveillance and area hot spot surveillance are equally efficient. Overall, guardians are most efficient in the segregated society. Both the ring and the distributed society are second, and guardians in the equal society are least efficient.

Scaling Up

The simulations discussed above all were performed in a world of 5x5 (25 locations), with 4 offenders and 2 to 20 guardians. To test whether these results are independent of the size of the society, we increased the size of the simulation. We created a larger world (10x10 = 100 locations), and also multiplied the number of guardians and offenders by 4. This yields a setting with 16 offenders and 8 to 80 guardians (for the time being we only considered the situation with 8 guardians). We only made a comparison between the randomly patrolling guardian (Type 1) and the hot spot patrolling guardian (Type 2). The results are shown in Table 1 and 2. As can be seen, scaling up does not have a significant influence on (normalized) findings.

Table 1

Comparing Worlds with Different Sizes - Type 1 and Type 2 Guardians

Type 1 Guardians

	5x5	10x10
crime rate	0.0368	0.0369

Type 2 Guardians

offender hot spot rate	0	0.0006
guardian efficiency	0.0412	0.0399
guardian hot spot rate	0.0015	0.0026

	5x5	10x10
crime rate	0.0357	0.0359
offender hot spot rate	0	0.0006
guardian efficiency	0.0544	0.0525
guardian hot spot rate	0.0017	0.0027

Discussion

The simulation experiments described above illustrate the usefulness of simulation as an analytical tool to investigate consequences of criminological theories under certain assumptions. In this project, the routine activity theory (Cohen & Felson, 1979; Felson, 2008) was taken as a point of departure, and a number of assumptions that form the basis of the theory were formalized in sufficient detail to be able to generate a simulation model. The simulation model was focused at the domain of burglary. It allowed us to create artificial societies and define varying circumstances for these societies, such as different attractiveness distributions of targets, different numbers of guardians, and different guardian strategies. By running the simulation model for these varying circumstances, various “experiments” were performed that enabled us to examine consequences of the theory (of course, still given certain assumptions) that we would not have been able to derive by means of traditional methods. For example, a first finding was that, in our simulations, hot spot surveillance and area hot spot surveillance turned out to work better than random patrolling, unless all targets were equally attractive. This makes sense, because, when all targets have the same attractiveness, probably no hot spots will occur at all. Moreover, hot spot surveillance turned out to usually work better than area hot spot surveillance, unless the amount of guardians was almost as big as the amount of locations. In such a situation, it is more efficient to distribute guardians over locations to prevent a situation where multiple guardians are guarding the same location and thereby wasting resources. With respect to the different geographical makeups of the societies, our simulations suggested that the crime rates were highest in situations where there were specific locations with a high concentration of attractive targets (such as in our segregated or ring society). Finally, the effect of scaling up the size of the society turned out to be small. Apparently, the (relative) crime rates do not increase much when a larger area is considered, as long as the number of offenders and guardians are increased proportionally.

Obviously, these results should be interpreted with some care. As discussed above, a simulation model is by definition an approximation of reality. As for any simulation model, some simplifying assumptions were made when developing the simulation model, (for example, about the distances between targets, the movement of the agents involved, and the individual decision making processes of the agents). In addition, the experiments described were only performed for some particular sets of parameter settings. Therefore, when interpreting the results, one should keep in mind that these were found under the given assumptions. Nevertheless, we hope to have convinced the reader that the results shed some light on interesting issues to be further investigated, such as the finding that area hot spot surveillance only works better than hot spot surveillance if the number of guardians is sufficiently large, to name a concrete example.

For future research, the current model can be extended in various directions. For instance, it would be interesting to investigate what happens if the offenders are made more intelligent (i.e., if they are able to “learn” the behavior of the guardians). Similarly, the guardians can be made more intelligent, for example, by having them anticipate the expected movements of the offenders instead of reacting to their actual movements. Finally, an interesting extension would be the addition of passers-by to the model (e.g., citizens that go to their work at 9 am and go back home at 5 pm, via some standard route) and study how the presence of these passers-by would influence the patterns found so far.

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