Exploring Theories of Victimization Using a Mathematical Model of Burglary

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Abstract

Research concerned with burglary indicates that it is not only clustered at places, but also in time. Some homes are victimized repeatedly, and the risk to neighbors of victimized homes is temporarily elevated. The latter type of burglary is referred to as a near-repeat. Two theories have been proposed to explain observed patterns. The boost hypothesis states that risk is elevated following an event reflecting offender foraging activity. The flag hypothesis, on the other hand, suggests that time-stable variation in risk provides an explanation where data for populations with different risks are analyzed in the aggregate. To examine this, the authors specify a series of discrete mathematical models of urban residential burglary and examine their outcomes using stochastic agent-based simulations. Results suggest that variation in risk alone cannot explain patterns of exact and near repeats, but that models which also include a boost component show good qualitative agreement with published findings.

INTRODUCTION

Criminology is a multidisciplinary subject but the application of mathematics has been fairly

limited in the study of crime patterns (for recent exceptions, see Short et al., 2008; Short et

al., 2010). The advantages of using a mathematical approach are numerous and range from

the conceptual clarity that arises from using formal expressions to describe systems, to the

ability to model non-linear complex systems, to the possibility of developing control strategies

if systems are adequately specified. In this paper, we use mathematical models to examine

theories concerned with space-time patterns of victimization at the level of place and consider

how concepts commonly used in mathematics may be helpful in formalizing and exploring

theories of this kind.

Whatever the method, the unit of analysis selected will directly affect the reliability of

inferences drawn. For example, where research concerns theories of crime concentration, the

analysis of data aggregated to large geographical units will often be inappropriate and invite

errors of inference. A common example is the ecological fallacy (Robinson, 1950) of assuming

that patterns observed in the aggregate across an area will apply to all places within it. Rarely

will this be the case. For example, Bowers et al. (2005) demonstrate that for domestic

burglary irrespective of what type of area they live in, the type of house (e.g. flats, row homes

and so on) a resident lives in significantly affects their risk of victimization (see also, Budd,

1999). Likewise, a series of studies demonstrate that regardless of area-level risks, how

connected a block face is to the surrounding street network significantly influences the risk of

burglary to homes located on it (e.g. Bevis and Nutter, 1977; Beavon et al., 1994; Hillier, 2004;

Johnson and Bowers, 2010). Stated more explicitly, the importance of place in the study of

crime – where places may include meaningful units of analysis such as block faces or individual homes - has been acknowledged for some time (e.g. Eck and Weisburd, 1995).

However, location is not the only dimension of importance in the study of crime patterns. Crimes occur at a point in time as well as a place, and to neglect one aspect may lead to an inadequate understanding of the contribution of the other. For example, where the dimension of time is ignored the stability over time of factors that affect crime risk at places may be overestimated. In line with this, whilst it has been established for some time that crime clusters in space at a range of spatial scales from areas to micro-level places (e.g. Pease, 1998; Ratcliffe, 2004; ; Sherman, Gartin, and Buerger, 1989; Shaw and McKay, 1969; Weisburd, Bushway, Lum, and Yang, 2004;), research shows that it clusters in *both* space *and* time (e.g. Johnson et al., 2007; Townsley et al., 2003; Grubesic and Mack, 2008). For example, at the finest spatial scale, numerous studies (for a review, see Farrell, 2005) have shown that some homes are repeatedly victimized more often than would be expected on a chance basis, assuming the risk of crime were uniform. Moreover, when repeat burglary victimization occurs it is more likely to do so swiftly than after some time has elapsed. In fact, the time course of repeat victimization fits an exponential decay function rather well (Johnson et al., 1997; Polvi et al., 1991; Townsley et al., 2001). More recent work (e.g. Grubesic and Mack, 2008; Johnson et al., 2007; Johnson et al., 2009; Short et al. 2009; Townsley et al., 2003) suggests that this phenomenon extends to nearby homes such that when one house is victimized, those nearby also appear to experience a temporary elevation in risk. When this occurs it has been referred to as a *near repeat* (Morgan, 2001; Townsley et al., 2003).

With respect to repeat victimization of the same home, places would be defined as individual households (Eck and Weisburd, 1995). However, this has the potential to imply that individual homes might be considered independent units for which the risk of victimization is unaffected by features of their neighbors. That neighbors of victimized homes experience a temporary elevation in risk following an offense implies a dependency and that places may be better conceptualized as the slightly larger spatial units such as block faces, or small clusters of homes that immediately surround each individual housing unit. Alternatively, perhaps specifying places as individual homes *is* most appropriate but what is required is a better understanding of how particular places influence the risk of crime to others nearby. Thus, it would seem that further research is required to better understand how risk varies at the level of place and for the testing or refinement of theories that might explain observed patterns.

Two theories have been proposed to explain patterns of repeat victimization and by association, near repeats. According to the *flag hypothesis*, observed patterns can be explained in terms of (relatively) time-stable variation in risk heterogeneity across units (Nelson, 1980; Sparks, 1981). This variation in risk may be influenced by a variety of factors including those already discussed, such as accessibility and target attractiveness. These may vary at both the individual household, block face and neighborhood level, suggesting that the risk of victimization at places may be influenced by the time-stable characteristics of the spaces within which they are located as well as features of the places themselves.

An alternative focus suggests that the risk of victimization at places varies (to some extent) over time as a function of *current* patterns of victimization. Simply put, following one victimization the risk of crime is said to be temporarily *boosted* (Pease, 1998) to victimized

homes and those nearby (Johnson and Bowers, 2004; Johnson et al., 2007; Johnson et al., 2009; Townsley et al., 2003), most likely reflecting dynamic foraging strategies on the part of offenders (Johnson and Bowers, 2004; Johnson et al., 2009). Thus, risk is considered to be a function of changes in offender awareness (e.g. see Brantingham and Brantingham, 1993, 2008) and perceptions of crime opportunities at particular places within spaces.

As discussed by Johnson (2008), taken on face value, the time course of repeat victimization would appear to support the boost account of repeat victimization; if the risk of victimization was time stable why would an exponential decay in risk be observed? However, this perception may be illusory and instead reflect a type of statistical artifact that can occur when data are aggregated for groups of places that experience very different risks (for a more general discussion of heterogeneity's ruses, see Vaupel and Yashin 1985). The potential problem is that the researcher may erroneously assume that aggregate patterns reflect those for individual places. To illustrate, consider an area in which there are three classes of home; those with stable-high, -medium and -low risks of victimization. Even on a chance basis, some homes from each group would experience repeated victimizations. If these occurred purely by chance - insofar as they were unrelated in terms of who committed the offenses - and analyses were performed independently for each class of home, the time course of repeat victimization would be uniform over time for each group. However, if the data for the three groups were combined, a curve is likely to be generated. To elaborate, the high risk homes would be victimized the most and would be the most likely to be re-victimized swiftly. Considering the low risk group, they would be victimized least often, but might still be re-victimized. When they are, the time to re-victimization would typically be longer than that for

the other two groups. The medium risk group would experience repeat victimization at a rate

somewhere between the other two groups. Mixing the patterns for the three groups would

generate a curve for which the coefficient would be a function of the differences in risk for the

three populations; the greater the differences the more accentuated the curve. Thus, risk

heterogeneity can plausibly explain the observed time-course of repeat victimization. The

same explanation can be extended to patterns of space-time clustering more generally (near

repeats) if there is sufficient variation in risk across – but homogeneity within – neighborhoods

or (for example) street segments.

To examine these theories, a number of research methods can, and have been

employed. For example, to examine repeat victimization, multivariate statistical methods

have been used to estimate the extent to which patterns of concentration observed in cross

sectional data can be explained by measured heterogeneity across homes (Osborn and

Tseloni, 1998). Such analysis suggests that heterogeneity explains some but not all of the

variation in concentration observed. Analyses of crimes detected by the police suggest that

crimes committed at the same location or nearby are likely to be the work of the same

offender(s) (e.g. Kleemans, 2001; Bernasco, 2008; Johnson et al., 2009), and interviews with

offenders provide further support for both the boost (e.g. Ericsson, 1995; Ashton et al., 1998)

and flag (e.g. Rengert and Wasilchick, 2000) explanations.

However, criticisms of these approaches suggest that the use of other complimentary

methods would enhance criminological understanding. For example, as Eck and Liu (2008a)

discuss, detection rates are so low that while analyses of such data are important, it is possible

that the data are biased, reflecting the behavior of a limited sample of offenders, who are (for

example) perhaps those easiest to apprehend. A similar critique can be applied to much of

the ethnographic research, as offenders are usually identified through contact with the

criminal justice system, and thus only represent those known to authorities.

In contrast, where response rates are high, data obtained from large scale surveys may

be relatively unbiased and provide a good estimate of actual patterns. Unfortunately, data

collected using sample surveys will rarely (if ever) provide detailed data that allow the analysis

of micro-level spatial and temporal patterns of crime. For crimes recorded by the police there

will generally be issues with under-reporting (e.g. Xie et al., 2006), but for some types of crime

(such as burglary with loss) this may be less of a problem for other types of crime. However,

for both types of data (survey and police recorded crime data), the types of analysis

conducted essentially rely on correlation as an approach to hypothesis testing. That is, data

for a series of independent variables – intended to represent theoretical constructs of interest

– are collected and a statistical model used to estimate the degree to which they are

associated with the dependent variable of interest. Whilst fairly sophisticated models are

available, that can be used to estimate and control for the influence of measured and

unmeasured variables, correlation does not imply causation and nor does it help to specify the

precise mechanism(s) through which outcomes are generated (see Eck and Liu, 2008a).

In contrast to inductive approaches, mathematical and simulation models are used to

formally specify a theory and to then evaluate whether the model can generate patterns

which resemble "statistical signatures"[1] or even precise outcomes (Gilbert, 2008). This type of

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[1] Patterns that are believed to be describe the general distribution of real world phenomena. For example, the time course of repeat victimization has so far proven to be ubiquitous and so can be considered a statistical signature.

approach has a number of merits to recommend it. We will not discuss all of these here, as they are dealt with elsewhere (Eck and Liu, 2008b), but some points are as follows. First, such models require that the precise mechanisms through which a pattern is thought to emerge are explicitly stated, along with assumptions made. This formal specification requires a level of precision that can be absent in theories expressed in spoken languages (Eck and Liu, 2008a), allowing the internal logic of the theory to be tested. This is, in and of itself, a useful exercise. Second, such models allow theory falsification; if a model cannot generate a pattern then the theory can be considered insufficient (Eck and Liu, 2008a). Third, such models can generate data for analysis, but unlike other research methods, models can be executed numerous times allowing outcomes to be examined for consistency, or to allow the effects of particular manipulations to be observed. Thus, mathematical models may provide a useful additional method of theory testing, particularly where representative data are difficult to obtain.

For such reasons, using a simple stochastic simulation model, Johnson (2008) examined the plausibility that the time course of repeat victimization might be explained by a ruse of heterogeneity (see also Short et al., 2009), but concluded that this alone could not explain observed patterns. This is important but no research of which we are aware has examined this for more general patterns of space-time clustering (i.e. near repeats) and hence this is the focus of the current paper. Moreover, in the previous studies, because of the ways the models were specified, the risk to each home was essentially independent of every other. In reality, it may be the case that the risk of victimization to any home is a function of the target attractiveness of that place but also of those located nearby. For example, while a home of low attractiveness might be at little risk of victimization when considered

independently, it may be at a greater risk if it is surrounded by homes that represent good

targets for burglary which might attract the attention of offenders already in the locale.

In this paper, our goal is to examine the potential contributions of the two theoretical

mechanisms in the generation of space-time patterns of burglary victimization using a simple

mathematical model which takes account of the fact that the risk to one home may be partly a

function of the target attractiveness of those located nearby.   Our aim is not to reproduce

observed patterns precisely but rather to test the more general middle range theories (see

Gilbert, 2008) described.   As such, in what follows we do not compare our results to those

observed for a particular area, but to the statistical signatures summarized above.

In what follows, we consider a home's attractiveness to burglary as the statistical rate

of burglary when a burglar is present, as described in Short et al. (2008). We will describe a

modified version of their mathematical model that will govern the dynamics of the

attractiveness of places and burglar movement. Stochastic agent-based simulations will then

be used to generate burglary data that can be checked for qualitative agreement with

observed patterns reported in the existing research literature.

THE MATHEMATICAL MODEL

According to the boost hypothesis, a burglary event causes the risk of further victimization to

be elevated at the burgled house and those nearby. This elevation in risk decays in time and

as distance from the burgled house increases.

We consider a uniform square lattice with one home located at each lattice site *s* and

characterize each home by its attractiveness to burglary, measured by the sum of two

variables: and   , where   is a static component and   is a dynamic component for the time period (t, t+δt), where time is measured in days. The static component   represents the risk from factors associated with places that do not tend to change over a short timescale, and the dynamic component   captures the boost to burglary risk caused by previous burglaries. The total attractiveness of a home at site s for the time period (t, t+δt) is then given by:

$$(1)$$

The total attractiveness   can be thought of as the rate of burglary when a burglar is present. Burglary is assumed to follow a Poisson process with rate parameter   , so that the mean number of burglaries during the time period (t, t+δt) is   . When δt is small, we can assume that only one burglary event can occur per time-step. This means that the probability a burglar at house s commits a burglary during the time period (t, t+δt) can be simplified to

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We update the dynamic attractiveness after each time-step according to a stochastic difference equation. To formulate this equation, we assume that a proportion of the dynamic attractiveness – at a site s moves to each of its four neighbors after each time-step and that the proportion   of the dynamic attractiveness remains at site s. The parameter eta   is used to model the rate of spatial diffusion per unit time; the larger the value of eta, the faster risk diffuses. According to the boost hypothesis, dynamic attractiveness should also fade over time, and hence a multiplicative decay term   is included, where δt is the

time-step size in days and $1/\omega$ is the mean lifetime of dynamic attractiveness. Every time there is a burglary at a site s, dynamic attractiveness increases by ─ , where describes the magnitude of the boost effect per burglary and   is a measure of carrying capacity for dynamic attractiveness. The inclusion of a parameter to model carrying capacity ensures that the attractiveness of each home does not exceed an unrealistic level. Expressed another way, if the risk to a home continues to increase, we assume that there will be a tipping point after which the risk of victimization will decrease (until it is back to the tipping point). Carrying capacity may be thought of as reflecting the effects of a police response to an observed elevation in crime concentration in a neighborhood (or at a specific place), defensive behavior on the part of the residents, or offenders' anticipation of one or both of the two. To model the number of burglaries that occur at a site s, we let   be a random variable for the number of burglaries that occur at site *s* during the time period (t, $t+\delta t$). If there is no burglar at a site s during the time period (t, $t+\delta t$) then   takes a value of zero. Otherwise, it is Poisson distributed with mean   , i.e.   . This leads to the stochastic difference equation:

$$\text{─} \qquad\qquad\qquad \text{─} \qquad\qquad (2)$$

Note that   must be between zero and one to be sensible. The notation $s'\,o\,s$ refers to all the sites adjacent to site *s*, which according to the assumptions in this model, are the four nearest-neighbors on the square lattice (see Figure 1). Equation (2) is similar to Equation (2.5)

in Short et al. (2008)[2] but with the addition of the carrying capacity term and the stochastic random variable   . The carrying capacity term   is important for theoretical reasons but it also limits the sensitivity of the model to changes in parameter values. For example, an increase in   causes the number of burglaries to increase but the carrying capacity term ensures that the total number of burglaries will be within a reasonable bound, and hence that the volume of crime does not go off to infinity.

FIGURE 1 ABOUT HERE

In order to determine where burglaries occur, it is necessary to define the rules that govern the location and movement of burglars on the lattice. These are summarized in Figure 2 and articulated in a little more detail here. We assume that burglars are generated at particular locations by way of a Poisson process with rate parameter that is the sum of a spatially uniform component   and a component dependent on target attractiveness (   ). In other words, we generate burglars on the lattice according to a Poisson process with mean   , where   and   are positive constants.

FIGURE 2 ABOUT HERE

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[2] Short et al. keep the equation deterministic by considering the expected number of burglaries instead of the random variable   .

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We assume that burglars tend to move towards houses with higher attractiveness. To model this, for each time-step and each burglar located at house *s,* we calculate the following movement probabilities

$$3(a)$$

$$3(b)$$

$$3(c)$$

$$3(d)$$

where the subscripts indicate the nearest-neighbor to *s* on the square lattice, and   is the sum of the attractiveness of all the nearest-neighbors to house *s* for time period $(t, t+\delta t)$, i.e.

$$(4)$$

The four movement probabilities sum to one, i.e.

$$(5)$$

We then sample a random number, call it *r*, from the uniform distribution on the interval [0,1] so that the rules of burglar movement are

$$(6a)$$

$$(6b)$$

$$(6c)$$

Else $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ (6d)

Burglars can only move once per time-step, so the size of the time-step δt tells us how fast burglars move from house to house. We have used $\delta t = 1/2000$, meaning that burglars

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move every 43.2 seconds. This gives each burglar the chance to assess the potential target[3].

As a result of the use of a biased random walk, the risk to each home is influenced by its own

attractiveness and that of its neighbors.

Burglars eventually get tired and leave the lattice after f days (the ``fatigue time''). For

simplicity in the current study, we have used f=1/24 (or one hour) for all agents. Other

possibilities, such as varying this parameter across agents, are acknowledged but not

examined here.

It is important to note that this model was designed to examine patterns of crime at

the level of place. It is not unit free and cannot be realistically applied to very different spatial

scales. For example, each site s cannot represent a unit such as an entire county because

burglars cannot evaluate the relative attractiveness of neighboring counties and cannot travel

quickly between them; but they can do so with neighboring houses. As a general point, very

rarely will the same model be valid for all spatial scales. In fact, an entire branch of

mathematical modeling - multi-scale modeling – is devoted to understanding large complex

systems by linking together different models on different spatial scales. A recent example of

this is Shipley and Chapman (2010) where multi-scale modeling is used to link different models

for fluid and drug transport in vascular tumours. The model on the capillary length-scale is

different from the model on the tumour length-scale, and special mathematical techniques

are used to link the two models together. We do not apply such techniques here, but their

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[3] We acknowledge that in the real world burglars will differ in the strategies used and some may spend a
considerable amount of time assessing each potential target (e.g. Rengert and Wasilchick, 2000). However, in
the absence of data which can be used to estimate the relevant distributions, in the current paper we use the
same value across agents.

consideration may be useful in future research concerned with how factors that operate at different spatial scales influence crime at places.

Counting repeats and near-repeats

For n burglaries (where $n>1$) occurring at a house s, each of the possible $n(n-1)/2$ burglary pairs are counted as repeats. For example, consider three burglaries that all occur at house s. The first burglary occurs on day one, the second on day three and the third on day six. In this case, the number of repeat burglaries at house s is three and the times between repeats are two days (between the first and second burglary), three days (between the second and third burglary) and five days (between the first and third burglary).

The alert reader may ask why we do not simply count the $(n-1)$ intervals between sequential events? The reason for this becomes clearer when considering near repeats. In this case, when a burglary occurs close in space and time to more than one other, we would have to generate a clear set of rules for determining which of the previous burglaries should be counted for the purpose of determining the space and time between near-repeats. Should one favor closer distance in determining near-repeats or a shorter time between events? It would be difficult to give an objective answer to this question, so we instead consider every possible burglary pair.

There is also a counting issue with the square lattice. When a burglary occurs, there are more homes $n+1$ doors away than n doors away. For example, when a burglary occurs, there are four homes one door away but eight homes two doors away (diagonal moves are

counted as two doors away in a Von Neumann neighborhood). To account for this, one solution is to divide the number of burglaries that occur n doors away from a previously burgled home by $4n$ for $n \geq 1$. Failing to standardize the results by opportunity in this way would confound interpretation of the results. Accordingly, the vertical axes in all graphs that follow are labeled ``Number of burglaries (adjusted)''.

However, there is also an issue with using a finite spatial domain in the model since places near the boundary do not have as many close neighbors as those further away from it; a spatial edge effect (Boots and Getis, 1988). The influence of the edge effect is a function of two things. Firstly, it will be inversely proportional to the size of the spatial domain. Second, it will be a function of the distance over which effects are measured. For example, if we only considered events that occurred within 2 homes of each other, the edge effect would be much less pronounced than if we examined those for homes 100 doors apart. To correct for this, we derived a general equation for calculating the mean number of opportunities in an N x N grid that are n homes apart[4] which can be used to standardize the results:

$$\qquad \overline{\qquad} \qquad (7)$$

To illustrate the scale of the edge effect (which is quite small) for a grid of 100x100 homes, for homes that are 4 doors apart, rather than standardizing the results by dividing the number of observed events by $4n$ (16), we divide by 15.36. For homes that are 10 doors apart, we divide not by 40 but by 36.07.

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[4] A short note on this formula, and an illustration of the edge effect for the type of analysis presented is available from the authors upon request.

Numerical simulations

All simulations were implemented using Matlab and run on a 100 x 100 house uniform lattice with no-flux boundary conditions on both the burglars and dynamic attractiveness. Having no-flux boundary conditions simply means that there is effectively a wall around the domain through which neither dynamic attractiveness nor burglars can escape. For the results that follow, the parameter values used are shown in Table 1.

Random burglaries

Before looking at the boost and flag models, we examined the results of a model in which burglary is the result of a purely random Poisson process (hereafter the null model). It is important to do so to determine to what extent (if any) observed patterns in the subsequent models are a product of the general form of the model; that is, a Poisson process with burglars that have a finite lifetime.

For each run of this simulation, patterns are simulated over a ten-year virtual time period with static attractiveness   =0.0153 (the same for every *s*)[5]. There is no dynamic component of attractiveness (is set to zero for all *t*). Hence, the starting locations of newly generated burglars follow a uniform distribution across all lattice sites. In each time interval, burglars burgle with probability:

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[5] This generates a rate of approximately two burglaries per 100 homes which, at the time of writing approximates the mean risk for Burglary with entry in the UK (Moley, 2009).

Since   is constant across the domain,   is constant for all space (as well as constant in

time).

Burglars perform a random walk on the lattice until they have been in the lattice for f

days, at which point they are removed. Twenty-five runs of the simulation (over a virtual

period of ten-years) were performed and the mean results inspected. It was clear that for the

null model few homes were re-victimized (none were victimized more than four times) and

there was no evidence of space-time clustering. To illustrate, while an average of 2017

burglaries occurred over the ten year simulated interval, on average only 1.2 repeats occurred

within one week of a previous burglary. Of course, if we increase   the number of (swift)

repeat victimizations would increase, but so too would the total number of burglaries. In

short, for this model the frequency of repeat and near-repeat victimization (and their time-

course) was in line with expectation but not with the patterns observed in real-life burglary

offenses.

Flag models

Having found that the results generated by the null model were in line with expectation we

examined a series of models to examine the flag hypothesis. To do this, we imposed on the

domain a spatially inhomogeneous static component of attractiveness,   . Everything in the

simulation is the same as that used to test the null model except   is no longer constant over

the domain. As before,   is set to zero for the duration of the simulation, and so does not

evolve according to equation (2). This means that as with the null model there is no boost to

attractiveness as a result of a burglary.

In addition to target attractiveness varying across homes, as discussed above the

spatial distribution of target attractiveness may vary in systematic ways (in what follows we

will use the terms risk and target attractiveness interchangeably). Consider that spatial

variation may be completely random with high risk homes neighboring high and low risk ones

with equal likelihood. Alternatively, the variation in risk may be spatially patterned with

homes closest to each other being more likely to experience similar risks than those located

some distance apart. Research (for a recent discussion, see Weisburd, Bruinsma, and

Bernasco, 2008) suggests that crime risk is clustered in space and so complete random

variation seems unlikely. However, even where target attractiveness is auto-correlated,

different spatial configurations are plausible. Thus, rather than examining the role of risk

heterogeneity alone, we examine how three different types of spatial configuration influence

simulated patterns of crime.

The configurations used are only conceptual representations of possible distributions

but their use allows us to examine the influence of risk heterogeneity in a more systematic

way. For the first configuration, we use a stripe pattern, analogous to target attractiveness

varying along streets, with some streets experiencing particularly high risk. In the second, we

model a scenario in which four areas are essentially crime hot spots, with risk being the

greatest at the center of each spot and decaying as a function of the distance from it. In the

final model, the risk allocated to each home is the function of a uniform random number

generator and a smoothing function. In this model then, the risk of victimization varies across

homes but the smoothing function ensures that homes that are near to each other will have

some degree of similarity. Thus, for the latter model the degree of spatial auto-correlation is

considerably weaker and less systematic than for the other two but is still apparent. The

mean values of   over the domain to two significant digits are 0.0087 (SD=0.010) for the

stripes configuration; 0.012 (SD=0.0084) for the spots configuration; and 0.015 (SD=0.0027)

for the final configuration.

INSERT FIGURES 3-5 ABOUT HERE

As before, results were averaged for twenty-five (ten year) simulation runs for each

configuration. Results are shown in Table 2, and Figures 3 to 5. Over the ten-year simulation

period, there were an average of 1930 burglaries for Configuration 1 (stripes), 2083 for

Configuration 2 (spots) and 2036 for Configuration 3 (random and smoothed). Considering the

patterns of repeat victimization proper, it is evident that the patterns vary across the three

configurations.

TABLE 2 ABOUT HERE

With respect to the spatial patterns, for two of the configurations tested, there is

evidence of spatial auto-correlation whereby neighbors of burgled homes are more likely to

be victimized than those located further away. For the third, there was no pattern. There was

no evidence of a temporal pattern for any of the models tested. That is, the results show that

burglary is approximately as likely to be close in space to a previous burglary if that previous

burglary occurred one or two weeks before. The fact that this finding is stable across the

three configurations tested leads us to believe that it is unlikely that risk heterogeneity alone

can explain the combined spatial and temporal patterns seen in real burglary data.

Boost Models

To examine the boost hypothesis, we examine two models. For the first, there is no risk

heterogeneity, instead   was given the constant value of 0.0145 for each lattice site in the

domain, and the simulation is initialized with starting values for   of 0.0025 across all

locations. The results of twenty-five averaged simulation runs over a simulation time period

of ten years are shown in Figure 6. For this model, there were an average of 1992 burglaries

and more repeat victimizations than for the null model. There is also some evidence of

spatial-autocorrelation in the distribution of simulated burglaries. Moreover, we see that the

risk of repeat and near-repeat victimization decays from the first week after a burglary event

to the second. Thus, it appears that a very simple implementation of the boost hypothesis

generates spatially and temporally correlated simulated burglary data under the assumptions

of the model. However, the effect is subtle.

INSERT FIGURE 6 ABOUT HERE

For the second model, we model the effects of both risk heterogeneity and event dependency. For this model, we use the spots configuration with a mean value of 0.0106 (SD=0.0077) for   . This generates an average of 2109 burglary events per simulation. Figure 7 shows that for this model the pattern of repeat victimization and spatial auto-correlation is accentuated and, that the space-time pattern generated provides better qualitative agreement with patterns observed in real burglary data than the boost model for which risk is homogenous across homes.

INSERT FIGURE 7 ABOUT HERE

Parameter values other than those shown in Table 1 could and were used, but the results generated were generally consistent with those presented above. Where alternative parameter values were used for the flag models, it was evident that none of those tested generated events that clustered in space *and* time. With respect to the boost models, increasing the values of the parameters   and   generated results which approached those of the flag models but this is, of course, to be expected.

DISCUSSION

Theories of spatial crime patterns have developed considerably over the last three decades with those factors that influence crime placement being explored at ever more precise levels of resolution (i.e. places) both theoretically and empirically. However, while the importance of

time is implicit in most theories, and whilst research has considered how crime patterns vary by time of day, with a few exceptions (e.g. Braga et al., 2010; Weisburd 2004; Spelman, 1994) relatively less attention has been given to how crime patterns evolve over time, where time refers to days, weeks, or months. This is evidenced in the types of statistical analysis typically employed in research studies. For example, those with an interest in spatial patterns tend to use statistical models that focus on spatial distributions of crime, analyzing data aggregated for long intervals of time. Those with an interest in temporal patterns instead use a variety of time-series methods, but rarely are the two types of analysis integrated. Thus, for one type of analysis, time is typically ignored whereas for the other space is neglected. Much may be learned by considering the two dimensions together.

In addition to the focus on time and space, it also is important to focus on the finest level of resolution possible, in our analyses—places rather than spaces. In the present analysis, we have focused on patterns of crime at the level of the individual household but also consider how variation in risk in the surrounding space might influence patterns of victimization.

In particular, our aim was to consider space-time patterns of burglary and to examine two theoretical models that have been proposed to explain them. The use of mathematical models allowed us to formally specify and explore models outcomes using stochastic simulations. In the introduction to this paper we discussed the possibility that observed space-time patterns of crime may be explained by a statistical artifact that occurs when results are aggregated for populations with very different risks (the flag account). However, the results of a series of simulations suggest that such models (as specified here) were insufficient

and did not generate the types of pattern that are observed in real world data. Thus, while the role of risk heterogeneity is undisputed in the generation of spatial patterns of crime, it seems unlikely that the very distinct patterns of space-time clustering that have so far proven to be ubiquitous across studies can be explained in terms of the flag explanation alone.

In contrast to the flag hypothesis, our results suggest that the boost account may offer a plausible explanation for why crime clusters in space *and* time. Of course, in reality, and as shown by our combined model, both explanations are likely to have a part to play. This seems sensible given that decades of research (e.g. Rengert and Wasilchick, 2000) demonstrate the role of target attractiveness in offender decision making and, that an offender has to first select a home (and they must do so using some selection criteria) before the risk to that location can be boosted. One of the challenges for future research will be to try to quantify what the relative contributions of these two mechanisms are and, if the balance between them is time-stable, and whether it varies across space (and space-time), and offenders.

However, it is important to acknowledge that while the combined model did generate the qualitative patterns we sought to simulate, this does not demonstrate that it is necessary or that it is the only model that could generate them (see Eck and Liu, 2008a). A range of alternative models may exist and these may generate outcomes that are still more consistent with those of interest. Such models may involve subtle variations, such as using a multiplicative boost function (see Johnson, 2008), or they may reflect very different theoretical perspectives. Without testing different models, it is not possible to evaluate whether the model implemented does explain observed patterns just that it remains a candidate explanation. Considered in concert with the cumulative findings of research that

has used very different methods, our results add further credibility to the boost hypothesis, but they do not and cannot show that it is necessary to generate the patterns of interest.

Moreover, the boost hypothesis would benefit from further attention, theoretical and empirical. In the current research and that presented elsewhere (e.g. Johnson et al., 2009), the assumption is that when a home is burgled the risk to that home and those nearby is temporary elevated. And, that the reason for this is that the offender who committed the prior offense(s) will return to those places for which the rewards outweigh the associated risk and effort expended. This represents a foraging model (Johnson and Bowers, 2004; Johnson et al., 2009; Bernasco, 2008) and assumes that the offender is a rational agent (Cornish and Clarke, 1986). However, while analyses of crimes detected by the police certainly suggest that (near) repeats are typically the work of returning offenders (Bernasco, 2008; Johnson et al., 2009) what remains unclear is precisely why offenders decide to return to some places but not others, and what types of offenders operate in this way. Considering the first point, it is certainly not the case that all homes are repeatedly victimized or that near repeats always follow a previous offense. Thus, determining whether there are regularities in the types of places that are most likely to encourage space-time clustering would be a logical next step. Such conditions might include particular characteristics of victimized homes or those on a block face, or other localized features of the urban backcloth. For example, near repeats may be more (or less) likely on streets segments which offer good visibility (Bowers and Johnson, 2005), or on particular types of street segment (e.g. arterial or local roads). Some time ago, such research would have been unthinkable but with the increasing availability of data at such

small units of analysis and the proliferation of Geographic Information Systems it is now a possibility.

Considering the offender as forager hypothesis, it is unlikely that all offenders adopt foraging strategies, or that they would do so all of the time. Thus, exploring the characteristics of those offenders who do adopt them and the extent to which this is their preferred strategy will be important. It may be the case that for many offenders, the use of foraging strategies is episodic or even random whereas for others it is the dominant strategy employed. Drawing upon the ecology literature (e.g. Pyke, 1984), for which theories of foraging are well established, is likely to prove valuable. The types of questions to be explored may be addressed using a variety of research methods including mathematical models, offender interviews (see Summers et al., 2009) and the analysis of crimes detected by the police. In fact, it is unlikely that an accurate picture will be reached through the use of one method alone and so the use of different methods is encouraged.

In the current paper, we have focused on the crime of burglary. However, the available evidence suggests that the type of space-time clustering we sought to explain is evident for other types of crime including vehicle related offenses (Johnson et al., 2009), robbery and assault (Grubesic and Mack, 2008), gun crime (Ratcliffe and Rengert, 2008), and even insurgent activity in Iraq (Townsley et al., 2008; Johnson and Braithwaite, 2009). Thus, further research might usefully investigate the role of time-stable and dynamic factors in the generation of these crime types. One challenge for such research will involve the conceptualization of the appropriate level of place at which time stable and dynamic factors might be modeled.

To conclude, analyses conducted at the micro-level using a range of different methods suggest that there is a flux to crime that cannot be explained in terms of time-stable variation in risk across places alone, but that time-stable do factors have a part to play. One challenge for research concerned with spatial patterns of crime at the micro-level then is to try to not only better understand how features of the environment influence crime risk but how stable such factors are and at what levels (place or space) influences are exerted and experienced.

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Table 1 Parameter values for the mathematical model

Parameter	Value
	1/2000
	1/5000
	0.18
	0.18
	1/42
	1/100
	5
f	1/24

Table 2 Homes victimized one to *n* times for each model

Number of times victimized (*n*)	Mean number of homes burgled *n* times (2 d.p)					
	Null	**Spots**	**Stripes**	**Smoothed**	**Boost**	**Spots+Boost**
1	1645.16	851.52	639.00	1607.52	1566.72	760.16
2	166.08	92.44	283.04	186.72	184.72	95.68
3	12.24	38.92	127.64	15.84	16.24	39.28
4	0.64	28.12	50.52	1.76	1.68	23.64
5	0	20.08	17.60	0.16	0.08	20.80
6	0	18.28	6.44	0	0	17.88
7	0	14.32	1.56	0	0	13.32
8	0	11.44	0.28	0	0	10.72
9	0	10.56	0.04	0	0	9.80
10	0	7.56	0	0	0	8.72

Figure 1 Four nearest-neighbors on the square lattice (Von Neumann neighborhood)
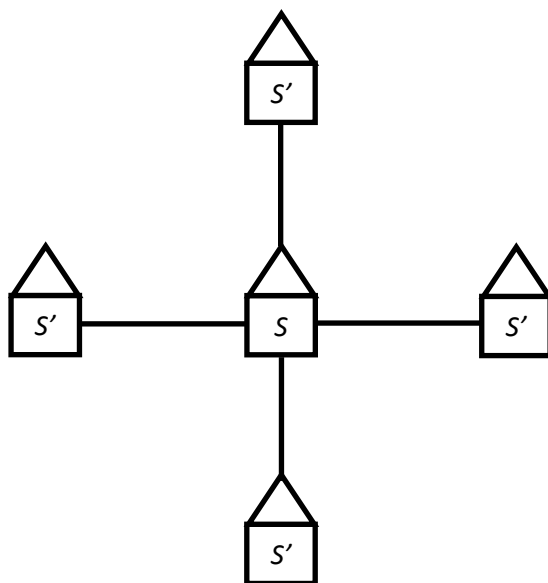
Figure 2 Overview of the algorithm used in the simulation

```
┌─────────────────────────────────────────────────────────────────────────┐
│                                                                           │
│   ┌──────────────────────────┐                                            │
│   │ Initialize burglar        │                                           │
│   │ locations and             │                                           │
│   │ home attractiveness       │                                           │
│   └──────────────────────────┘                                            │
│                 │                                                          │
│                 ▼                           ┌────────────────────────┐     │
│   ┌──────────────────────────┐              │ Move burglars to        │    │
│   │ Check if burglars commit  │──────────▶  │ adjacent homes (biased  │    │
│   │ a burglary                │              │ toward high    )        │    │
│   └──────────────────────────┘              └────────────────────────┘     │
│                 ▲                                        │                  │
│          t → t+δt                                        ▼                  │
│                 │                            ┌────────────────────┐         │
│                 │                            │      Update         │        │
│   ┌──────────────────────────┐              └────────────────────┘         │
│   │ Generate new active       │                         │                  │
│   │ burglars                  │◀─────────── ┌────────────────────────┐      │
│   └──────────────────────────┘              │ Remove fatigued         │     │
│                                             │ burglars                │     │
│                                             └────────────────────────┘      │
│                                                                           │
└─────────────────────────────────────────────────────────────────────────┘
```
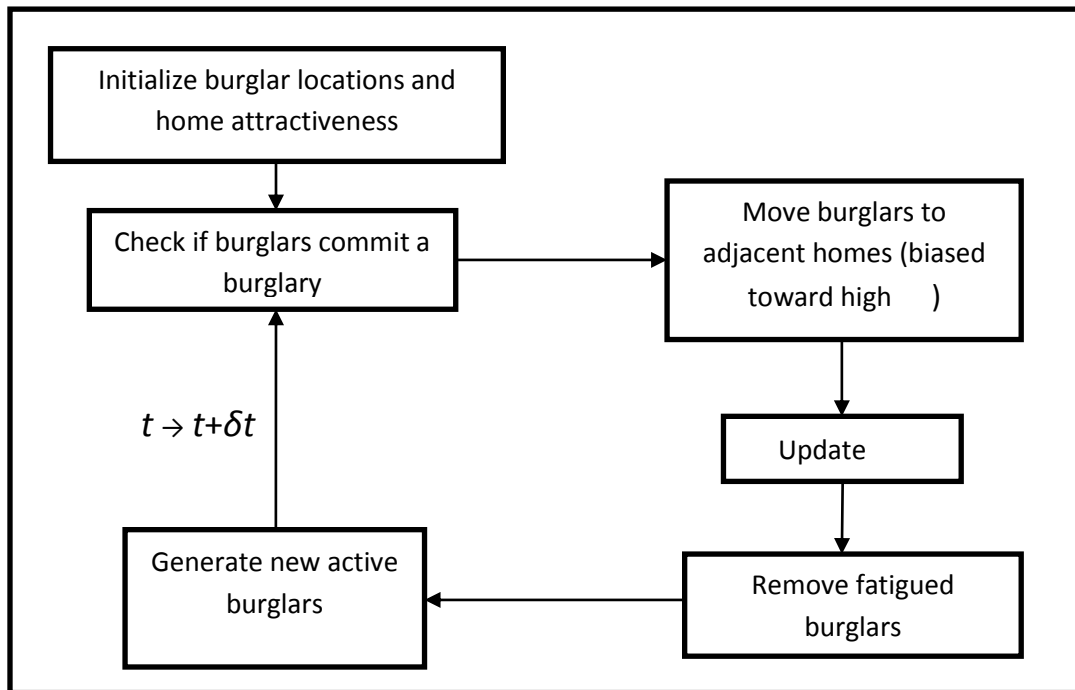
$t \rightarrow t+\delta t$

Figure 3 Results of 25 simulations for the model with heterogeneous risks across homes (spots configuration; error bars show minimum and maximum values)
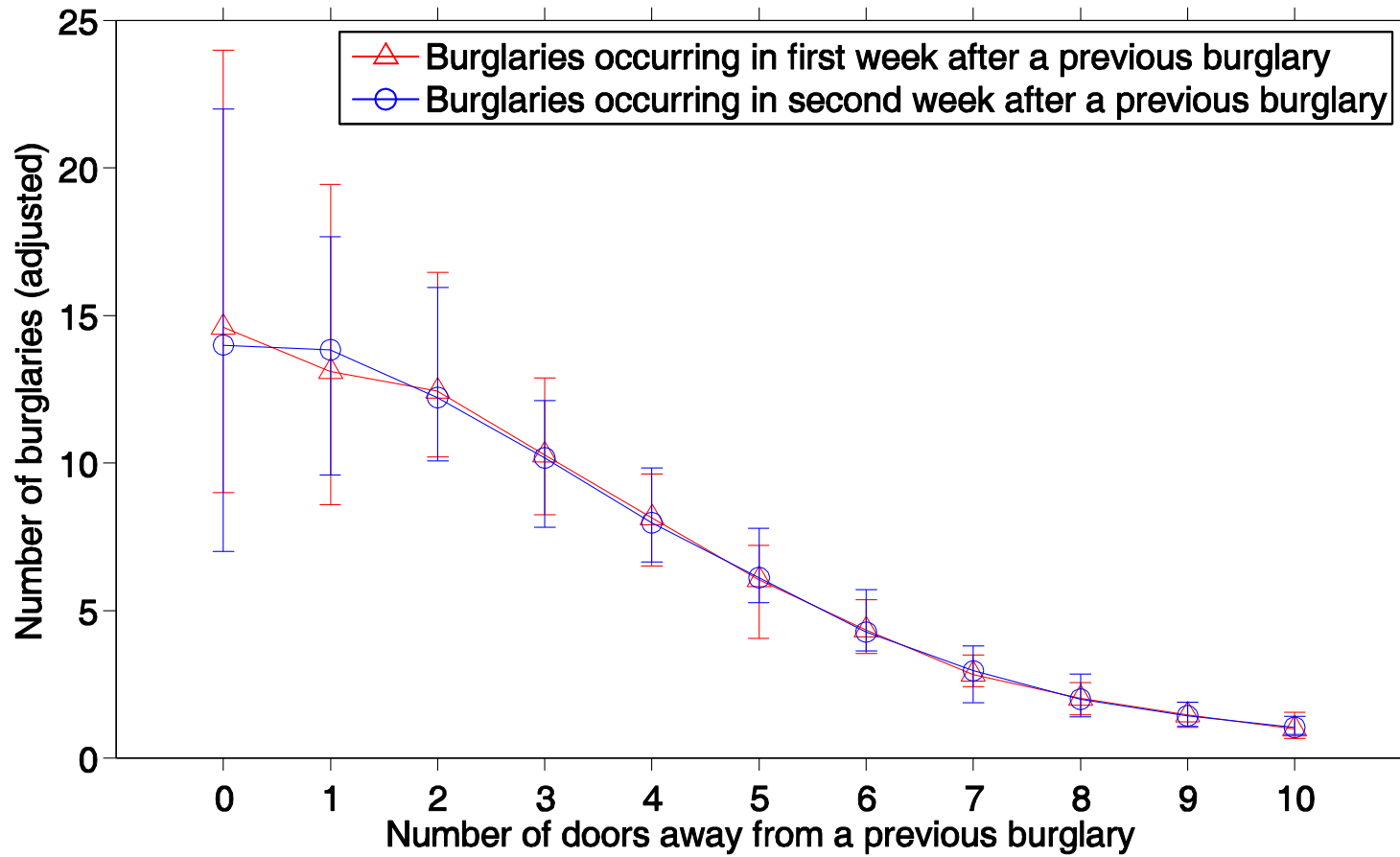
Figure 4 Results of 25 simulations for the model with heterogeneous risks across homes (stripe configuration; error bars show minimum and maximum values)
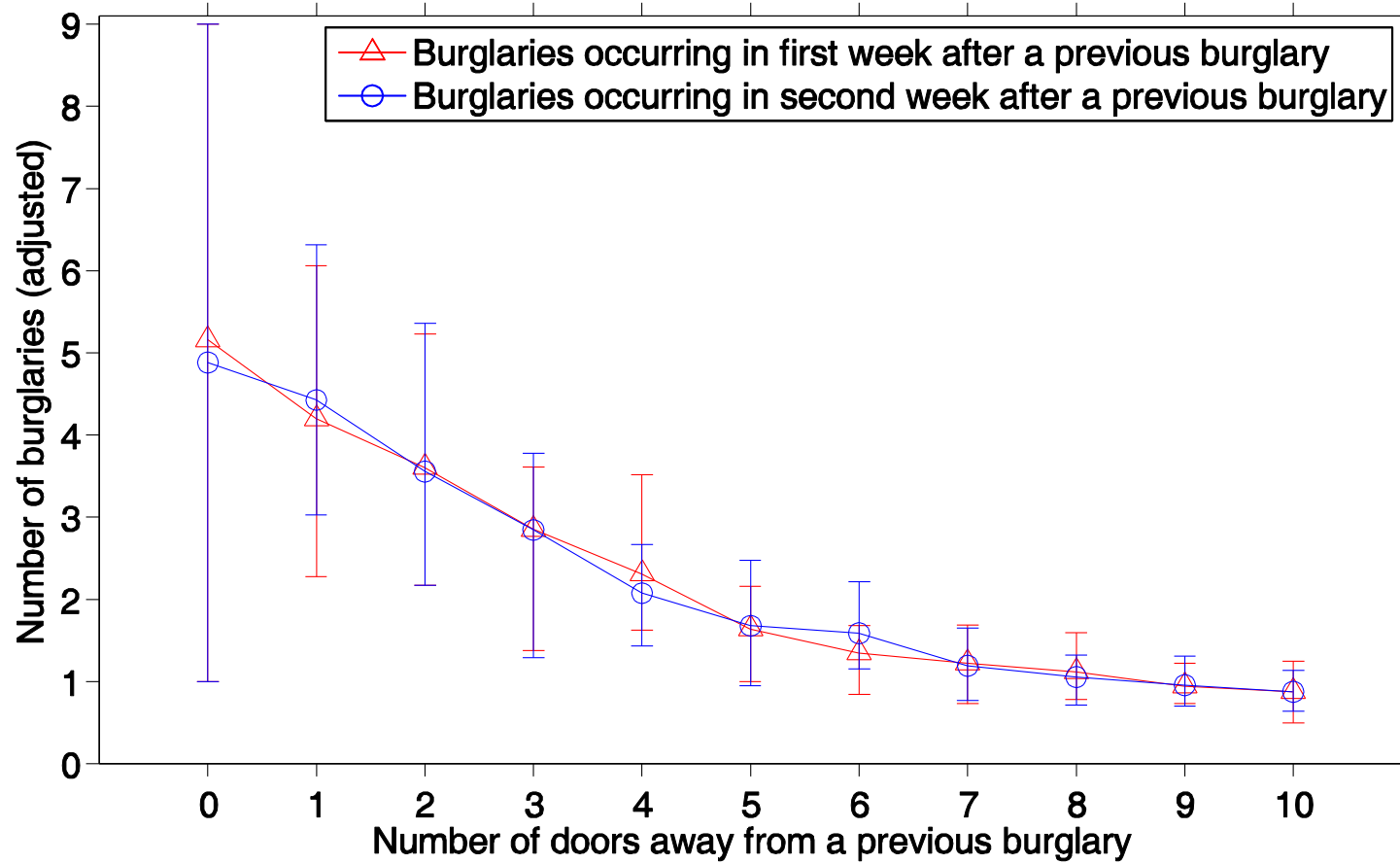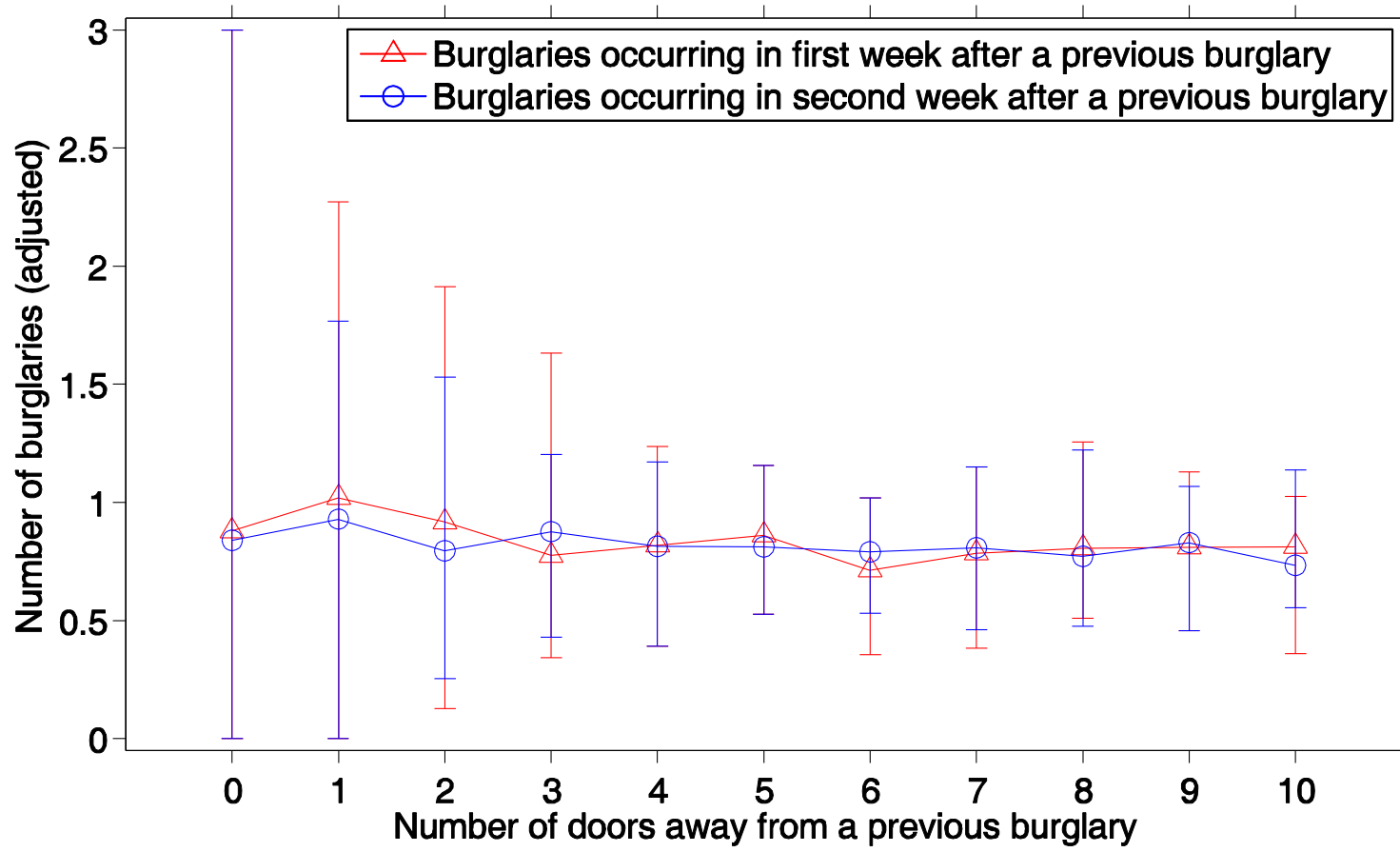
Figure 5 Results of 25 simulations for the model with heterogeneous risks across homes (smoothed configuration; error bars show minimum and maximum values)

Figure 6 Results of 25 simulations for the boost model with homogeneous risks across homes (error bars show minimum and maximum values)
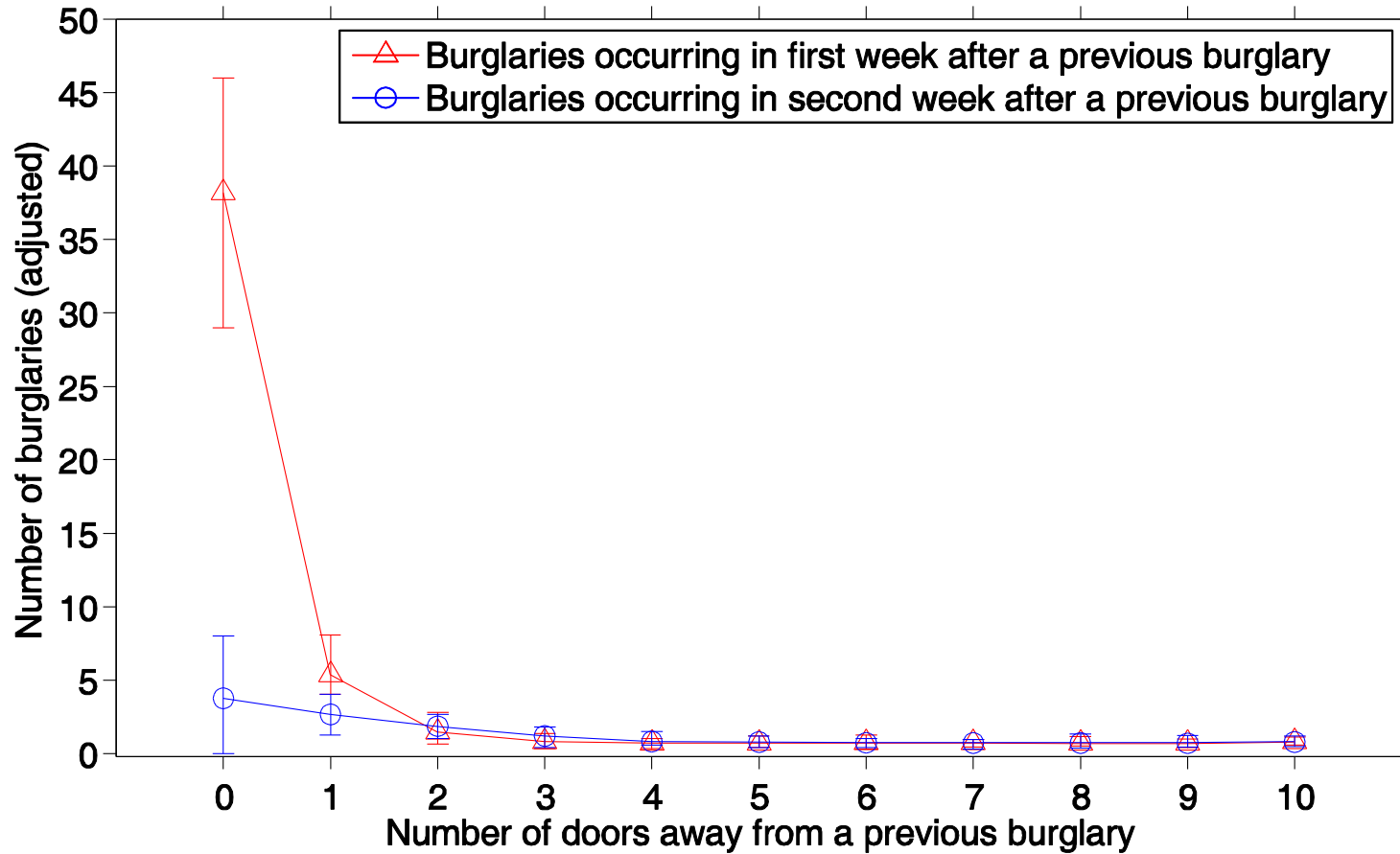
Figure 7 Results of 25 simulations for the boost model with heterogeneous risks across homes (spots configuration; error bars show minimum and maximum values)