

STREET NETWORK STRUCTURE AND CRIME RISK: AN AGENT-BASED INVESTIGATION OF THE ENCOUNTER AND ENCLOSURE HYPOTHESES*

DANIEL BIRKS¹ and TOBY DAVIES²

¹Griffith Criminology Institute, Griffith University

²Department of Security and Crime Science, University College London

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Street networks shape day-to-day activities in complex ways, dictating where, when, and in what contexts potential victims, offenders, and crime preventers interact with one another. Identifying generalizable principles of such influence offers considerable utility to theorists, policy makers, and practitioners. Unfortunately, key difficulties associated with the observation of these interactions, and control of the settings within which they take place, limit traditional empirical approaches that aim to uncover mechanisms linking street network structure with crime risk. By drawing on parallel advances in the formal analyses of street networks and the computational modeling of crime events interactions, we present a theoretically informed and empirically validated agent-based model of residential burglary that permits investigation of the relationship between street network structure and crime commission and prevention through guardianship. Through the use of this model, we explore the validity of competing theoretical accounts of street network permeability and crime risk—the encounter (eyes on the street) and enclosure (defensible space) hypotheses. The results of our analyses provide support for both hypotheses, but in doing so, they reveal that the relationship between street network permeability and crime is likely nonlinear. We discuss the ramifications of these findings for both criminological theory and crime prevention practice.

One of the central principles of environmental criminology is the idea that crime can be understood in terms of the interaction between the key actors involved in criminal events: offenders, victims, and preventers (Brantingham and Brantingham, 1981). From a spatial perspective, one of the most immediate corollaries of this is that the distribution of crime should be influenced by urban morphology: The structure of the built environment determines the places people visit in the course of their day-to-day activities, the routes they take in moving between them, and the interactions that they experience as they do so. Motivated by this, a substantial volume of research has been aimed at examining spatial

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Direct correspondence to Daniel Birks, Griffith Criminology Institute, Griffith University, 176 Messines Ridge Road, Room 3.01N, Technology (M10), Mt Gravatt Queensland 4122, Australia (e-mail: d.birks@griffith.edu.au).

theories of crime by exploring the existence and form of such relationships, with particular emphasis on the role the street network plays in shaping activity. The results of this research indicate that not only does the concentration of crime display pronounced regularities at the network level (Weisburd, 2015), but also that its variation can be reconciled with the structure of the network (e.g., Davies and Johnson, 2015).

Despite the apparent relationship between network configuration and crime, however, the mechanism by which activity patterns give rise to crime is not well understood. Although environmental theories—most notably Brantingham and Brantingham's geometric (Patricia Brantingham and Paul Brantingham, 1981) and pattern (Paul Brantingham and Patricia Brantingham, 1993) theories of crime—provide a compelling rationale from the perspective of offender target awareness, most extant empirical evidence is correlational in nature. Furthermore, theoretical perspectives concerned with the influence of other elements in the crime event are much less clear cut. Most notably, the role of guardianship—the third element of the “crime triangle”—is the subject of several competing discourses (Jacobs, 1961; Newman, 1972), with differing implications for the relationship between movement patterns and crime. This tension is typified by the disparity between the “encounter” and “enclosure” principles of urban design.

The encounter and enclosure hypotheses are both concerned with the relationship between movement patterns and crime, but they differ in their assessment of the relative contributions of competing mechanisms. Put simply, in the encounter hypothesis, it is asserted that the movement of people through places confers a guardianship effect, and that places that experience greater use will therefore be safer. In contrast, in the enclosure hypothesis, it is suggested that such a guardianship effect is overstated, and in fact, it is outweighed by the increased exposure to offenders that frequent use implies; it therefore predicts that less readily used—that is, more “enclosed”—places will be safer. As the extent to which places are used is determined to a large extent (although not completely) by their position within the wider urban configuration, the street network is of clear relevance in assessing the relative merits of these arguments.

Evidently, therefore, understanding the way in which the street network shapes the interactions that lead to (or, indeed, prevent) crime is of substantial potential significance for theory. Investigating this issue empirically, however, is highly challenging: Although correlational studies can reveal associations, the identification of causal mechanisms is hindered by several significant obstacles. Some of these are logistical: It is not feasible, for example, to manipulate the structure of real-world street networks systematically to the extent that would be necessary to enable causal inferences in an experimental setting. There are, however, more fundamental barriers to traditional approaches. The inherent difficulty of observing behaviors of interest (e.g., individual movements) means that it typically cannot be established with certainty that a hypothesized mechanism is responsible for an observed spatial pattern (O'Sullivan, 2004). This can be seen most starkly when considering the role of guardianship, which is a phenomenon defined by the absence, rather than by the presence, of an event: Establishing a counterfactual in such cases is highly problematic.

In this article, we aim to gain new insights into the encounter and enclosure hypotheses by combining two recent methodological advances from the field of environmental criminology: 1) a formal approach to network analysis that has recently been applied in empirical studies of crime and 2) a computational model of offender behavior that has been shown to reproduce many features of real-world offending. Through the use of these

techniques, we carry out a series of simulated experiments exploring the relationship between street network structure, individual activity patterns, and several theoretical propositions describing crime commission and guardianship, with the aim of addressing fundamental questions that are mostly inaccessible to traditional empirical techniques. In doing so, our primary aim is to examine the theoretical causal sufficiency of the encounter and enclosure hypotheses by investigating the extent to, and means by, which guardianship effects, as shaped by the street network, influence the volume and distribution of property crime, in this case—mirroring much of the extant empirical research—focusing on residential burglary. In building toward this, we also explore the relationship between network structure and offending more generally, seeking insight into the behavioral mechanisms that offer a causally explicit account of crime concentration at the street segment level.

The remainder of the article is structured as follows. We begin by describing extant theoretical and empirical research that is concerned with the relationship between street network structure and crime risk. We then outline the computational agent-based modeling approach we leverage to increase this understanding. Subsequently, we describe our scientific instrument: an agent-based model of residential burglary and its explicit theoretical underpinnings. We integrate these sections as a means of specifying both the model itself and the decisions made in its construction. After describing our instrument, we present several tests of its validity before proceeding to set out a series of simulation experiments in which it is used to address our primary research question. Subsequently, we present our findings and discuss their ramifications for both the theories that underlie our model and crime prevention interventions that draw on them. We conclude by discussing several potential weaknesses of our approach and by setting out how, in continuing our research in this area, we aim to address them.

THEORETICAL BACKGROUND

Much of the theory concerned with the relationship between environment and crime is grounded in the basic framework provided by routine activity theory (Cohen and Felson, 1979). This sets out the fundamental observation that, for a direct-contact crime to occur, three elements must coincide in time and space: a suitable target, a motivated offender, and the absence of a capable guardian. From this assertion, it follows that the overall spatiotemporal characteristics of crime can be understood in terms of the movements and behaviors of these three elements.

As the primary substrate for routine human activities, the street network plays a crucial role in determining where the convergences of these elements occur. In many cases, potential targets are located, and thus encountered by offenders, at some position on the network: This is particularly apparent for crimes against fixed targets, such as burglary, but also it applies to interpersonal crimes that take place in the urban environment. In addition, offenders will typically use the street network when traveling to and from offenses. Importantly, these principles apply not only to the movements and presence of offenders but also to those of citizens in general, thereby influencing the supply of potential guardians at particular places. In all these cases, the locations and movements of the key actors involved in the crime event are constrained to a large extent by the structure of the street network.

The idea that the street network is a crucial structure in understanding the role of environment in crime is at the heart of crime pattern theory (Paul Brantingham and Patricia Brantingham, 1993; Brantingham, Brantingham, and Andresen, 2017). Pattern theory asserts that offenders typically choose to offend against targets they encounter during noncriminal activities. This is conceptualized as a process by which offenders build up “awareness spaces” of familiarity in the course of their daily lives; according to the theory, it is where these spaces intersect with attractive criminal opportunities that offenders are most likely to commit crime. When framed in this way, understanding the distribution of crime is equivalent to understanding where targets are most likely to be encountered by potential offenders. Where the population of potential offenders is large, this involves understanding which places are likely to feature most prominently in the aggregated awareness spaces of the population as a whole.

As awareness spaces are built up in the course of routine activities, their shape and extent are governed by the movement patterns that are generated during these activities. In pattern theory, it is suggested that these activity spaces are structured around just a few key “activity nodes” (e.g., homes, workplaces, or entertainment facilities) that act as anchors for movement (Golledge and Spector, 1978). It is around these nodes, and on the routes between them, that awareness is thought to be centered, and it is in places where they overlap for many people that elevated levels of crime may be observed.

Because travel plays such a key role in the formation of awareness spaces, it is natural to expect that the street network should exert an influence. In particular, the reasoning of pattern theory can be refined to reflect this: Rather than thinking of awareness spaces as amorphous forms, they can be more concretely specified in terms of the routes and streets that they comprise. When framed in these terms, it is along popular or easily accessible streets that the greatest exposure to potential victimization is to be anticipated (if all else is equal). As these characteristics are determined to some extent by the position of streets within their wider network, this invites analysis of the relationship between the structural properties of streets and their criminal character.

Although the range of structural properties that can be considered for networks is large, a few are particularly pertinent to the arguments outlined earlier. The concepts of “permeability” and “connectivity” are frequently invoked in discussions of crime and urban form (Patricia Brantingham and Paul Brantingham, 1993; Johnson and Bowers, 2010), and even though neither are typically defined in formal terms, both refer to the ease and regularity with which places can be accessed. Such concepts can be considered at the global or local level: Street networks are permeable if they are readily accessible or if their design encourages through movement (White, 1990), and individual streets are highly connected if they carry high volumes of traffic (Davies and Johnson, 2015). From both perspectives, the basic hypothesis is the same: *Greater connectivity implies greater exposure, both to cities as a whole and to particular locations within them.*

ENCOUNTER AND ENCLOSURE

Although the argument that highly connected streets will be subject to greater offender awareness is a compelling one, the question of whether this will be manifested in higher levels of crime is, however, far from straightforward. This is because the reasoning presented so far concerns only two of the elements for crime—the target and the offender—while failing to account for the effect of guardianship. The implications in this regard are

much less clear, and a tension exists between two alternative views, known commonly as the “encounter” and “enclosure” hypotheses.

The encounter hypothesis is based on the observation that a large proportion of potential guardians (i.e., the public at large) will be subject to the same movement principles as offenders: That is, they will tend to flow along more “central” streets (in the sense of their role in movement patterns). Thus, the supply of potential guardians will be greatest in such places, and they will be more likely to be present when opportunities for crime arise. If this provides a sufficient deterrent effect, it is argued, then more connected streets should be safer: Jacobs’s (1961) notion of natural surveillance through “eyes on the street” captures this idea succinctly. If this is the case, then networks that encourage through flow, and therefore encounters, are least susceptible to crime.

An alternative perspective is provided in the enclosure hypothesis, in which it is argued that the deterrent effect on which the encounter hypothesis relies is overstated. The rationale for this concerns the mostly transient nature of traffic on highly connected streets: Passers-by may be inattentive, and their presence may even provide cover to outsiders. If the level of deterrence is not sufficient to counteract the increased exposure in such places, then they will experience higher risk. According to this argument, crime will be prevented when places are “enclosed”: reducing through traffic of potential offenders, limiting their awareness of viable criminal opportunities, and promoting locals’ abilities to recognize and respond to outsiders and potential wrongdoers, which is in line with the notion of “defensible space” proposed by Newman (1972).

The encounter and enclosure arguments have diverging implications for the expected distribution of crime across street networks. As such, they represent testable hypotheses: Empirical examination of patterns at the network level can provide support or otherwise for each argument (and thus offer insight into the nature of guardianship in urban areas). This can be done by comparing observed patterns of crime against measures of network structure that reflect the behavioral principles outlined earlier.

STREET NETWORK STRUCTURE AND CRIME RISK

The relationship between network structure and crime risk has been examined in several empirical studies. Most of these have been focused on residential burglary, which is analytically convenient and constitutes a natural application of crime pattern theory. The studies do vary considerably, however, in their measurement of network properties, with each capturing a subtly different aspect of network structure.

The earliest example of network analysis within criminology is the study of Bevis and Nutter (1977), in which residential burglary was examined in Minneapolis, Minnesota. At the local level, it was found that more connected block types (through streets, as opposed to cul-de-sacs, for example) experienced greater levels of crime. In addition, the study also included area-level analysis, in which the street network density in each census tract (defined as the ratio of segments to junctions) was measured. This metric, which corresponds to a general notion of permeability, was found to be positively associated with burglary risk.

White (1990) also studied residential burglary at the area level, by instead examining neighborhoods in Massachusetts from the perspective of accessibility. In particular, the number of direct connections to a major road was measured for each area, with this providing an indication of accessibility to external traffic. Again, this was found to be

positively associated with risk, suggesting that these connections had the effect of exposing those areas to offenders. Several more recent studies have been focused on the street segment as a primary unit of analysis. Beavon, Brantingham, and Brantingham (1994), for example, used the number of neighboring streets as a measure of each segment's connectivity in Ridge Meadows, Canada. This was again found to be positively associated with burglary risk, after controlling for other demographic factors.

Crime has also been studied through use of an approach known as "space syntax," which seeks to quantify urban form by building networks based on lines of sight (see Hillier, 1996). Findings from London and Australia conflict somewhat with those from earlier research, with less connected streets found to be safer (Hillier, 2004). Notably, however, this relationship was found to be reversed when additional permeability was added in the form of alleys and other potential escape routes. The work of Johnson and Bowers (2010) also examined street segments, with their number of immediate neighbors and administrative classification used as measures of connectivity. Through the use of a nested statistical approach, they also found that higher connectivity was associated with greater burglary risk.

A particular challenge when studying the street network concerns how to measure the structure of networks in a way that reflects their use. Many of the measures typically employed suffer from several shortcomings: Either they offer little granularity (as with street classification) or relate obliquely to true patterns of use (e.g., number of connections). Davies and Johnson (2015) sought to address this by applying terminology and techniques from the mathematical field of graph theory. They considered the network measure "betweenness," which estimates how frequently street segments will be used in travel through the network. This was shown to be positively associated with burglary risk in Birmingham, United Kingdom, suggesting that exposure to movement flows is indeed associated with victimization. In addition, a variant of betweenness has also been shown to predict offender target choice at the street segment level (Frith, Johnson, and Fry, 2017).

It is clear from the literature that, for the crime of residential burglary at least, street connectivity is positively associated with crime risk. Nevertheless, several questions remain unanswered. Significantly, the correlational nature of previous studies dictates that the underlying behavioral hypotheses have not been rigorously tested; possible confounding factors that vary systematically across street types cannot yet be ruled out (Davies and Johnson, 2015). Furthermore, the contribution of guardianship is not known: These patterns may arise because of, or despite, variation in the presence of guardians. To investigate the existence and form of a causal relationship between centrality and crime, it is necessary to examine how variations in network structure influence the distribution of crime while controlling for all other potential sources of variation.

Ideally, issues of causality such as this are investigated by using an experimental approach, in which the hypothesized cause is manipulated and the effect observed. In the present context, however, this is clearly not feasible because it is not possible to manipulate the structure of real-world street networks systematically. This fact alone precludes traditional experimentation and indicates that a new approach is required.

By drawing on recent advances in the study of individual-level crime event mechanisms, in this study, we employ a computational modeling approach that allows us to explore the implications of behavioral theories in a synthetic environment that confers absolute observation and manipulation (Townsend and Birks, 2008). In doing so, our goal is to

construct a computational laboratory, which encodes individual-level behavioral theory, and through which the impact of varying street configurations on crime and guardianship events can be systematically explored, free from logistical constraints that have inhibited empirical investigation in this significant area of enquiry. This approach allows us to examine the theoretical causal sufficiency of the theories encoded in the model, with the hope of guiding subsequent theoretical advancement and, where appropriate, complementary empirical efforts.

COMPUTATIONAL CRIMINOLOGY AND AGENT-BASED MODELING

Recently, the results of several studies have demonstrated how agent-based modeling (ABM) can provide insight into the complex systems that produce crime events and the theoretical models we use to describe them (e.g., Birks, Townsley, and Stewart, 2012; Groff, 2007, Weisburd et al., 2017). ABM allows researchers to create artificial societies and populate them with simulated actors—referred to as agents—whose characteristics and behaviors are derived from theoretical propositions, empirical insight, or both. Through analysis of the interactions of these synthetic populations, and the aggregate outcomes that emerge as a result, ABM can be used to explore the causal links between proposed individual behavior and aggregate societal outcomes (Epstein and Axtell, 1996). This task is mostly inaccessible to empirical approaches, as a result of a host of constraints associated with observing, manipulating, and characterizing human systems (Birks, Townsley, and Stewart, 2014; Bonabeau, 2002).

Through the construction of models that formalize key propositions of criminological theory, the use of ABM provides the means to assess theoretical causal sufficiency: the degree to which a proposed construct is capable of generating outcome patterns compatible with reality (Birks, Townsley, and Stewart, 2012). Where competing accounts exist, ABM can thus be used to conduct a form of “theoretical” experimentation, where system components are systematically manipulated to reflect differing configurations of assumptions, and the causal sufficiency of each is assessed. In this way, the use of ABM enables *in silico* social science, where confidence in theoretical accounts can be strengthened or weakened through simulation (Epstein, 1999).

To illustrate, Birks, Townsley, and Stewart (2012) described an ABM of residential burglary in which an abstract urban environment is inhabited by offender agents whose movement, target selection, and learning behaviors are derived from key propositions of routine activity theory, the rational choice perspective, and crime pattern theory. By performing a series of controlled experiments, the authors demonstrated that patterns of simulated crime exhibit both individual- and aggregate-level offending patterns that are congruent with a range of empirical signatures of residential burglary, which in turn strengthened confidence in the validity of theories enacted within the model.

Where a plausible model of crime events is constructed—that is, one that produces a range of outcome regularities consistent with those observed in empirical study (Berk, 2008)—ABM can also be used to explore the potential impacts of changes to actor behaviors or environmental configurations that might ultimately be manipulated in real-world settings. In this way, the use of ABM offers a platform to prototype potential crime prevention intervention prior to costly empirical study (Birks, 2017; Groff and Birks, 2008; Weisburd et al., 2017).

Here, for those unfamiliar with the approach, it is important to note that although ABM is capable of ascertaining theoretical sufficiency, it cannot be used to identify the necessity of a proposed explanation. Neither can it replace empirical study: The outputs of ABM represent only the logical consequences of the assumptions upon which the models are grounded. Nevertheless, when triangulated with theoretical and empirical efforts, ABM constitutes a new and insightful approach to hypothesis testing and theory building. It is under this rationale that we now proceed and indeed that our results should subsequently be interpreted.

RESEARCH AIM

In this article, we seek to address two key research questions concerning the relationship between urban morphology and crime risk:

- How does street network structure influence the distribution of crime risk?
- To what extent are the encounter and enclosure hypotheses supported by the spatial variation in guardianship effects?

The first of these questions acts as a foundation for the latter: By determining how and where street morphologies influence the interactions that lead to crime occur, we establish a baseline against which we can quantify the viability of guardianship effects proposed by theory.

To investigate these issues, we build on ABM published in Birks, Townsley, and Stewart (2012, 2014) and employ a model of residential burglary in a stylized urban environment that is both theoretically and empirically informed. In line with previous research, we validate this model by assessing its ability to generate multiple distinct patterns of crime consistently observed in empirical studies of residential burglary. After having done so, we examine our primary research questions by carrying out a series of controlled simulation experiments that systematically manipulate the simulated street network structure in ways that would be infeasible through traditional empirical enquiry.

By carrying out our analysis in a generalized framework—rather than attempting to replicate any particular setting—we aim to shed light on the fundamental relationships proposed by competing theoretical accounts that link street network structure, activity patterns, crime risk, and guardianship. Consequently, it is important to note that although several factors undoubtedly influence burglary risk, such as investment in security, home occupancy, and so on, here we seek only to provide insight into the underlying dynamics that link network permeability and crime risk as put forward by the encounter and enclosure hypotheses. Indeed, it is this accumulation of potentially explanatory factors that obfuscate our understanding via empirical study and, thus, motivates application of the model, which in turn enables a separation of such factors wholly untenable in traditional research. To this end, we now describe the primary scientific instrument associated with our study: a computational ABM of residential burglary.

METHOD

THEORETICAL AND COMPUTATIONAL MODEL

We conceive an abstract urban environment inhabited by three types of agent: offenders, citizens, and residential properties. We simulate residential burglary events that take

place when motivated offender agents going about routine activities find known, attractive targets in the absence of capable guardians. We use this model to examine how systematic manipulations to the street network shape patterns of crime event actor activity and convergence and, in turn, the impacts these have on both the volume and the distribution of property victimization. In addition, being motivated by the assertions of the encounter and enclosure hypotheses, we investigate the role that passer-by guardianship plays in shaping these relationships, considering—in the absence of compelling empirical evidence—several theoretically informed hypotheses concerning its extent and deterrent effect.¹

The model operationalizes the following underlying assumptions:

1. Offenders and nonoffenders undertake routinized, spatially structured activities (via the street network) that primarily originate from their home (Brantingham and Brantingham, 1981; Golledge and Spector, 1978).
2. Offenders find targets for crime going about these day-to-day activities (Brantingham and Brantingham, 1981).
3. Offenders consider some targets more attractive than others (Cornish and Clarke, 1986).
4. Offenders incrementally develop awareness of the locations they frequent, such that increased awareness aids in the commission of crime at these locations (Brantingham and Brantingham, 1981).
5. For a crime to occur, a motivated offender must converge with a suitable target in the absence of capable guardians (Cohen and Felson, 1979).
6. Guardians who prevent crime are typically people going about their day-to-day activities (Felson and Eckert, 2015; Reynald, 2011).
7. The capability of potential guardians to prevent crime is variable and context dependent (Reynald, 2011).

The model is now described in more detail. In addition, its key parameters, the constructs they seek to capture, and their associated initialization and manipulation conditions are summarized in appendix A in the online supporting information.²

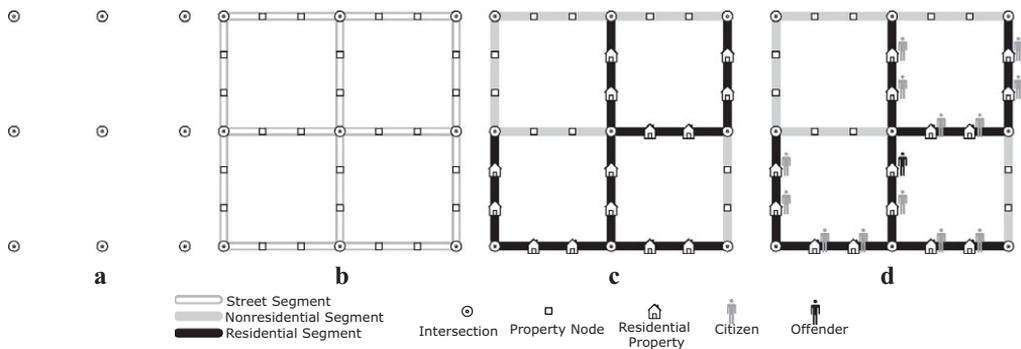
MODEL ENVIRONMENT

In our model, agents act and interact on an abstract urban street network. It is via this street network that all activities take place, thereby dictating where and when offenders find potential targets, as well as where and when guardians are present potentially to prevent them from victimization. The environment is made up of three key components: street links, intersections, and property nodes. This environmental model and its construction are now described as follows:

1. The simulated street network conforms to a standard block-based layout, and its instantiation begins with the creation of a uniform grid of intersections (see figure 1a).

1. Our model is implemented using Netlogo, “a multi-agent programmable modeling environment” (Wilensky, 1999, para. 1) that has been widely used in both the natural and social sciences.

2. Additional supporting information can be found in the listing for this article in the Wiley Online Library at <http://onlinelibrary.wiley.com/doi/10.1111/crim.2017.55.issue-4/issuetoc>.

Figure 1. Stepwise Simulation Environment Initialization

NOTE: Panels show: (a) placement of intersections; (b) arrangement of property nodes and street links between them; (c) selection of residential segments; and (d) assignment of citizens and offenders to residences.

2. Between each pair of intersections, a uniform number of property nodes—representing land parcels—are created. The connections between neighboring property nodes and intersections are referred to as street links (which collectively between two intersections constitute a “street segment” in the traditional sense). Figure 1b depicts an illustrative environment of 3×3 intersections, with two property nodes (and therefore three street links) per segment. In our simulations, we use a grid of 15×15 intersections with 10 property nodes per segment.
3. Overall, 50 percent of all streets segments are designated as residential streets, leaving the remaining 50 percent as nonresidential (see figure 1c).
4. For each residential street, a residential property agent is instantiated at each property node (see figure 1c), and a measure of its target utility is randomly generated (see Residential Property Agents section below).
5. For each residential property agent, an occupant agent is instantiated (see figure 1d). This occupant can be a citizen agent (with $p = .95$) or an offender agent (with $p = .05$).
6. Depending on the experimental configuration of the model, any manipulations to the street network are performed (see figure 2).

Having described the simulation environment, we now specify the agents that act within it.

AGENTS

Our model incorporates three classes of agent: residential properties, citizens, and offenders. We now describe these agents, their characteristics and behaviors, and the theoretical or empirical rationale that underlies their inclusion in the model.

RESIDENTIAL PROPERTY AGENTS

Residential burglary involves commission of crime at a residential property. Thus, potential targets for our simulated offenders are represented as residential property agents. Each residential property agent stores a single characteristic representing its

attractiveness to offenders: *utility*. The formulation of this measure is informed by the rational choice perspective's depiction of criminal decision-making (and from previous computational formalizations of it; see Birks, Townsley, and Stewart, 2012, 2014), and encapsulates the rewards, risks, and efforts associated with victimizing a target. It can be considered the outcome of a cost–benefit calculus, such that utility increases as rewards become greater and risks/efforts decrease (and vice versa). In terms of model behavior, utility simply represents the probability that an offender agent will find a target attractive, and it is incorporated into offender agents' offending behavior (see the next section). Utility is heterogeneous across residential property agents and generated uniformly at random in the range [0, 1].

OFFENDER AND CITIZEN AGENTS

Two further types of agent inhabit the simulated environment: offenders and citizens (nonoffenders). Their characteristics and behaviors are now summarized.

CHARACTERISTICS

Home Location: All citizen and offender agents are allocated a home location in the form of a residential property agent. It is here that an agent is instantiated when the model is initialized.

Routine Activity Space: In addition to the home node, both offender and citizen agents are allocated a routine activity space that consists of four³ other randomly selected property nodes. These may or may not host a residential property agent, and therefore they represent both residential (e.g., homes of friends or family) and nonresidential (e.g., workplace or bar) routine activity nodes.

BEHAVIORS

In our model, offender agents employ three key behaviors—navigation, learning, and offending—and citizen agents employ two—navigation and guardianship. These behaviors, and their theoretical and empirical underpinnings, are now described.

NAVIGATION BEHAVIOR (CITIZEN AND OFFENDER AGENTS)

In specifying agents' navigation behaviour, we draw on crime pattern theory, routine activity theory, and more general assertions of human geography, so that both offender and citizen agents undertake anchor-based (Golledge and Spector, 1978) routinized spatial activities. As in the model of Birks, Townsley, and Stewart (2012, 2014), agents begin the simulation at their home location, from where they randomly select one of their routine activity nodes at random and travel to it via the street network. Once a routine activity node is reached, agents either return to their home location (with high probability, $p = .8$) or randomly select another routine activity node and navigate to it (with $p = .2$). Navigation is performed by using a simple shortest path algorithm

3. The selection of four activity nodes mirrors the approach taken in Birks, Townsley, and Stewart (2012, 2014), where additional robustness testing demonstrated minimal impact from differing numbers of routine activity nodes (see Birks, Townsley, and Stewart, 2012: 242).

(Dijkstra, 1959): Agents plan a route to their destination⁴ and follow it in discrete jumps between property nodes and intersections (traversing one street link at each step).

LEARNING BEHAVIOR (OFFENDER AGENTS)

Crime pattern theory proposes that as individuals go about their day-to-day activities, they develop awareness spaces that reflect knowledge of their local environment. Because offenders tend to commit crime at locations known to them, it is argued, these spaces determine where an individual's offending is most likely to occur. As in the model of Birks, Townsley, and Stewart (2012, 2014), we conceptualize a learning behavior that allows offender agents to build up awareness of the locations they visit. When a simulation is initialized, offender agents have no awareness of their environment; subsequently, the relationship between time spent at a location and an offender's awareness of it follows a simple logistic function:

$$\text{awareness}_{(s,t)} = \left(\frac{1}{1 + e^{-\left(\frac{t(s)}{b}\right)}} \right) \quad (1)$$

where $t(s)$ is the time spent at location s , b is the rate at which offender agents learn about the locations they visit,⁵ and e denotes the exponential function. According to this behavior, offender agents incrementally build awareness spaces that reflect knowledge of their local environment; in principle, this awareness value simply represents the probability that an agent is sufficiently aware of a location to consider committing crime there.

OFFENDING BEHAVIOUR (OFFENDER AGENTS)

We conceptualize an offending behavior that incorporates key propositions of the routine activity approach, rational choice perspective, and crime pattern theory. Whenever an offender agent encounters a residential property node during its routine movements, it decides whether to attempt commission against that target. This decision is made probabilistically, on the basis of a behavioral calculus that takes into account 1) the offender's motivation⁶; 2) the utility of the target (see earlier); and 3) the offender's awareness of the target location. This is calculated as the product of these quantities, so that the probability of commission at a location s and time t is given by:

$$p(\text{commission})_{(s,t)} = \text{motivation}_{(s,t)} \times \text{utility}_{(s,t)} \times \text{awareness}_{(s,t)} \quad (2)$$

The decision taken here refers to the intention to commit crime; that is, it determines that crime will take place in the absence of all other effects. Our model also incorporates guardianship effects, however, whereby the presence of one or more citizen agents at the

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4. In the event that there are multiple paths of equal length between origin and destination, one is selected at random.
 5. As in Birks, Townsley, and Stewart (2012, 2014), the learning rate is selected such that offender awareness of a given location approaches 1 after it has been visited 50 times.
 6. As in Birks, Townsley, and Stewart (2012, 2014), given our focus on proximal influences of crime rather than on criminality, offender motivation was considered uniform across all model configurations ($p = .1$).

commission of crime may dissuade an offender and therefore prevent victimization from occurring.

MODELING GUARDIANSHIP

Modeling guardianship poses a particular challenge in an agent-based context because there is little empirical evidence on which to base the specification of behaviors (see Hollis-Peel et al., 2011). Although guardianship itself is well researched, few studies have been aimed at addressing the issue being considered here—that is, guardianship in the course of routine interactions—in a quantitative way. Not only does this limit grounding for the model, but it also poses problems for validation: The lack of stylized empirical facts (guardianship is, by nature, mostly unobserved) means there is little basis to assess validity.

We attempt to address these challenges in three main ways. First, the model we employ is a minimal one in the sense that it 1) is restricted to only the form of guardianship that is relevant to our research question, and 2) includes only those basic features that would be common to any such model. Although this means that our model does not provide a comprehensive account of guardianship, it minimizes the number of assumptions we must make. Second, in recognition that these assumptions, although both theoretically and empirically informed, are undesirable, we also explore the robustness and sensitivity of our findings under variations to this mechanism. Third, in the absence of established empirical regularities concerning guardianship itself, we assess the validity of the model by examining the consistency of its outputs with both consistent patterns of residential burglary (as in Birks, Townsley, and Stewart, 2012), and those of correlational studies aimed at examining the relationship between network structure and crime risk. We assert that, although guardianship was not the explicit focus of these, its effect must necessarily be present and therefore accounted for in observed results.

Our model of guardianship is grounded in the routine activity approach, so that the presence of a citizen agent at the point where an offender agent encounters a residential property may prevent the commission of crime. Given the focus of this study, we consider only “on street” guardianship, that is, that provided by passers-by during routine activities and, consequently, influenced by variations in street morphology. Although it is certainly true that other forms of guardianship will play a role in the real world—most notably, home occupancy (see Garofalo and Clark, 1992)—they are not directly relevant to the key issues of encounter and enclosure: There is no reason to expect that such effects will vary with urban configuration. In addition, we assume that guardianship occurs only at the point of commission. Even though this is a simplification, it mirrors approaches taken in previous ABM that incorporate guardianship (e.g., Bosse, Elffers, and Gerritsen, 2010; Groff, 2007). Furthermore, any more complex formulation would require further assumptions and its only consequence would be to amplify the effects already present.

As their implications for the model are identical, we also make no distinction here between active guardianship, whereby an individual intervenes during commission, or passive guardianship, whereby the presence of that individual deters an offender (unknownst to the guardian; see Felson and Eckert, 2015). The extent to which these effects disrupt crime is unknown; evidence, however, demonstrates that capability depends on several contextual factors (Reynald, 2011). In particular, there is empirical support for the role of territoriality (Brown and Altman, 1981; Reynald and Elffers, 2009), which is

in line with Newman's (1972) theory of defensible space, and we thus incorporate a simple mechanism that increases or decreases citizen's guardianship capability dependent on context.

GUARDIANSHIP BEHAVIOR (CITIZEN AGENTS)

In line with the rationale described earlier, the underlying guardianship mechanism is identical in all model configurations and it is enacted whenever one or more citizen agents are present when an offender decides to attempt victimization of a residential property agent. In such cases, each citizen has a probability $p(\textit{guard})$ of providing capable guardianship and of thus preventing commission. Importantly, each potential guardian acts independently: If more than one is present, then each in turn may prevent the crime (and it will only occur if none do; conversely, if one is successful in preventing crime, no other citizen may also prevent that crime). If, under this calculus, a citizen does prevent an offender from successfully offending, we describe this as a *guardianship event*. In exploring this behavior, we manipulate both the presence of guardians and their capability based on context.

Guardianship Configuration A (Control): In the first model configuration, the world is inhabited only by offenders, who (for the sake of establishing an appropriate comparator) we assume cannot provide guardianship.⁷ This control configuration allows us to observe the impact of street network manipulations on the occurrence of crime in the absence of any guardianship effect. This observation provides a baseline measure of the influence of the street network on target-offender convergences, and the effect of guardianship can be measured by comparison with this.

Guardianship Configuration B (Defensible Space): In our second model configuration, we populate the environment with citizen agents who have the potential to act as guardians when present at an attempted crime commission. In keeping with Newman's (1972) defensible space hypothesis, these citizens have a greater propensity to prevent crimes occurring on their home street than those that they encounter elsewhere. In particular, when a citizen agent is present at the attempted commission of crime on his or her home street segment, there is a one-in-three chance he or she will prevent crime; that is, $p(\textit{guard})_{\textit{home}} = .33$. Conversely, if the citizen agent encounters crime away from home, then his or her capability is reduced to the extent that there is only a one-in-five chance (i.e., $p(\textit{guard})_{\textit{away}} = .20$). Although these values are consistent with those found in experiments concerned with the willingness to intervene in property crime (e.g., Hindelang, Gottfredson, and Garofalo, 1978; Moriarty, 1975), we acknowledge that they remain somewhat arbitrary. We also therefore explore the robustness of our primary results with respect to two further conceptualizations of capability.

In the first, *Guardianship Configuration C (Uniform Capability)*, we set $p(\textit{guard}) = .2$ in all circumstances, so that citizen agents have a one-in-five chance of preventing crimes they encounter, regardless of whether they are on their home street. In the second, *Guardianship Configuration D (Strong Home Advantage)*, we explore a stronger

7. Although unlikely a reflection of reality, we prevent offenders from acting as guardians. This is done to allow the control model (where only offender agents are modeled) to represent the complete absence of guardianship and, subsequently, to allow direct comparisons between this and other model configurations.

version of our defensible space conceptualization, in which the capability of preventing crime on the home street is increased to one in two—i.e., $p(\textit{guard})_{\textit{home}} = .50$ —whereas the capability away from home remains $p(\textit{guard})_{\textit{away}} = .20$. We undertake these ancillary experiments to ensure that the results of our primary experiments are not wholly driven by the capability assumption, for which we have the least empirical support. The results of these experiments are discussed in the robustness section of our Results section.

THE SIMULATION CYCLE

As with all ABM, in our model, we simulate the repeated actions and interactions of agents at discrete time intervals called “cycles.” At each simulated cycle, all agents execute behaviors that represent a single sequence of perception, cognition, and action. The order in which these occur is as follows: 1) Citizen and offender agents execute movement behavior; 2) where appropriate, offender agents execute offending behaviors, and where relevant, citizen agents execute guardianship behavior; and 3) offender agents execute learning behavior.

SIMULATION EXPERIMENTS

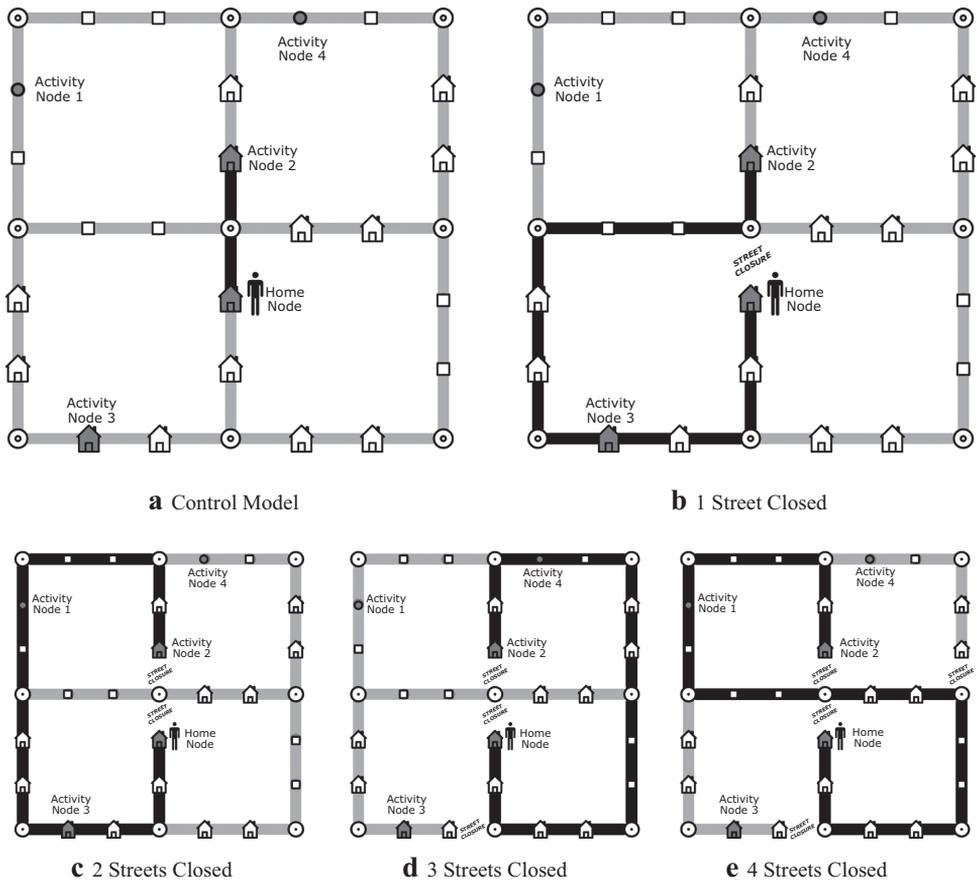
Our primary interest in this study concerns the role of the street network in shaping the interactions between offenders, targets, and guardians, and the consequences of this for the level and distribution of crime. To examine this, we manipulate the structure of our simulated street network in ways that affect the movements and interactions of agents, and we observe the resulting patterns of both crime and guardianship events. Because all other factors are held constant throughout these manipulations, this allows us to isolate the effect of urban form, and to assess the relative merits of the encounter and enclosure hypotheses.

The manipulations we carry out are designed to reduce gradually the permeability of the simulated street network. This is accomplished by randomly removing the connections between some terminal property nodes (i.e., those at the end/start of a street) and their neighboring intersections; in effect, converting through-streets to cul-de-sacs. This procedure maintains the configuration of property nodes in the street network while altering the structure of viable paths that exist within it. This causes changes in the relative usage of street segments, whereby some segments may experience substantial increases in use, for example, as agent navigation paths are rerouted to take account of the new structure.

Figure 2 depicts illustrative manipulations of a simple model environment and the resultant impact on a single agent’s navigation between their home node and, in this example, activity node 2. Plot 2a represents our control model configuration—a fully connected grid—and subsequent plots 2b–2e depict the shortest paths used by the same offender agent as a result of incremental street closures.

EXPERIMENTAL SCHEDULE

We perform simulations under five distinct environmental configurations: a fully connected street network (our control model) and four increasingly disconnected networks. To generate these, we begin by initializing a fully connected network, including environmental characteristics, and then proceed to disconnect segments gradually using the

Figure 2. Impact of Network Manipulation on Agent Navigation

NOTE: Panels show how the shortest route between an offender's home and selected activity node changes as links are removed.

procedure described earlier. At each stage, we disconnect 10 percent of segments,⁸ so that we eventually have networks with 10 percent, 20 percent, 30 percent, and 40 percent of the original streets disconnected.⁹

The fact that these environments are derived sequentially (i.e., the closure of streets is cumulative) is crucial because it means that, aside from network structure, all other components of the experimental environments remain unchanged across the five conditions. Thus, residential property nodes and their ascribed utility characteristics, as well as the routine activity spaces of offenders and citizen agents, remain fixed across each of the five

8. In selecting street links for closure, we ensure that the street network remains connected, that is, that all locations remain accessible from all others.
9. Note that such closures do not reflect any proposed intervention strategy, but they simply offer a parsimonious means to manipulate network connectivity without fundamentally changing the layout of the network or the number of property nodes within it.

environmental configurations, and only the configuration of the street network on which agents navigate alters. Figure 3 depicts five such environmental configurations.

Each simulation is run for 25,000 cycles, and because our model is stochastic, it is necessary to repeat each simulation multiple times. We therefore replicate our simulations of the five environmental configurations 100 times, with a different randomly generated initial configuration each time.¹⁰ Because the environmental conditions are held constant over the five conditions in each case, our approach is equivalent to closing street segments systematically through five increasingly disconnected configurations in 100 distinct study areas.

In addition to these environmental manipulations, we also vary the guardianship behavior, exploring the two conceptualizations discussed earlier and the two further robustness configurations. Thus, our experiments can be cast in a traditional 5 (environmental configurations) \times 4 (guardianship configurations) design, producing 20 unique experimental configurations, for each of which 100 replications are carried out.

FINDINGS

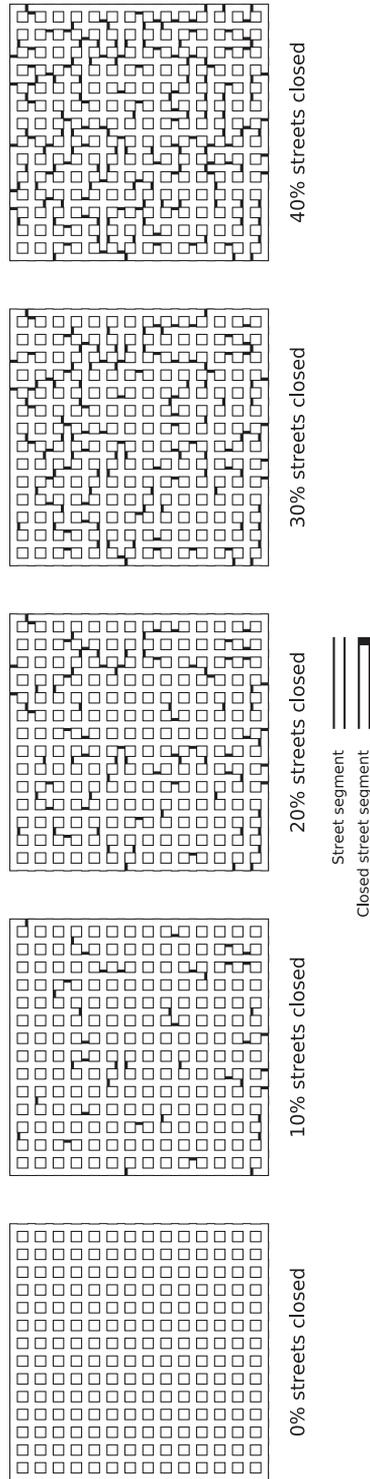
Before carrying out our experiments, we must first validate the base model of offending (Berk, 2008, Birks and Elffers, 2014; Groff and Birks, 2008). We do this by assessing whether simulated crime patterns are compatible with consistently observed empirical patterns of residential burglary. For reasons of brevity, we do not describe these tests here—they are explained in detail in Birks, Townsley, and Stewart (2012)—but their results are shown in appendix B in the online supporting information. In summary, we observe simulated burglary patterns that mimic those observed empirically, such that they are 1) spatially concentrated; 2) disproportionately experienced by a small number of repeat victims; and 3) display a distance decay relationship in the journey to crime.

This finding is in fact a meaningful extension of the tests of theory presented by Birks, Townsley, and Stewart (2012) because our new model incorporates a theoretically informed guardianship mechanism that was absent in the earlier model. In light of the incorporation of this new behavior, we see that simulated crime patterns remain consistent with those observed empirically.

Having demonstrated that our model produces plausible outcomes, we now detail the results of our experiments that seek to estimate the impact of street network permeability on offending and guardianship. We divide these into three distinct analytical studies, the first addressing the impact of global street network permeability on offending levels, and the second and third considering the influence of permeability at the individual street segment level. At both spatial levels, results in the guardianship-free configuration offer insight into the role of the network in shaping offender–target interactions. Having established this baseline, the addition of guardianship allows us to quantify its effect, which in turn informs our assessment of the encounter and enclosure hypotheses.

10. In accordance with the observations of Lee et al. (2015), selection of the total number of cycles a model is run for, and the number of replications per configuration, were informed by preliminary analyses of variance stability—that is, by examining the variance of key outcome variances.

Figure 3. Cumulative Street Network Manipulation (Seed = 100)



NOTE: At each stage, a proportion of street segments are randomly selected for disconnection, resulting in an increasingly irregular structure.

Table 1. Mean and Standard Deviation of Crime and Guardianship Event Counts by Network Permeability and Guardianship Configuration (100 Model Replications)

% Streets Closed	Crime Events		Guardianship Events	
	Guardianship Configuration A: Control (No Guardians)	Guardianship Configuration B: Defensible Space	Guardianship Configuration A: Control (No Guardians)	Guardianship Configuration B: Defensible Space
0%	719 (127)	611 (98)	0 (0)	73 (16)
10%	757 (125)	642 (114)	0 (0)	90 (22)
20%	770 (126)	655 (112)	0 (0)	107 (27)
30%	714 (113)	583 (106)	0 (0)	129 (30)
40%	544 (103)	394 (94)	0 (0)	145 (37)

STUDY 1: MACRO-SCALE IMPACTS: THE RELATIONSHIP BETWEEN GLOBAL STREET NETWORK PERMEABILITY AND CRIME RISK

Table 1 depicts the relationship between global network permeability and incidence of both crime and guardianship events. The first of these refers to a successful crime commission against a residential property agent by an offender agent, whereas the latter represents the successful prevention of a crime event by an on-street citizen agent enacting the guardianship behavior. These results are summarized across both our control and defensible space configurations of guardianship.

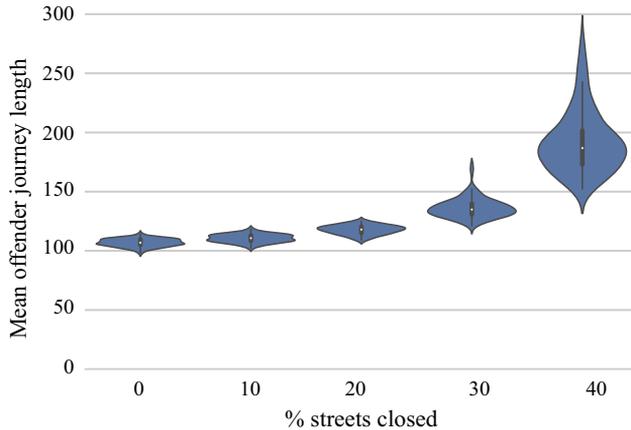
Several primary observations can be made from examination of table 1. First, in both realizations of the guardianship behavior, there is a curve-linear relationship between network permeability and crime commission. This relationship sees moderate reductions in network permeability ($\approx 10\text{--}20$ percent road closures) resulting in increased levels of victimization. Subsequently, at some inflection point (≈ 30 percent road closures), further reductions in permeability lead to overall reductions in the incidence of crime.

The results for configuration A represent an important benchmark because they show how the model behaves in the absence of guardianship. The pattern observed in these cases cannot be a result of guardianship events, and it must therefore be caused exclusively by changes in offender behavior. The nature of these can be reasoned by considering the evolution of offender awareness spaces.

When the network is completely regular, offenders have a plurality of routes for each possible journey and their awareness is therefore diffuse. The removal of connections has the effect of concentrating their activity on particular routes, thereby increasing their awareness and probability of offending, and ultimately leading to the initial increase in victimization. Further network manipulation, however, has the effect of lengthening paths as agents are forced to take more convoluted routes: Figure 4 shows how the lengths of offenders' routine trips vary across the five environmental configurations. This lengthening of trips means that offenders take fewer trips, on average, over the course of a simulation: Although their movements are concentrated on certain (longer) routes, they visit the locations on those routes less frequently. This has the effect of diluting awareness, and the fact that agents no longer have a high level of familiarity with a small number of targets leads to an overall reduction in risk.

Further consideration of this point suggests an alternative approach to the comparison of results across configurations. The fact that the average number of trips completed by

Figure 4. Distribution of Trip Lengths for Offender Journeys between Home Locations and Routine Activity Nodes by Network Permeability Configuration [Color figure can be viewed at wileyonlinelibrary.com]



NOTE: Values presented are averaged across all replications.

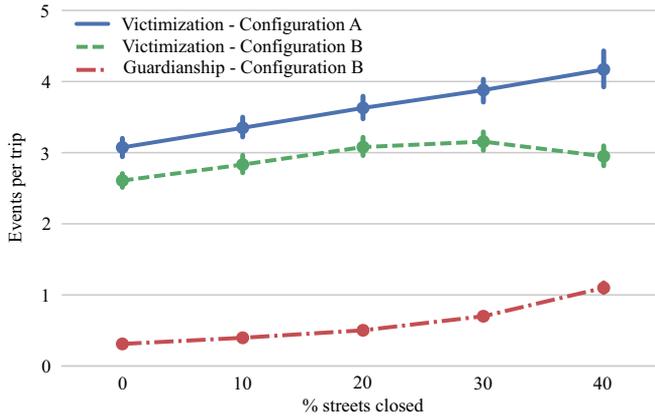
Table 2. Mean and Standard Deviation of Crime and Guardianship Rates, Rescaled by Trip Count (100 Model Replications)

% Streets Closed	Crime Rate		Guardianship Rate	
	Guardianship Configuration A: Control (No Guardians)	Guardianship Configuration B: Defensible Space	Guardianship Configuration A: Control (No Guardians)	Guardianship Configuration B: Defensible Space
0%	3.07 (0.56)	2.61 (0.40)	0 (0)	0.31 (0.07)
10%	3.35 (0.57)	2.83 (0.49)	0 (0)	0.40 (0.10)
20%	3.63 (0.62)	3.08 (0.50)	0 (0)	0.50 (0.12)
30%	3.88 (0.64)	3.16 (0.52)	0 (0)	0.70 (0.18)
40%	4.17 (0.94)	2.95 (0.48)	0 (0)	1.10 (0.26)

agents varies across simulations means that even though model runs are equivalent with respect to opportunities encountered by offenders (in that offenders evaluate the same number of potential targets in all configurations), they may not be in terms of the volume of routine activity they represent. Because trips, rather than model cycles, may be considered the basic unit of routine activity, it is necessary to adjust the results to compare simulation runs over equivalent volumes of activity (i.e., numbers of trips). To do this, we rescale the results for each simulation by dividing by the average number of trips completed by offenders in each case: This gives a measure of the number of crime and guardianship events “per trip.” The results of these analyses are shown in table 2 and figure 5.

Under this rescaling, there is a qualitative change in the relationship with permeability for configuration A: The decrease in victimization for more irregular networks is no longer present, with the adjusted victimization rates instead continuing to rise.

Figure 5. Variation in the Mean Volume of Victimization and Guardianship Events across Environmental Configurations [Color figure can be viewed at wileyonlinelibrary.com]



NOTE: The values plotted represent the volume of events “per trip”; that is, raw counts have been rescaled by dividing by the mean number of routine trips carried out by offenders in each simulation.

To a large extent, this can be explained by the fact that offenders in these environments travel farther on each trip, and so they encounter more targets: All else being equal, they will therefore commit more crimes per trip. Nevertheless, a comparison of figures 4 and 5 shows that this factor is not in itself sufficient to explain the trend in victimization. If it were, the per-trip victimization rate would be directly proportional to the average trip length in each case. The fact that the increase in victimization rate is approximately linear, and lags behind the super-linear increase in trip lengths, implies that there remains a reduction in per-encounter risk for more irregular networks.

The results for configuration B are qualitatively similar in both raw and rescaled versions: an initial increase in victimization as networks become less permeable followed by a decrease at higher levels of irregularity. This pattern can be reconciled with the trend in guardianship events, the numbers of which increase super-linearly as permeability is reduced. The turning point occurs when the increase in guardianship is sufficient to counteract the increase in offending that was identified in configuration A, leading to an overall decrease in victimization.

In overall terms, this finding supports the enclosure hypothesis, in the sense that decreases in network permeability ultimately lead to reductions in crime. Nevertheless, it should be noted that the mechanism by which this takes place is yet to be established and may, in fact, be consistent with elements of the encounter hypothesis. In particular, one possibility is that the increases in guardianship we observe result from the increased concentration of both offenders and guardians on routes that become increasingly central as a result of cumulative reductions in network permeability. If this is the case, increases in offender–target–guardian convergences on these routes may result in a localized “eyes on the street” guardianship effect, driving macro-level reductions in crime. If so, this raises the possibility that the encounter hypothesis may be true in a

local sense—that is, on individual streets—whereas the enclosure hypothesis is reflected in the aggregated results. Indeed, the enclosure hypothesis may be supported, in part, because it concentrates and accentuates encounter-like effects on certain parts of the network. To investigate whether this is the case, it is necessary to examine the distribution of both crime and guardianship events across the individual streets that form the network.

STUDY 2. MICRO-LEVEL IMPACTS: THE RELATIONSHIP BETWEEN LOCAL STREET SEGMENT BETWEENNESS AND CRIME RISK

Having investigated the behavior of our model at the aggregate level, we now consider the patterns that it generates in spatial terms. In particular, we explore one of the central themes of the article: the way in which the distribution of criminal activity is shaped by the structure of the street network. On the one hand, this is done with the aim of further validating the model by examining the extent to which the patterns it generates are consistent with real-world empirical studies. Nevertheless, our experimental setup allows us to go further than this by exploring how the influence of the network varies under changes in its structure.

As outlined previously, our primary interest concerns the relationship between street centrality, offender targeting, and guardianship. Following assertions of the encounter and enclosure hypotheses, we wish to explore the role of the network in shaping the interactions between offenders, targets, and citizens, and to establish whether increases in such interactions in our model are associated with either greater risk (as a result of exposure) or greater security (as a result of guardianship). To begin, we examine the hypothesis that street segments that are more likely to feature in the activity spaces of individuals will experience higher levels of victimization. This was the issue investigated by Davies and Johnson (2015), and to assess the consistency of model outputs with their empirical findings, we take a similar approach to theirs.

In Davies and Johnson's work (2015), they argued that the likely prominence of individual streets in activity spaces could be quantified using the network metric "betweenness." Betweenness measures the number of times that a street features in paths through the network, thereby providing a proxy measure for the level of traffic it is likely to experience. It can be defined formally using graph-theoretic notation (see Davies and Johnson, 2015), but the principle can be illustrated most clearly by describing how it is calculated:

- Initialize a betweenness value of 0 for all segments.
- Consider all pairs of vertices, v and w .
- In each case, find the shortest path(s) through the network between v and w .
- For each segment that appears on one of these paths, increment its betweenness by $1/m$, where m is the number of shortest paths between v and w (m will only be greater than 1 when multiple distinct paths have exactly the same length).

For any network, therefore, betweenness is a measure of the extent to which movement activity is concentrated on particular segments. As such, its overall distribution is highly dependent on network structure: The greater the extent to which traffic is "funneled" down particular streets (and therefore away from others), the more dispersed the values of betweenness will be. In real-world settings, variation in these structural characteristics

cannot be explored independently of other factors because network structures are fixed. Our systematic variation of network structure, however, allows us to do this: Figure 6 shows how betweenness is affected by cumulative street closures, in terms of its spatial patterning (top row) and numerical distribution (bottom row).¹¹

From an analytical perspective, our setting is simple: Whereas in real-world studies it is necessary to control for variation in factors such as opportunity (e.g., address count) and property characteristics (e.g., investment in security), all residential streets in our environment are known to be identical in all respects other than their position in the network. Quantifying the influence of network structure is therefore simply a matter of examining the bivariate relationship between crime risk and betweenness. As the distribution of betweenness is approximately exponential, we first take its logarithm (as is done by Davies and Johnson [2015]).

Because our data are spatial in nature, it is also necessary to employ an analytical method that accounts for the possibility that spatial autocorrelation is present. The results of preliminary diagnostic analysis show that the data are indeed spatially autocorrelated; therefore, to adjust for this, we employ a “spatial error” regression model (Anselin, 1988). This regression model incorporates spatial dependence between error terms and corrects for spatial structure. For our models, this results in an increase in log-likelihood relative to ordinary least-squares regression.

In table 3, we present regression coefficients for the effect of betweenness on the proportion (i.e., normalized count) of victimization across all street segments.¹² In each case, average values across all 100 model environments are given, along with their standard deviations. The most immediate observation that can be made here is that a positive relationship between crime risk and betweenness is apparent in all cases. This result agrees with the findings of Davies and Johnson (2015)—and, indeed, with crime pattern theory—and suggests that the model produces behaviors that are consistent with reality in this sense.

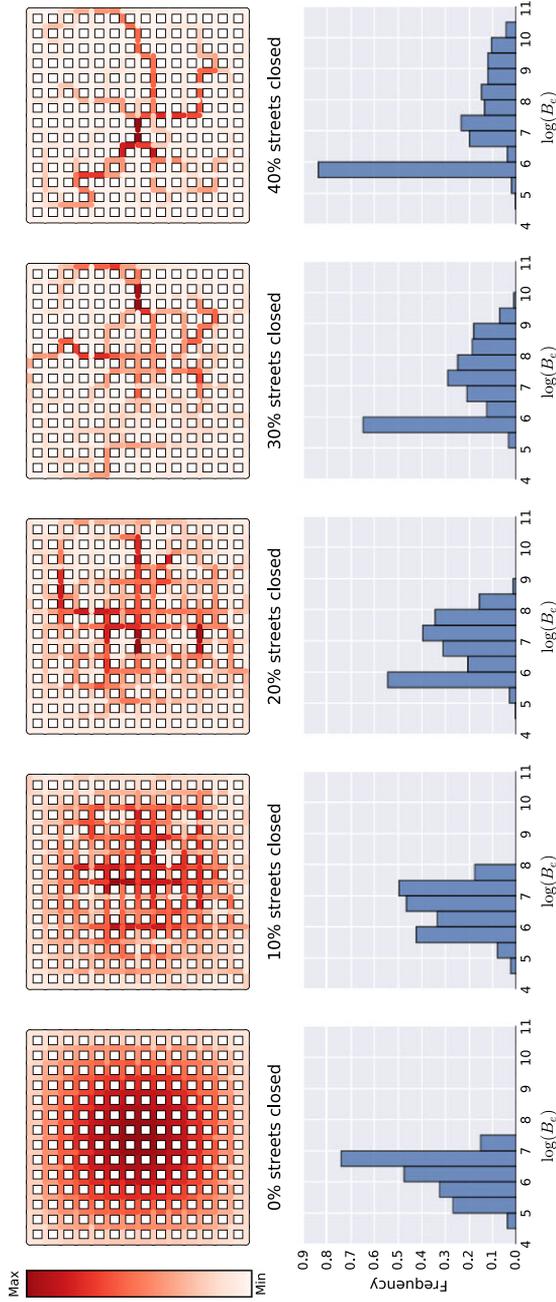
A second notable observation is that the association between victimization and betweenness becomes stronger as the networks become more irregular. This can be rationalized by considering that one effect of street closure is to increase the variance between streets in terms of their activity levels (as illustrated in figure 6). From the perspective of offender–target interaction, this implies that crime will be more concentrated on certain streets—those that are more central—and betweenness therefore represents a more powerful predictor of offending levels. Essentially, the increased variation in betweenness means that it carries more information with respect to exposure to offenders.

Our results also show how the relationship with betweenness is affected by the introduction of guardianship. The coefficients for configuration B, although still positive, are lower than those for configuration A at all levels. The reason for this is the increased guardianship effect on higher betweenness streets as a result of their greater supply of potential guardians. This means that some events that would otherwise have resulted in

11. Although betweenness is subject to edge effects, their inclusion is not unrealistic because they reflect lower usage patterns at the outskirts of urban areas.

12. Note that because values are normalized against the total volume of events in each simulation, the issue of variable trip length identified for study 1 is not a factor here. The analysis relates only to the distribution of offending across the network, regardless of its total volume.

Figure 6. Cumulative Street Network Manipulation and Corresponding Betweenness (Seed = 100).
[Color figure can be viewed at wileyonlinelibrary.com]



NOTE: Top row reflects spatial patterning of betweenness. Bottom row histograms of the logarithm of betweenness across all segments in the environment

Table 3. Spatial Regression Coefficients—Street Segment Betweenness vs. Proportion of Crime Events

% Streets Closed	Guardianship Configuration A: Control—No Guardians	Guardianship Configuration B: Defensible Space
0%	4.35 (1.09)	3.82 (1.26)
10%	4.50 (1.13)	3.73 (1.17)
20%	4.88 (0.94)	4.30 (1.03)
30%	5.71 (0.82)	4.93 (0.85)
40%	7.18 (0.97)	6.10 (0.78)

NOTE: For each replication ($n = 100$), regression is performed on the 210 residential street segments in each environment; the mean of these values is given in this table, and the figures in parentheses give the standard deviations.

Table 4. Spatial Regression Coefficients—Street Segment Betweenness vs. Prevention Rate

% Streets Closed	Guardianship Configuration B: Defensible Space
0%	6.32 (1.44)
10%	7.17 (1.16)
20%	7.23 (1.01)
30%	7.67 (1.01)
40%	8.61 (0.92)

NOTE: For each replication ($n = 100$), regression is performed on the 210 residential street segments in each environment; the mean of these values is given in this table, and the figures in parentheses give the standard deviations.

victimization are instead prevented, thereby moderating the effect of betweenness in exposing those targets to offenders.

This effect can in fact be tested by examining the proportion of crime events that are prevented on each segment. Specifically, we can define the prevention rate, r_p , as:

$$r_p = \frac{\#guardianship\ events}{\#guardianship\ events + \#crime\ events} \tag{3}$$

The denominator of this expression is the total number of potential crime events (all of which would result in victimization, in the absence of guardianship), and r_p therefore represents the probability that an event will be prevented by guardianship. To examine this, we adopt the same spatial regression approach used for victimization, and in table 4, we show regression coefficients for the relationship between r_p and betweenness for configuration B.

It is evident here that the prevention rate is positively associated with betweenness, and that—as with victimization itself—the relationship is stronger for more irregular networks. Put simply, this means that crimes are more likely to be prevented on more central streets, as would be expected given their greater supply of potential guardians.

Taken together, these results allow us to reflect on the overall effect of network structure on crime risk. It is clear that guardianship is more strongly manifested on more central streets in the sense that individual offenses are more likely to be prevented. Nevertheless, the fact that victimization is also higher on these segments implies that this effect is not sufficient to counteract the increased exposure to potential offenders. In other words,

the risk to more central streets is sufficiently great that, even if a higher proportion of offenses is prevented, they are still likely to experience more victimization.

In terms of the encounter and enclosure hypotheses, these results have several implications. The fact that less accessible locations experience lower crime—in both the presence and the absence of guardianship—is clearly in accordance with the enclosure hypothesis, and it implies that the intersection of offender awareness and viable criminal opportunities provide the dominant driver of crime. On the other hand, the high risk associated with high-betweenness streets, even when guardianship is introduced, appears to cast doubt on the encounter hypothesis. Nevertheless, consideration of this in tandem with the findings of study 1 again demonstrates the distinction between local and global effects. The fact that increasing the irregularity of networks ultimately leads to reductions in crime at the macro level means that the overall effect is positive: The reduction in risk on low-betweenness streets outweighs the increase on more central streets. As the regression results show, this is because of the greater rate of guardianship on those streets: Crimes are pushed toward more central streets, where they are more readily prevented.

STUDY 3: MICRO-LEVEL IMPACTS: THE RELATIONSHIP BETWEEN SUCCESSIVE STREET SEGMENT MANIPULATION AND CRIME RISK

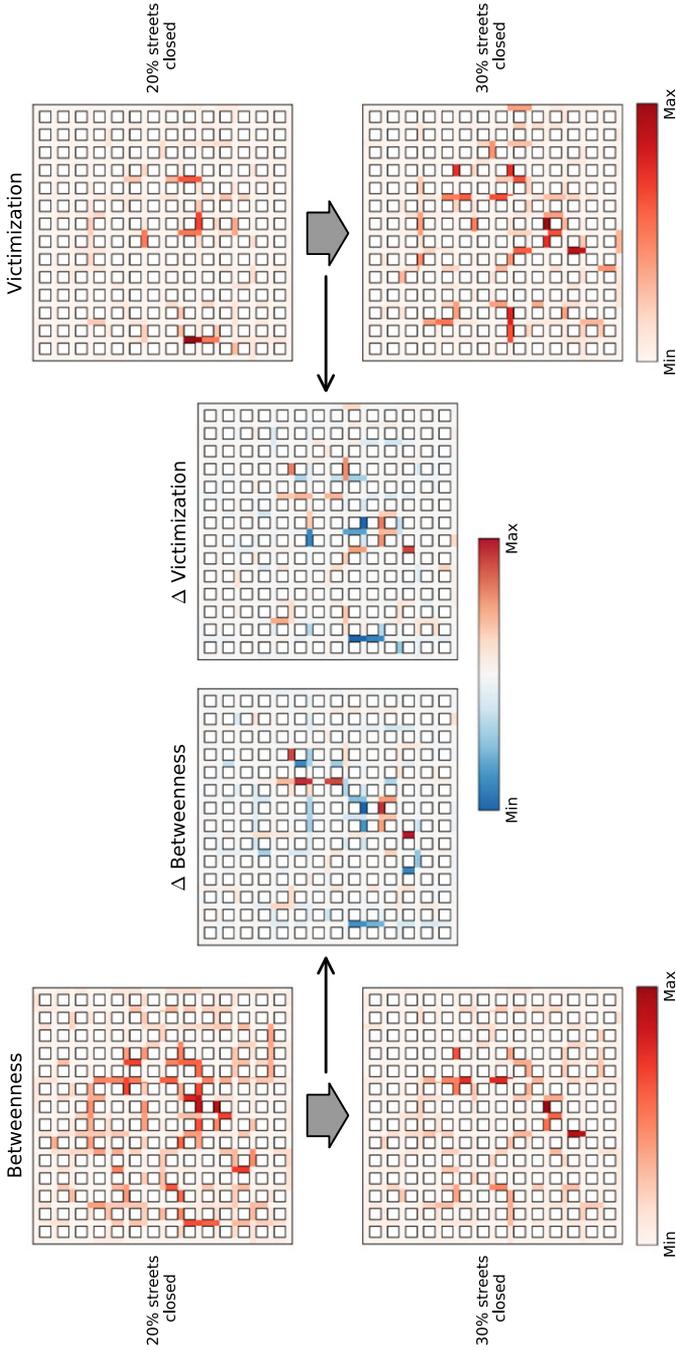
As well as considering each simulation individually, we can also examine changes that occur between the five successive environmental conditions in each of our 100 model replications. In particular, we can examine whether changes in betweenness caused by the closure of network connections are associated with changes in the levels of victimization: Do streets that become more central experience more crime, and vice versa? Examining these changes—“delta” values for both betweenness and victimization—is of interest for two reasons.

First, exploring the results in this way helps to control for the influence of initial conditions on each replication. In each simulation, just as in the real world, crime risk is dependent on several factors—the locations of offender agents’ homes and activity nodes—that, in our simulation, are randomly generated for each replication. These factors cannot be captured by betweenness (or any other structural variable) and therefore represent a source of uncertainty in each simulation (a low-betweenness street, for example, may experience high crime simply because an offender happens to live nearby). Because these factors remain constant across environmental manipulations, however, this variation is accounted for when examining delta values.

Second, analysis of this type also offers insight into one of the potential policy implications of our findings. In light of the apparent relationship between centrality and crime, it may be suggested that network modification (e.g., road closure) could be a feasible means of either reducing crime or reshaping its distribution. By examining the changes under exactly this kind of intervention, we can explore the likely consequences of this.

Figure 7 illustrates our analytical approach for one example replication. The maps on the left show the betweenness values of all residential street segments under the 20 percent and 30 percent closure conditions, with the impact of additional closures clear to see. The “ Δ Betweenness” panel summarizes these changes, showing the increases and decreases in each segment’s betweenness under this manipulation. The maps on the right, on the other hand, show the proportion of victimization accounted for by

Figure 7. Illustrative Comparison of Changes in Street Segment Betweenness and Victimization.
[Color figure can be viewed at wileyonlinelibrary.com]



NOTE: Maps on the left show changes in betweenness across experimental conditions, while maps on the right show the difference in victimization. Comparison of the two central maps reveals whether changes in betweenness are reflected in crime risk

Table 5. Spatial Regression Coefficients—Change in Street Segment Betweenness vs. Change in Crime Event Count

Δ % Streets Closed	Guardianship Configuration A: Control—No Guardians	Guardianship Configuration B: Defensible Space
0%–10%	3.69 (1.43)	2.91 (1.50)
10%–20%	4.60 (1.76)	3.63 (1.43)
20%–30%	5.73 (1.58)	4.73 (1.29)
30%–40%	7.35 (1.57)	6.00 (1.36)

NOTE: For each replication ($n = 100$), regression is performed on the 210 residential street segments in each environment; the mean of these values is given in this table, and the figures in parentheses give the standard deviations.

each segment, with the “ Δ Victimization” plot again depicting the change between the two conditions. Comparison of the two “ Δ ” panels indicates broad qualitative agreement, suggesting a positive relationship between changes in betweenness and changes in crime risk.

To explore this relationship formally, regression coefficients for these difference values are presented in table 5. These demonstrate that the changes in centrality that result from environmental manipulations are positively associated with changes in crime risk. In simple terms, this means that streets that receive greater traffic as a result of changes in network structure will, as a result, experience higher rates of victimization (and vice versa). Importantly, this is true when all other environmental conditions are held constant.

The fact that the relationships observed become stronger as the network becomes more irregular reveals that the effect of network manipulation is nonlinear. Initial disturbances to the regular structure have less impact than those that occur later because they affect activity spaces only minimally. As more connections are removed, however, it is increasingly likely that offenders will be forced to modify their routes. In such circumstances, they will naturally be drawn toward those segments that act as key conduits; that is, precisely those whose betweenness will have increased. Of course, this argument also applies to potential guardians, and the results therefore provide further evidence that their increased presence on these streets is not sufficient to counteract the increased exposure to offenders. Nevertheless, they do have a moderating effect: Aggregate results imply that the increased offending on these streets is lower than it would be if the reductions on less-between streets had simply been displaced.

MODEL ROBUSTNESS

As previously discussed, in addition to the two guardianship configurations examined earlier, we also carried out robustness tests to explore model outcomes across two further configurations to ensure that our observed results are not wholly driven by assumptions about both the relative strength and the context dependency of guardianship capability. The global network analyses undertaken in study 1 were replicated, and table 6 depicts the results of these analyses. In summary, the outcomes that result from our two further active guardianship configurations are almost indistinguishable from those observed under configuration B.

In addition, we also conducted a series of robustness tests aimed at exploring the impact of varying quantities of offenders inhabiting the world and, thus, the relative mixing ratios

Table 6. Robustness Test Results—Mean and Standard Deviation of Crime and Guardianship Event Counts by Network Permeability and Guardianship Configuration (100 Model Replications)

% Streets Closed	Crime Events				Guardianship Events			
	Configuration A: No Capability	Configuration B: Defensible Space	Configuration C: Uniform Capability	Configuration D: Defensible Space (Strong)	Configuration A: No Capability	Configuration B: Defensible Space	Configuration C: Uniform Capability	Configuration D: Defensible Space (Strong)
0%	719 (127)	611 (98)	613 (100)	608 (98)	0 (0)	73 (16)	70 (16)	80 (19)
10%	757 (125)	642 (114)	649 (112)	642 (113)	0 (0)	90 (22)	86 (22)	96 (23)
20%	770 (126)	655 (112)	657 (111)	652 (107)	0 (0)	107 (27)	105 (25)	115 (29)
30%	714 (113)	583 (106)	582 (105)	574 (104)	0 (0)	129 (30)	124 (29)	131 (28)
40%	544 (103)	394 (94)	398 (99)	393 (90)	0 (0)	145 (37)	146 (37)	148 (37)

of offenders and potential guardians. The analyses undertaken in study 1 were replicated, and table 7 depicts the output of these analyses. As before, the functional form of our primary finding relating permeability and crime risk remains consistent in both additional model configurations where the world contains more (~10.0 percent of the population) or less (~2.5 percent) offenders and simply scales resulting in greater or lesser amounts of crime, respectively.¹³

DISCUSSION

Quantifying the role that street networks play in situating, enabling, and inhibiting crime events is a foundational, yet currently underdeveloped, research enterprise that has the potential to be transformational in several distinct settings. For theorists, such an understanding would support the empirical testing of theoretical constructs; for policy makers, it would inform prioritization of areas in terms of risk; and for practitioners, it would provide applied principles for local policing and planning activities. Although research findings increasingly demonstrate the significance of street segments in analyzing and understanding urban crime problems, studies aimed at revealing the relationship between street network structure, human activity patterns, and crime risk are rare (for a review, see Johnson and Bowers, 2010). This shortfall in knowledge is the direct consequence of several mostly unassailable logistical constraints that encumber empirical studies in this area.

In this article, we aimed to circumvent some of these problems by combining parallel advances in mathematical and computational modeling of street networks and crime events. To do so, we constructed a theoretically informed, computational, agent-based model capable of investigating the likely impacts of street network permeability on offender and guardian activities patterns, as well as the resultant crime commission and guardianship events they give rise to. In particular, we sought to assess the viability and veracity of two long-standing hypotheses linking street network permeability, on-street guardianship, and crime risk—the encounter and enclosure hypotheses—that, for the reasons mentioned earlier, have remained mostly inaccessible to traditional empirical enquiry.

In investigating these hypotheses, we began by assessing the validity of our model, demonstrating that agents operating according to key principles of the routine activity approach, crime pattern theory, and the rational choice perspective generated patterns of property victimization that were congruent with a range of well-established empirical regularities. Subsequently, we presented a suite of simulation experiments in which we systematically manipulated the environmental model within which our agents interacted and, in turn, examined the crime events that resulted across a range of prescribed street network morphologies.

At the micro level, our results reveal that the betweenness centrality of street segments is significantly positively associated with property crime commission and prevention (through on-street guardianship). The former of these accords with the findings of Davies and Johnson (2015), suggesting that the behaviors encoded in our model provide

13. Readers are also directed to Birks, Townsley, and Stewart (2012) where the underlying model is shown to be robust to a range of other significant parameter manipulations (e.g., number of routine activity nodes, offender motivation, etc.).

Table 7. Robustness Test Results B—Mean and Standard Deviation of Crime and Guardianship Event Counts by Network Permeability, Guardianship Configuration, and Ratio of Citizen to Offender Agents (100 Model Replications)

% Streets Closed	Crime Events						Guardianship Events					
	Configuration A: ~2.5% Offenders		Configuration B: ~2.5% Offenders		Configuration A: ~10% Offenders		Configuration B: ~10% Offenders		Configuration A: ~2.5% Offenders		Configuration B: ~2.5% Offenders	
	Configuration A: ~2.5% Offenders	Configuration B: ~2.5% Offenders	Configuration A: ~10% Offenders	Configuration B: ~10% Offenders	Configuration A: ~2.5% Offenders	Configuration B: ~2.5% Offenders	Configuration A: ~10% Offenders	Configuration B: ~10% Offenders	Configuration A: ~2.5% Offenders	Configuration B: ~2.5% Offenders	Configuration A: ~10% Offenders	Configuration B: ~10% Offenders
0%	349 (94)	291 (72)	1,412 (190)	1,226 (140)	0 (0)	0 (0)	0 (0)	0 (0)	36 (12)	0 (0)	0 (0)	141 (20)
10%	375 (87)	310 (74)	1,501 (202)	1,293 (147)	0 (0)	0 (0)	0 (0)	0 (0)	44 (13)	0 (0)	0 (0)	170 (28)
20%	378 (87)	310 (71)	1,524 (200)	1,287 (148)	0 (0)	0 (0)	0 (0)	0 (0)	56 (19)	0 (0)	0 (0)	201 (34)
30%	355 (78)	272 (66)	1,422 (220)	1,147 (156)	0 (0)	0 (0)	0 (0)	0 (0)	64 (18)	0 (0)	0 (0)	246 (44)
40%	264 (72)	185 (49)	1,075 (225)	784 (150)	0 (0)	0 (0)	0 (0)	0 (0)	71 (21)	0 (0)	0 (0)	281 (66)

a plausible explanation for the higher risk on more central streets. On the other hand, the relationship between guardianship and network structure is not one that has previously been examined empirically; indeed, the difficulty in establishing a counterfactual was a key motivator for the presented study. The relationship we observe is broadly in line with expectation: The higher rate of prevention on more central streets is simply a result of the higher throughput of potential guardians on such segments.

Taken together, our micro-level results allow us to draw stronger conclusions (in the context of our study) than were possible for Davies and Johnson (2015). On the one hand, the nature of our environment means that the possibility of confounding variables can be eliminated; our analysis of differences at successive levels of network modification is particularly conclusive on this point. Perhaps more significantly, though, the fact that guardianship could be observed explicitly in this study (albeit in a synthetic context) means that its potential influence on crime patterning can be better understood. Our results show that the increase in risk on more central street segments occurs despite a simultaneous increase in guardianship: Here, the increased exposure simply outweighs the greater likelihood of prevention. This finding is significant because it provides an indication of the relative magnitudes of the two effects.

Furthermore, the results of our robustness tests that explore differing conceptualizations of the guardianship mechanism indicate that increasing or decreasing guardianship capability, in both context- and noncontext-dependent situations, has limited impact on the frequency of guardianship events above and beyond levels associated with simply the presence of guardians. These results mimic those of observational studies of guardianship behavior and property crime risk (Reynald, 2009), in turn increasing the confidence we have in our model's validity.

At the macro level, our analysis was motivated by a desire to examine the contrasting "encounter" and "enclosure" hypotheses. Ultimately, our results provide support for both arguments. The fact that moderate deviations from a regular network structure lead to increased offending supports the encounter hypothesis, such that offenders find greater opportunity for crime when their movements are concentrated. The reversal of this relationship at higher levels of manipulation, however, is consistent with the enclosure hypothesis, and it can be explained by offenders' reduced awareness of viable targets. When guardianship is added, the combination of these two effects ultimately leads to a reduction in offending when the permeability of the network is reduced past a certain turning point. In fact, the results of our micro-level analyses reveal that the decrease in victimization in these cases can mostly be attributed to a localized encounter-like mechanism, such that increases in offender–target–guardian interactions on some routes drive subsequent reductions in offending. This finding is significant and highlights that the encounter and enclosure hypotheses may have different (and complementary) consequences at different spatial scales.

Ultimately, the absence of a simple relationship between permeability and offending may itself be the most significant outcome of our analyses. This result reflects the complexity of the system of interest and highlights that elements of both arguments are likely to be valid, depending on context. Our results suggest that both permeable and impermeable networks can reduce offending but that structures between these extremes may be more risky. Furthermore, they demonstrate that macro-level reductions in offending may come at a cost for some areas, in the form of more pronounced concentrations of offending on certain well-used routes.

As we have previously discussed, the triangulation of theoretical, empirical, and computational efforts should serve to advance our understanding of crime problems and the veracity of those theories we employ to describe them. Consequently, although we hope that our findings will support the incremental development of theory, they may also warrant consideration by those concerned with applied crime prevention. To this end, our models suggest that manipulation of street network structure can influence both the volume and the distribution of crime, and it is therefore natural to consider how such manipulation might be realized in the real world. The most immediate way in which this could be done mirrors the approach used in our algorithm: the closure or disconnection of street segments. This strategy has indeed been proposed as a potential crime control measure (Clarke, 2004), and it has been used in several real-world interventions (Lasley, 1998; Matthews, 1993, 1997). Although the results of such studies have generally been positive, notions of connectivity and permeability were not their primary focus, and work remains to be done in examining whether any changes can be explained in these terms.

The complex nature of our results, however, suggests that the potential consequences of road closure are not straightforward. Our simulations indicate that closures may produce both positive and negative impacts on the incidence of victimization, contingent on the existing road structure of the intervention area in question. This clearly highlights the importance of understanding the structure of an existing street network to predict the consequences of modifying it. Nevertheless, it is also important to note that real-world closures can be targeted in a way that was not considered in our study: Rather than removing connections at random, closures can be performed in such a way that a prescribed distribution of centrality is achieved.

Of course, the systematic closure of streets is unlikely to be practically viable in many real-world contexts, and it is therefore also worthwhile to consider alternative ways in which street networks can be shaped. The most natural avenue for this is through urban planning and design; that is, by altering network structures before, rather than after, they are constructed. In suggesting network manipulation as a course of action, however, we must be careful to note that the consequences of changes can be highly complex. Betweenness, for example, is mostly a “zero-sum” quantity: Because the overall number of journeys to be taken remains constant, any changes that result in decreased use of a particular segment must be balanced by increases elsewhere. Interventions that seek to reduce crime on a street by reducing its betweenness may risk promoting offending elsewhere (in a way that is not necessarily predictable). This may not necessarily be an adverse outcome—the potential virtue of crime “placement” has been discussed elsewhere (Barr and Pease, 1990), and our results suggest that this may augment guardianship—but the issue reveals an underlying complexity that must be considered when considering such interventions.

Now that we have summarized our findings and their immediate implications, we will outline several weaknesses associated with our approach and consider how they might be addressed in future work. Most immediately, we must acknowledge that our model remains just that: a model. Although we have sought to validate it using commonly accepted techniques—and have assessed its sensitivity to several significant parameter changes—we can never be sure that it truly reflects the behaviors and interactions involved in real-world offending. This is, of course, true of any model (computational or otherwise), and our results should be viewed in the context of the general goal of the approach: to explore the consequences of hypothesized behaviors in a rigorous and quantifiable way. Even

though our results are robust, therefore, they are only applicable to reality to the extent that the hypothesized behaviors are valid. It should also be noted that, like all studies in which recorded crime data are relied on, our efforts to validate our underlying model rest on the assumption that the signatures of crime against which we benchmark our simulated crime, which are predominantly derived from studies of reported crime, are representative of patterns of unreported crime.

Furthermore, our model clearly incorporates several assumptions that represent simplifications of reality. Although the street network undoubtedly plays a significant role in influencing activity patterns, so do the relative locations and functions of facilities within that network. Given our aim to study the influence of network structure on crime, here we make the assumption that residential streets, agent residences, and agent activity nodes are randomly distributed throughout the environment. In reality, urban areas are likely to be more structured than this: Residential properties typically cluster in certain parts of the street network, and offender residences often cluster within those residential areas.

Perhaps most importantly, our assumptions regarding citizen guardianship capability are, at best, empirically informed estimations. Although we have done our best to assess the impact of these necessary assumptions through varying model configurations and robustness tests (see table 6), clearly empirical parameterization of these values is desirable. In the future, we hope to conduct empirical studies capable of estimating these values, although designing and carrying out such experiments to produce reliable estimates is unlikely to be an easy task.

Nevertheless, even though these weaknesses are acknowledged, we believe that the controlled nature of the model configurations means that their impact is limited within the confines of our stated goals. In each of the 100 model replications we perform, the only factor that is manipulated across conditions is the structure of the street network: All other factors are held constant and cannot be responsible for variation. In this sense, our approach is equivalent to examining the consequences of the modeled behaviors in 100 unique urban configurations. We suggest that this serves to attenuate the influence of the individual biases outlined earlier.

A final point concerns the fact that, in its current form, the model depicts routine activities as mostly atemporal, such that agents only follow a spatially referenced routine. This fails to account for daily rhythms, for example, and the fluctuations of activity that may result from them. Here we believe that the impact of this assumption is likely to be diminished by the fact that our analysis is primarily concerned with property victimization. As this is a crime against static targets, the confluence of offenders and targets is not dependent on the movements of target agents (which would be more strongly subject to temporal fluctuations), and its spatial character is therefore driven more strongly by offender awareness.

With regard to this point, an obvious extension to the work presented here is to use a similar model to simulate patterns of interpersonal victimization across varying street network configurations. We anticipate that even stronger effects than those observed here may arise in that case: The dynamic nature of victims is likely to drive criminal events even more strongly toward centers of activity.

A further opportunity to extend the external validity of the model relates to the consideration of alternative street network structures. The networks used in our experiments are variations on a basic grid structure, and although this is certainly an elementary configuration, it is far from true that all real-world networks conform to this template. Indeed,

the structural properties of street networks are the subject of highly quantitative research outside of criminology, and attempts have been made to both develop typologies of network forms (Louf and Barthélemy, 2014; Strano et al., 2012) and model their evolution (e.g., Barthélemy and Flammini, 2008). Future applications of our model could draw on such approaches by generating synthetic environments that represent generic examples of common network archetypes. Simulating crime events on this corpus of street networks would allow us to seek generalizability across a wide range of environmental contexts.

In continuing these efforts, we hope to support a groundswell of research findings that demonstrate the importance of understanding crime risk at the street segment level, providing a more nuanced depiction of this critical unit of analysis, not as a solitary feature, but instead as part of a complex interconnected and interdependent entity.

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Daniel Birks is a member of the Griffith Criminology Institute, Griffith University. His current research interests are broadly based in the fields of environmental criminology, crime analysis, and computational methods.

Toby Davies is a lecturer in the Department of Security and Crime Science at University College London. His research is concerned with the quantitative analysis and mathematical modelling of crime, with particular emphasis on its spatio-temporal characteristics.

SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Appendix A. Key Model Parameters

Appendix B. Model Validity—Mean and Standard Deviation of Nearest Neighbor Index (Crime Spatial Concentration), Gini Coefficient (Victimization), and Pearson's Coefficient of Skewness for Journey to Crime Curves by Network Structure and Guardianship Configuration