CRIMINOLOGY

CAN HOT SPOTS POLICING REDUCE CRIME IN URBAN AREAS? AN AGENT-BASED SIMULATION*

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Over the past two decades, there has been a growing consensus among researchers that hot spots policing is an effective strategy to prevent crime. Although strong evidence exists that hot spots policing will reduce crime at hot spots without immediate spatial displacement, we know little about its possible jurisdictional or large-area impacts. We cannot isolate such effects in previous experiments because they (appropriately) compare treatment and control hot spots within large urban communities, thus, confounding estimates of area-wide impacts. An agent-based model is used to estimate area-wide impacts of hot spots policing on street robbery. We test two implementations of hot spots policing (representing different levels of resource allocation) in a simulated borough of a city, and we compare them with two control conditions, one model with constant random patrol and another with no police officers. Our models estimate the short- and long-term impacts on large-area robbery levels of these different schemes of policing resources. These experiments reveal statistically significant effects for hot spots policing beyond both a random patrol model and a landscape without police. These simulations suggest that wider application of hot spots policing can have significant impacts on overall levels of crime in urban areas.

After decades of increasing crime rates, the United States experienced a surprising crime drop during the 1990s that continued through the 2000s. Policy makers, academics, and journalists attempted to sort out the various explanations for the puzzling crime decrease, such as a strong economy, improved policing, high imprisonment rates,

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stabilizing crack cocaine markets, immigration, new gun policies, and demographic shifts (e.g., Blumstein and Wallman, 2006; Levitt, 2004; Zimring, 2007). A careful read of the available scientific evidence suggests that no single factor can be invoked as the cause of the 1990s crime decline; rather, the explanation seems to lie with several mutually supportive, reinforcing factors. Although it is difficult to specify their exact contributions, innovative police strategies are commonly credited as plausible influential factors in the crime drop (Wallman and Blumstein, 2006; Weisburd and Braga, 2006; Zimring, 2012).

The most compelling scientific evidence supporting the crime-control effectiveness of innovative policing strategies comes from controlled evaluations designed to test interventions at a subset of places within jurisdictions (National Research Council, 2004). Over the past two decades, the results of a series of rigorous evaluations have suggested that police can be effective in addressing crime and disorder when they focus on small units of geography with high rates of crime known as hot spots (see Braga, Papachristos, and Hureau, 2012, 2014; Lum, Koper, and Telep, 2011; National Research Council, 2004; Telep and Weisburd, 2011; Weisburd and Eck, 2004). Policing strategies and tactics focused on these areas are usually referred to by researchers as hot spots policing or place-based policing (Sherman and Weisburd, 1995; Weisburd, 2008). The evidence base for the effectiveness of hot spots policing in reducing crime and disorder at crime hot spots is especially strong. In a Campbell systematic review of hot spots policing strategies, Braga, Papachristos, and Hureau (2012, 2014) found that 20 of 25 tests from 19 experimental and quasi-experimental evaluations resulted in significant and meaningful reductions in crime or disorder. Importantly, they also did not find evidence of immediate spatial displacement. Crime did not simply shift from hot spots to nearby areas (Braga, Papachristos, and Hureau, 2012, 2014; Weisburd et al., 2006); indeed, such areas were more likely to evidence a diffusion of crime-control benefits (Clarke and Weisburd, 1994).

Although the evidence supporting the effectiveness of hot spots policing in reducing crime and disorder at hot spots is strong, to date, we know little about whether and to what degree such tactics will influence crime rates in the larger urban areas within which such strategies are implemented. Because we do not have estimates of the area-wide benefits of this approach, it is difficult to assess whether hot spots policing strategies applied broadly in jurisdictions would have meaningful effects on overall crime trends. As such, it is difficult to know whether the emergence of hot spots policing, a key police innovation that was widely adopted by U.S. police departments over the course of the 1990s (Weisburd and Lum, 2005), can claim any credit for the 1990s crime drop.

In this article, we draw on agent-based modeling (Gilbert, 2008; Gilbert and Troitzsch, 2005; Grimm and Railsback, 2005; Johnson and Groff, 2014) to examine the crime-prevention impacts of hot spots policing on street robbery patterns in an urban area including four police beats, which we call a *borough*. As we detail in the next section, the findings from current studies do not allow us to draw direct conclusions about impacts of hot spots policing practices on overall crime trends in urban areas. At the same time, the findings of these studies allow us to draw specific conclusions about the impacts of such strategies in small areas or hot spots, including possible displacement and diffusion of crime-control benefits. By applying these estimates, and more general knowledge about geographic crime concentrations and their causes in cities, we develop models that estimate expected reductions in street robberies across the simulated police beats (and the borough overall) that result from hot spots policing strategies. We focus on street robberies because they have been perceived as a key measure of violence in studies of the crime drop (see Blumstein, 2006) and a major source of fear among the public (Tompson, 2012).

LIMITATIONS OF MAKING INFERENCES FROM HOT SPOTS POLICING EXPERIMENTS ON CRIME IMPACTS IN JURISDICTIONS/LARGE URBAN AREAS

In the 1970s, the aim of evaluations of police programs was generally focused on large urban-area impacts. The question that police and scholars asked was whether general strategies of policing led to crime reductions in a city or large sections of a city (e.g., boroughs, precincts, districts, or beats). Overall, the answer during that period was that such strategies were ineffective. For example, in 1974, the Police Foundation published an influential report on a large experimental field trial testing the effects of random preventive police patrol across police beats in Kansas City (Kelling et al., 1974). The results were unequivocal—increasing or decreasing random preventive police patrol in beats had no impact on crime or fear of crime. In another large-scale study supported by the National Institute of Justice, Spelman and Brown (1984) examined rapid response to citizen calls in four American cities. By interviewing 4,000 victims, witnesses, and bystanders related to 3,300 serious crime calls, they found that rapid response increased apprehension of offenders in only a limited set of circumstances.

The results from studies like these led police scholars to make inferences about the impacts of policing strategies on crime rates in cities. As a result, some scholars were skeptical of the ability of the police to do anything about crime. David Bayley concluded in 1994 (p. 3), for example, that:

> The police do not prevent crime. This is one of the best kept secrets of modern life. Experts know it, the police know it, but the public does not know it. Yet the police pretend that they are society's best defense against crime and continually argue that if they are given more resources, especially personnel, they will be able to protect communities against crime. This is a myth.

When reflecting on the more general acceptance of criminologists for this underlying skepticism about the traditional mechanism of police deterrence through detection of crime or apprehension of offenders, Michael Gottfredson and Travis Hirschi (1990: 70) wrote that, "no evidence exists that augmentation of police forces or equipment, differential patrol strategies, or differential intensities of surveillance have an effect on crime rates."

The emergence of hot spots policing must be considered in this context. Sherman and Weisburd (1995), in their introduction to the first large-scale field experiment in hot spots policing, argued that a key reason for the failure of policing strategies to impact crime was that they were dispersed across jurisdictions and did not focus on the specific places where crime was concentrated. In drawing on initial findings that crime was concentrated at micro-geographic hot spots (e.g., Pierce, Spaar, and Briggs, 1988; Sherman, 1987; Sherman, Gartin, and Buerger, 1989), they suggested that the police should not dilute the dosage of police interventions across entire beats but should focus it on crime hot spots. The results of subsequent studies have reinforced these observations, showing a fairly constant concentration of crime in cities at a small number of places (Andresen and Malleson, 2011; Braga, Papachristos, and Hureau, 2010; Brantingham and Brantingham, 1999; Crow and Bull, 1975; Curman, Andresen, and Brantingham, 2015; Pierce, Spaar, and Briggs, 1988; Roncek, 2000; Sherman, Gartin, and Buerger, 1989; Weisburd, 2015; Weisburd and Amram, 2014; Weisburd et al., 2004; Weisburd and Green, 1994; Weisburd, Groff, and Yang, 2012; Weisburd, Maher, and Sherman, 1992; Weisburd, Morris, and Groff, 2009). Weisburd (2015) has argued that this evidence points to a *law of crime concentration* at places (see also Weisburd, Groff, and Yang, 2012).

Sherman and Weisburd (1995) tested their assumption regarding a focus on micro-geographic hot spots in a large randomized field trial supported by the National Institute of Justice. The study design included randomization of 110 crime hot spots (about the size of a city block) to treatment and control conditions. On average, the treatment sites received between two and three times as much police presence as the control sites. For the 8 months in which the study was properly implemented, there was a significant and stable difference between the two groups (in terms of both crime calls to the police and observations of disorder in those areas). Crime, or at least crime calls and disorder, seemed to be prevented in the treatment as opposed to the control locations. Sherman and Weisburd (1995: 645) concluded that their results show "clear, if modest, general deterrent effects of substantial increases in police presence in crime hot spots." They noted that it was time for "criminologists to stop saying 'there is no evidence' that police patrol can affect crime" (Sherman and Weisburd, 1995: 647).

The results of subsequent studies of hot spots policing have provided strong support for the idea that focusing police activities at places where crime concentrates is an effective crime-prevention approach. A National Research Council (2004: 250) review of police effectiveness noted: "[S]tudies that focused police resources on crime hot spots provided the strongest collective evidence of police effectiveness that is now available." Campbell systematic reviews by Braga (2007) and by Braga, Papachristos, and Hureau (2012, 2014) have reached similar conclusions; the findings from most hot spots studies show statistically significant positive results, suggesting that when police focus on high-crime small geographic areas with high crime, they can reduce crime at these locations.

Perhaps as important as the evidence of the effectiveness of hot spots policing is the evidence that spatial displacement is not a major concern in hot spots interventions. Spatial crime displacement is the notion that efforts to eliminate crimes at a place will simply cause criminal activity to move elsewhere, thus, negating any crime-control gains. Braga, Papachristos, and Hureau (2012, 2014), however, in their systematic review of hot spots policing, found that displacement to nearby areas is unlikely in hot spots policing programs. Indeed, a more likely and significant outcome of such interventions was a diffusion of crime-control benefits (Clarke and Weisburd, 1994; Weisburd et al., 2006) in which the areas surrounding the target hot spots also show a decrease in crime and disorder.

In changing the geographic unit of focus, Sherman and Weisburd (1995) were able to alter prevailing skepticism of the ability of the police to do something about crime. But this change in focus has led as well to a limitation on the inferences that can be made from these studies. We know that hot spots policing can reduce crime at hot spots, but we do not know whether such activities will reduce crime overall in a large urban area. And we cannot mine existing studies to answer this question directly. An important methodological barrier comes from the design of hot spots policing evaluations. Generally, they use random allocation, or create quasi-experimental comparison areas within jurisdictions, so that the treatment and control conditions both exist within the same urban context. Although the use of experimental methods increases the confidence that we can have in these findings, and adds weight to their conclusions (Nagin and Weisburd, 2013), they make it difficult to answer the question of whether hot spots policing applied broadly will reduce crime in the urban area within which such strategies are implemented.

For example, in the Minneapolis Hot Spots Patrol Experiment (Sherman and Weisburd, 1995), there was no control condition or counterfactual for the citywide trends included in the experiment. To include a counterfactual for citywide trends, hot spots policing would have to be randomly allocated to treatment and control cities (not to treatment and control sites within a city). This is critical because citywide trends may be influenced by changes in trends in units that are not part of the experiment. For instance, given a static number of patrol hours, focusing on experimental crime hot spots may reduce the absolute levels of patrol in other areas of a city, so that the crime reductions gained within hot spots are offset by crime increases in areas where police patrol has declined. Added to this complexity is the specific design of the existing evaluations. They were used by researchers to identify whether hot spots approaches could be effective at reducing crime at hot spots. They were not used to address the question of how much hot spots patrol would be necessary to have significant impacts on crime in the larger urban area in which hot spots policing tactics are employed.

Instead, scholars and practitioners have relied on a logic model for the general crime-prevention effectiveness of hot spots policing in making inferences and drawing conclusions about the impacts of hot spots policing in the larger urban context. If hot spots policing can significantly reduce crime at chronic crime hot spots, and little evidence of displacement exists, then there inevitably should be an overall crime reduction in the urban area as a whole. In principle, one could use this approach to develop estimates of overall jurisdictional impacts of hot spots policing. In a randomized experiment in Dallas, Texas, for example, Weisburd et al. (2015) found that providing police managers with information on how unallocated police patrol time is used enabled them to increase patrols at crime hot spots. Although this approach led to significant reductions in crime at the hot spots, it did not lead to significant crime reductions in police beats. The authors attempted to use the estimates gained in the study to identify how much patrol at the hot spots would have to be increased to result in beat-level crime declines. Accordingly, they scaled up the prevention impacts gained from just 2 percent of unallocated patrol time employed at hot spots to 25 percent, and then they estimated that a 25 percent decrease in beat-level crime would have occurred. But this type of exercise does not take into account the potential interactions among police behavior, potential offenders, and suitable targets over time. Nor does it account for the fact that massive increases in police patrol at hot spots will naturally impact police patrol in other places. Simply scaling up cannot capture the complexity of the processes that generate crime trends in an urban area.

AGENT-BASED MODELS OF CRIME EVENTS

This research attempts to develop a more dynamic simulation of the impacts of hot spots policing by applying agent-based modeling (ABM). First, it develops and uses an ABM of street robbery and robbery hot spots. Next, it uses the robbery model to examine the specific impacts of hot spots policing programs on robbery rates under several different assumptions (Eck and Liu, 2008; Groff and Birks, 2008). Most critically, the approach includes a counterfactual for the large-areas impacts and allows for dynamic modeling over time. An ABM experiment allows us to examine the same units under different experimental conditions. In a traditional randomized experiment, "like units" are compared based on randomization. In an ABM, the same units experience treatment and control conditions. In this sense, ABM allows the development of true counterfactual conditions. It has the added rigor of exploring potential outcomes across a series of trials.

ABMs are unique in that they can incorporate heterogeneous agents who make decisions in an environment with dynamic situational characteristics. This combination allows simulated street robbery patterns to emerge from the interactions of individuals in the model. In this way, ABM represents a bottom-up approach that more closely approximates the crime patterns that emerge from interactions among people in the real world. For a comprehensive introduction to ABM, see Epstein and Axtell (1996), Gilbert and Troitzsch (2005), or Grimm and Railsback (2005).

There are three basic components to an ABM: agents, rules, and an environment. Agents most often represent people, but they can represent any decision-making entity in the model. Each agent can have a unique set of characteristics, which means we are not constrained to unrealistic assumptions to get computationally tractable models. The agents in the model have action rules that guide agent decision-making. These rules are based on theory or empirical evidence. The outcomes of agent interaction at one point in time influence agent interaction in subsequent time points. The dynamic nature of ABM over time is one of its important advantages over a simple extrapolation of observed crime-prevention benefits.

ABMs are getting increasing attention in the criminological literature (Johnson and Groff, 2014; for a collection of examples, see Eck and Liu, 2008). Brantingham and Brantingham (2004) inspired much of this interest with their seminal article in which they described how ABM could explicate opportunity theories. In their recent review, Groff, Johnson, and Thornton (2015) identified 43 ABMs of urban crime. ABMs have also been getting methodological attention. Several scholars have noted that ABM is a potentially powerful tool for evaluating crime-reduction programs (Groff and Birks, 2008; Groff and Mazerolle, 2008; Johnson, 2009; Verma, Ramyaa, and Marru, 2013).[1] ABMs comprise a theoretically informed approach to ask the question, "If this process is a reasonable reflection of reality, then what is the expected outcome?" (Eck and Liu, 2008: 416). In this sense, the theoretical basis of the model developed is the key to assessing whether the outcomes are valid.

The first stage of model building is to create a conceptual model. The next stage is to formalize that conceptual model into an implementation model. This step involves making conceptual relationships more concrete. At this point, the formalized model is

1. Johnson (2009) developed an ABM model assessing the jurisdictional effects of hot spots policing on burglary in a broader paper on computational methods to evaluate crime-prevention initiatives. Although the approach shows a significant impact on jurisdictional crime, the model was more an illustration than a test of hot spots policing. Johnson (2009: 36) cautioned that "the findings are of course only of any utility if the underlying model reflects the way the world is. There is no suggestion here that the model does."

programmed by researchers using a computer language. Finally, the researcher runs the completed computer program representing the model and collect the data. The sensitivity of model outcomes to changes in parameters is systematically tested, and the validity of the outcomes is evaluated. We discuss these topics later in the article.

There are some important limitations to ABMs, especially in the policy realm. First, this is a simulation of human behavior, and thus, the veracity of the results is dependent on what is included and excluded from the model. Second, it is possible that more than one model could produce similar results. Of course, these problems are encountered by other types of models and are not unique to ABMs (Gilbert and Terna, 2000). To mitigate these limitations, we grounded our model in theory, and whenever possible, we used empirical data to inform agent behavior and parameter choices. The next sections describe the theoretical basis for our operationalization of hot spots policing and for our representation of street robbery.

THEORETICAL FRAMEWORK FOR A MODEL OF HOT SPOTS POLICING

The crime-control effectiveness of hot spots policing is supported by two complementary theoretical perspectives: general deterrence and criminal opportunity reduction. Evaluation evidence has found support for both theoretical perspectives. For instance, in the Minneapolis Hot Spots Patrol Experiment, Sherman and Weisburd (1995) claimed evidence of place-specific general deterrence associated with increased police presence in hot spots areas. In Lowell, MA, Braga and Bond (2008) suggested that the crime-reduction impacts observed in their randomized experiment were primarily generated by problem-oriented policing strategies that modified the criminal opportunity structures at crime hot spots.

Deterrence theory posits that crimes can be prevented when the costs of committing the crime are perceived by the offender to outweigh the benefits (Gibbs, 1975; Zimring and Hawkins, 1973). General deterrence is the idea that the general population is dissuaded from committing crime when it observes that punishment necessarily follows the commission of a crime. The aim of much of the literature evaluating deterrence has been focused on the effect of changing certainty, swiftness, and severity of punishment associated with certain acts on the prevalence of those crimes (e.g., Apel and Nagin, 2011; Blumstein, Cohen, and Nagin, 1978; Cook, 1980; Paternoster, 1987). Findings from recent reviews of the deterrence literature have revealed that the certainty of apprehension is the most important ingredient in generating crime-control effects (Durlauf and Nagin, 2011; Nagin, 2013).

Traditional police crime-control strategies attempt to deter offenders from committing crimes by increasing their perceptions of the risks of criminal apprehension (and, by extension, enhancing the certainty of punishment). Unfortunately, standard practices, such as preventive patrol across jurisdictions, rapid response to calls for service, and follow-up investigations do little to change apprehension risks faced by potential offenders (National Research Council, 2004). In contrast, by concentrating police presence in high-activity crime places, hot spots policing strategies are well positioned to increase substantially the certainty of detection and apprehension at places and raise potential offenders' perceptions of risk at places (Nagin, Solow, and Lum, 2015). As such, would-be offenders attracted by criminal opportunities at high-crime places are more likely to perceive the risks of crime commission as higher than the benefits of crime commission (Nagin, Solow, and Lum, 2015).

Nagin (2013) identified a second crime-prevention function of police—the role of sentinels in their conventional patrol and monitoring activities—that emphasizes the opportunity reduction component of deterrence. By acting as sentinels, police increase levels of guardianship in criminally active places. Opportunity theories of crime, such as routine activity (Cohen and Felson, 1979), rational choice (Cornish and Clarke, 1986), and crime pattern theory (Brantingham and Brantingham, 1984), have often been used to understand the place characteristics, situations, and dynamics that cause criminal events to concentrate at particular places. Routine activity theory focuses on the criminal event and posits that criminal events occur when potential offenders and suitable targets converge in space and time in the absence of a capable guardian (Cohen and Felson, 1979). The increased presence of police augments the level of guardianship in targeted places. Heightened levels of patrol prevent crimes by introducing the watchful eye of the police as a guardian to protect potential victims from potential offenders.

WHY MODEL STREET ROBBERY?

We apply our theoretical model to explore the possible impacts of hot spots policing on robbery rates in beats and a cluster of police beats, which we term a city *borough*. We focus on one particular crime type for three reasons. First, from a theoretical perspective, Cornish and Clarke made a strong case for developing models of criminal decision-making "in relation to particular types of crime" (Cornish and Clarke, 1989: 104). Second, because theoretically based ABMs (which are what we are building here) need to reflect agent decision-making in particular situational contexts, their aim is typically to focus on particular crime types. Finally, street robbery is a serious crime often associated with the 1990s crime drop (Blumstein and Wallman, 2006) and there is a strong empirical base from which to develop a defensible model.

Robbery, and the fear it inspires, has a profound effect on the quality of life in certain urban neighborhoods (Cook, 2009). Robbers often make a series of rudimentary decisions in the commission of their crimes. Although the decision to commit a robbery may not follow classic rational choice models, it is consistent with the bounded rationality of the rational choice perspective (Clarke and Cornish, 1985). Based on interviews with robbers and other evidence, robbers' choices seem to reflect a desire to preempt resistance, secure as much property as possible, and then escape safely (Conklin, 1972; Jacobs, 2000; Wright and Decker, 1997). Location is of particular interest in the decision to commit a robbery. Robbers are attracted to places with targets that are vulnerable, accessible, and profitable (Feeney, 1986; Felson, 2006). The results of a recent analysis suggest that jurisdictional robbery trends may be best understood by examining micro-level trends at a small number of places in urban environments. Braga, Hureau, and Papachristos (2011) found that approximately 8 percent of street segments and intersections in Boston were responsible for 66 percent of all street robberies between 1980 and 2008.

THEORETICAL BASIS FOR A MODEL OF STREET ROBBERY

Over the past 10 years, several researchers have created theoretically grounded ABMs of street robbery (Birks, Townsley, and Stewart, 2014; Devia and Weber, 2013; Groff, 2007a, 2007b, 2008; Wang, 2009; Wang, Liu, and Eck, 2008). As a group, these models have used opportunity theories as their theoretical foundation, namely, routine activity theory (Cohen and Felson, 1979), the rational choice perspective (Cornish and Clarke, 1986), and crime pattern theory (Brantingham and Brantingham, 1984). In each of these models, the principles of opportunity theories have generated patterns of robbery data that exhibit known characteristics of observed robbery data. Our model draws from these earlier works. Specific instances where specifications come from other models are noted.

Following Groff's (2007a) formalization strategy, agents in our model make decisions based on the current situation given rules grounded in general deterrence and the crime opportunity reduction theories described earlier. Groff (2007a, 2007b, 2008) was the first to emphasize formalization, but most model specifications now do so; see Birks, Townsley, and Stewart (2012, 2014) for two other excellent examples. Opportunity theories hold that there is a supply of individuals in the population who are open to committing crime. Those individuals decide to offend based on their level of motivation and on the characteristics of a given situation, such as the suitability of targets and the amount of guardianship (Cornish and Clarke, 1986). Suitable targets for street robbery must be both visible and accessible, and the potential offender must perceive that he or she has something of value (Cohen and Felson, 1979; Cornish and Clarke, 1986). Potential offenders use bounded rationality when considering the potential risks and rewards (Cornish and Clarke, 1986). Other individuals at the same place and time affect the potential offenders' perception of risk. Police have a very high deterrent effect when they are present in a situation because they make arrest highly probable. Other individuals can also have a deterrent effect (Cohen and Felson, 1979; Cornish and Clarke, 1986). As in real life, the decisions made by individuals/agents at one point in time are influenced by their current characteristics and by the situation in which they find themselves. The outcomes, in turn, influence the decisions they make later in time.

Crime pattern theory (Brantingham and Brantingham, 1984, 1993) describes the important role of the physical environment in structuring human activity. The theory notes that individuals have activity spaces that consist of nodes and paths. The nodes are the places each person visits in the course of their daily routine (e.g., home, work, school, grocery store, dry cleaner, and gym). The paths are the routes they take between nodes. The configuration of a city structures activity spaces by bringing together differing numbers of people depending on the particular land use or combination of land uses. Furthermore, particular land uses and facilities are associated with differential levels of risk of street robbery. Thus, in our model, we include a risk surface that reflects the differing risk levels and the agents each have activity spaces. We collect the results of each decision to rob or not to rob and use them to represent the number and distribution of robbery events for different units of analysis.

METHODOLOGY

We implement the conceptual model of street robbery in NetLogo 5.1.0 (Tisue and Wilensky, 2004). Implementation of an ABM involves translating the conceptual model into computer software code. This process requires a level of detail and specificity that exceeds that found in theoretical specification, so we draw as much as possible from the earlier street robbery ABMs and empirical evidence to strengthen our model. As we describe the model, we provide the links to theory and empirical evidence that underpin

Table 1. Outcome Data From Agent-Based Model

Variable Name	Description
Societal-Level Outcome	
Total Robberies	Total number of robberies
Total Robberies by Chronic Offenders	Total number of robberies committed by chronic offenders
Total Robberies by Nonchronic Offenders	Total number of robberies committed by nonchronic offenders
Total Chronic Reoffenders	Total number of chronic offenders who have committed more than one robbery
Total Nonchronic Reoffenders	Total number of nonchronic offenders who have committed more than one robbery
Total Victims	Total number of civilians who are victims of street robbery
Total Repeat Victims	Total number of civilians who are repeat robbery victims
Place-Level Process	
Total Robberies per Grid Cell	Total number of robberies for each grid cell
Total Robberies per Beat	Total number of robberies for each patrol beat
Total Robberies for the Borough	Total number of robberies for the borough

NOTE: All are ratio-level data.

model parameters where available, and we provide the full "Overview, Design concepts, Details, and Decision-making (ODD+D) protocol" in the online supporting information (see table S.1).[2] Where no evidence is available, we use a plausible value as a starting point.

MODEL-LEVEL CHARACTERISTICS

The model environment simulates a representative urban area, which we call a borough. Our goal was to build an empirically based ABM using realistic population density, officers per population, and other baseline attributes that reflect the average across the top 20 largest cities in the United States. A 201 × 201 grid represents the borough landscape, which comprises more than 40,000 square grid cells. The length of each grid cell represents 47 feet in the real world, and this equates to roughly 3.2 square miles for the overall environment. Four equally sized police beats divide the borough (100 × 100 grid cells each).[3] The model is run for a 365-day period to examine deterrent effects. Each iteration of the model is called a *tick*, and one tick represents 1 minute of model time. To represent a 365-day period, the model runs for 525,600 ticks. Table 1 provides a summary of the data collected every 5 days (7,200 ticks) for each 365-day simulation.[4] A detailed description of the model parameters follows, and table 2 displays their default values.

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-1/issuetoc.
3. Abstract versus realistic landscapes are often the subject of debate in the ABM literature (see Elffers and Van Baal, 2008). A number of ABMs simulating routine activities have used grid cell landscapes. We weighed the computational demands of a spatially explicit landscape versus those of using a larger number of agents that would be more representative of the population density in a large city. We thought the latter issue was more critical and could not maximize both in a computationally feasible way.
4. The components of agent decision-making are assigned with random number distributions and change between simulations according to the random number seed that is set at the beginning of the *go* command. The starting seed is 100 and increases by 100 with each subsequent iteration. Model initialization was the same each simulation as a result of a static seed placed at setup (seed is 100).

Table 2. Model Parameters

Variable	Description and Rationale
Borough Size = 201 × 201	The simulated environment comprises 40,401 grid cells; 1 grid cell equates to 47 feet in the real world.
Police Beat = 100 × 100	Each of the 4 simulated police beats comprises 10,000 grid cells. The remaining 401 grid cells that fall on the x- and y-axes (201 × 2 – 1) are not assigned to a police beat.[a]
Grid Cells Traversed per Minute = $U(6-8)$	Each agent moves a random number of grid cells in the range 6 to 8 grid cells from a uniform distribution toward their target activity location (approximately 280–375 feet).
Model Termination = 365 days	Each simulation terminates after 365 days (or 525,600 ticks).
Number of Citizens = 40,000	Population size selected because it was large enough to examine the deterrent effects of the police, while being computationally feasible.
Number of Police = 36	The number of officers was based on the estimate of 2.8 officers per 1,000 residents made by the U.S. Department of Justice (2009) for cities with a population greater than 250,000. One third of the police force is on-duty at any given time, equating to 9 officers per beat and 36 officers in total.
Number of Target Grid cells: Citizens = 5 Police = 1	Each citizen starts with 5 potential destination grid cells (their home and 4 activity grid cells). The destination set for citizens is static over the course of a model run. Destinations for police are randomly selected from grid cells within their beat. New police destinations are randomly selected throughout the run.
Criminal Propensity Rate = 9.25%	9.25% of citizens have a criminal propensity value greater than zero.
Rate of Chronic Offenders = 5%	Of the 9.25% who have a criminal propensity, 5% received a propensity score of 10, whereas all others have a randomly selected score between 6 and 9. These values produce a model where 5% of offenders are responsible for around 50% of the crime (Moffitt, 1993).
Time to Offending (in ticks): Chronic = 0 Nonchronic = $U(0, 43{,}200)$	The amount of time that must pass after the citizen commits a robbery before he or she can potentially (re)offend is 0 days for chronic and a random number selected from a uniform distribution (0 to 30 days) for nonchronic offenders. This distribution is also used to vary the duration of time between the start of the model and when a citizen with criminal propensity begins to consider offending.
Amount of Time to Stay at Destinations: Activity Node = 15 ticks + $U(0, 480)$ Home Node = 1 tick + $U(0, 600)$	Once arrived at a destination location (a grid cell), the agent stays a random number of minutes selected from a uniform distribution based on whether he or she is at an activity location (15 ticks plus 0 to 480 ticks, 8 hours) or home (1 tick plus 0 to 600 ticks, 10 hours). This represents the varying times citizens spend at activity locations depending on the activity they are undertaking (i.e., we typically spend longer at work than at the grocery store).

(*Continued*)

Table 2. Continued

Variable	Description and Rationale
Probability of Home as Target Grid Cell = 80%	If the citizen is at an activity location, the probability of him or her going to a home location is 80%; otherwise, the citizen randomly selects one of his or her activity locations to travel to. If the citizen is at home, he or she randomly selects one of the activity locations to travel to.
Starting Seed = 100	This seed value initializes a pseudo-random number generator before the simulation starts (based on the Mersenne Twister algorithm). The seed increases by 100 after the completion of each 365-day model.
Victimization Score Threshold = 20	Parameter selected to generate robbery rates similar to the U.S. Department of Justice (2014) based on population size and duration of study.
Attractiveness = 5.5	Citizens assigned an attractiveness value from 1 to 10 based on a random distribution with a mean of 5.5 (SD = 1.2).
Perceived Guardianship = 5.5	Citizens assigned a perceived guardianship value from 1 to 10 based on a random distribution with a mean of 5.5 (SD = 1.2).
Perceived Capability = *U*(–5, 5)	A stochastic element is incorporated into perceived capability by adding a uniform number between –5 and 5 to the overall score.
Riskiness of Location = 0.19	Riskiness grid cell values are from a Poisson distribution ranging from 0 to 6.

ABBREVIATION: SD = standard deviation; U = uniform random number.
[a]These are fuzzy boundaries so officers may travel 15 cells into the adjoining beats (world wraps horizontally and vertically).

AGENTS IN THE MODEL

As mentioned, routine activity theory (Cohen and Felson, 1979) suggests that the convergence of a motivated offender and a suitable target at a particular place and time without capable guardianship represents the elements sufficient for a crime to occur. Thus, our model has two types of agents: citizens and police officers. There are 40,000 citizens (12,500 per square mile), which is consistent with the population density found in the top 20 largest cities in the United States (U.S. Census Bureau, 2014a, 2014b).

Some of the 40,000 citizens (9.25 percent) have a level of motivation to commit robbery that is greater than zero.[5] At this criminal propensity rate, 5 percent of offenders are responsible for approximately 50 percent of the robberies in the model (Moffitt, 1993; Wolfgang, Figlio, and Sellin, 1972). Motivation for all citizens is a static propensity score assigned at the initiation of the model by offender type: chronic offenders (propensity score is 10), nonchronic offenders (propensity score is a uniform random number between 6 and 9), or neither (propensity score is 0). In the absence of empirical evidence about the ebbs and flows of criminal motivation, we follow previous models (Birks, Townsley, and Stewart, 2012, 2014; Groff, 2007a, 2007b, 2008) and use a static level of motivation. This is a fertile area for future inquiry.

5. We are not aware of estimates related to the percentage of the population who commit street robbery. Because street robbery is a serious violent crime, we chose a value that was significantly less than the 20 percent estimate of the population that had ever committed a crime (Visher and Roth, 1986).

Only those citizens with a criminal propensity greater than 0 can commit a robbery. Some offenders with propensity for crime wait before they commit an additional robbery, whereas others will act on opportunities irrespective of whether they had already committed a robbery (Poynton, 2013). In our model, the time periods vary by type of offender and from one agent to another. Nonchronic offenders wait between 0 and 30 days, whereas chronic offenders have no restriction (see table 2 for details). At initiation of the model, nonchronic offender citizens are randomly assigned a minimum amount of time that must pass before they can commit a robbery (chronic offenders had no time restriction). In other words, they ignore attractive opportunities until a specified duration of time has passed (Brantingham and Brantingham, 1984). The time to offending is reset every time they commit a robbery.

There are 36 police officers patrolling the simulated borough, with 9 officers assigned to each beat. The population density of the borough determined the number of police officers and was based on national estimates, whereby there are 2.8 officers per 1,000 residents (U.S. Department of Justice, 2009) and one third of the police force is on duty at any given time.

ENVIRONMENTAL CHARACTERISTICS

Because the features of place are an important aspect in explaining the level and concentration of robbery in a city, we assigned each grid cell a riskiness of location value that represents environmental risks for robbery (Brantingham and Brantingham, 1981, 1984). The riskiness of location is a spatially inhomogenous Poisson distribution simulated by a Matern cluster process (Waagepetersen, 2007). This technique creates an environment where few grid cells in the world have disproportionate environmental risk for robbery and high-risk places tend to be spatially concentrated.[6] In other words, it produces the clustered pattern of land uses that attract high volumes of people and act as crime generators (Brantingham and Brantingham, 1995). The distribution of disproportionate risk approximates the Pareto principle (also known as the 80/20 rule), which has been applied to victims, offenders, and places (Clarke and Eck, 2005). The environmental risk also represents the absence of certain place aspects that serve to regulate behavior (crime enablers; Clarke and Eck, 2003). The riskiness of location value is a whole number ranging from 0 to 6, and the mean riskiness value of grid cells is .19.

ROUTINE ACTIVITY OF AGENTS IN THE MODEL

The implementation of citizen routine activities and movement in the model draws from research in behavioral geography (Horton and Reynolds, 1971), crime pattern theory (Brantingham and Brantingham, 1984), and previous ABMs of street robbery (Birks, Townsley, and Stewart, 2012, 2014; Groff, 2007a, 2007b, 2008). Accordingly, the agents in

6. We tested several combinations of input parameters before achieving a reasonable approximation of 15 percent of cells accounting for approximately 80 percent of overall risk. The final input parameters used in the *rMatClust* command in R included an intensity of the Poisson process equal to 500, the radius parameter of the clusters set at .02, and a mean number of points per cluster as 15. Risky values were computed by using the sum of points falling within each grid cell based on x–y coordinates. The distribution of risk is presented in figure S.1 in the online supporting information. Environmental risk values remain static across all model runs.

our model have activity spaces. At the initiation of the model, citizens are randomly assigned a home grid cell and four activity grid cells (two of these grid cells are selected from the subset of grid cells with a riskiness score > 0). This approach simulates the clustering among activity nodes found in the real world. For example, many people are attracted to grocery stores and malls as opposed to residential locations. In the language of environmental criminology, these places are crime generators (Brantingham and Brantingham, 1995). Citizens start from their home location, and the location of their home remains the same across simulations. To represent the variability in routine activities across a population, we assign each agent a different amount of time to wait at home before he or she leaves and heads to one of the activity grid cells (see table 2 for specifics). Each time the agent reaches an activity grid cell, he or she makes the decision whether to leave and go to one of the agent's other activity grid cells. The agent has an 80 percent probability of returning home (Birks, Townsley, and Stewart, 2012; Golledge and Spector, 1978).[7] Although the individual characteristics of citizens remain the same, the characteristics of police officers vary by model condition (described later).

When traveling among their assigned activity locations, citizens always travel the path with the shortest distance. Citizens travel between activity locations at varying rates to represent the differing amounts of time it takes to travel between two locations in the real world. Each minute they evaluate where they are in relation to where they need to go and move toward their next activity location. The distance they move is randomly assigned to between six and eight grid cells per minute, which translates to roughly a 17-minute per mile pace on average. At this rate, civilians travel approximately the length of a street segment each minute (280 to 375 feet). Civilian agents can become a victim of street robbery anytime they are traveling between activity locations. Civilians move multiple grid cells per tick and can be victimized only after each move is complete (i.e., if an agent moves six grid cells, he or she can only be victimized on the landing cell, not on any cell in between).

DECISION TO COMMIT ROBBERY

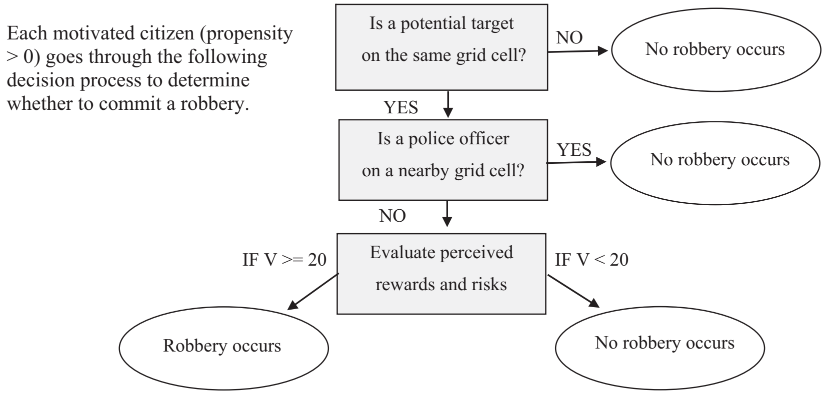
The navigation of the agents throughout the environment dictates whether a robbery occurs as it brings together motivated citizens and suitable victims in the absence of capable guardians (Cohen and Felson, 1979). Motivated citizens (criminal propensity greater than 0) who are traveling to their target grid cell assess the following in the decision to commit a robbery with each minute of the model (see figure 1):

1. Is a potential target on a grid cell?
2. Is a police officer on a nearby grid cell?
3. Do the benefits of robbing the citizen outweigh the risks?

Agents make the decision to commit a robbery using bounded rationality (Simon, 1957). First, the motivated citizen evaluates whether a potential victim is on his or her current grid cell. Any citizen that is traveling to the agent's target grid cell is a potential

7. Although a citizen may be assigned an activity grid cell for his or her initial target grid cell, citizens are assigned a random uniform number ranging from 1 to 480 (represents 1 minute to 8 hours) that must transpire since the initiation of the model before he or she can leave home. This prevents the mass exit of citizens from their homes at model initiation.

Figure 1. Decision to Commit a Robbery



ABBREVIATION: V = victimization score.

victim; citizens cannot be victims when they are at home or at an activity node. Criminally motivated citizens can also be victims. Second, if a potential target is available on the agent's current grid cell, the criminally motivated citizen then determines whether a police officer is nearby. Police officers serve as formal guardians—a robbery is prevented if an officer is within a radius of seven grid cells from the criminally motivated citizen (equivalent to 329 feet). This distance seemed reasonable given that it is about the length of an average city block in major cities (e.g., Seattle and Philadelphia). Although a visual sighting of a police officer might depend on the number of citizens on the street and weather conditions, for example, we think that on average when police officers are on a single street segment, their cars would be visible to the whole street segment. In turn, this distance parameter is drawn from evidence demonstrating a general deterrent effect at distances within 300 feet of a police officer (Wooditch and Weisburd, 2016).

Third, following the rational choice perspective (Cornish and Clarke, 1986), the robbery-motivated citizen evaluates the costs, benefits, and risks of an offending opportunity via a cumulative victimization score, which incorporates the victim's attractiveness and guardianship along with the agent's level of criminal propensity. A robbery occurs when the following equation, which describes the computation of the victimization score, is satisfied at a given grid cell in space and time (*x, y, t*):

$$\text{Attractiveness}_{(x,y,t)} - \text{Guardianship}_{(x,y,t)} + \text{Motivation}_{(x,y,t)} + \text{Riskiness of Location}_{(x,y)} \geq 20$$

Attractiveness in the equation refers to a randomly generated attractiveness score of the potential victim, whereby higher scores indicate greater target suitability. The attractiveness score is randomly assigned from a normal distribution that has a range of 1 to 10 at the initiation of the model [M = 5.5; standard deviation (SD) = 1.2]. The level of guardianship (G) is determined using two elements—the victim's ability for self-guardianship and the offender's perception of capable guardians present (other citizens). The computation of overall guardianship is as follows:

$$G = P_G + N_C$$

The self-guardianship score, P_G, is internal to each agent and represents how other agents view that agent's ability to protect him- or herself from victimization. P_G is a randomly selected number assigned at the initiation of the model, which ranges from 1 to 10 (M = 5.5; SD = 1.2). The perceived availability of capable guardians, N_C, is computed as follows:

$$N_C = (N_A - 2) + P_C$$

The term N_A is the sum of available citizens on the grid cell minus two for the active offender and his or her potential victim. The term P_C represents the perceived capability of guardians in a situation. It also adds a stochastic element into the formula by increasing or decreasing the perceived guardianship capability of other agents at the node (Groff, 2007a, 2007b; Groff and Mazerolle, 2008). This parameter is necessary to incorporate unknown factors in how robbery-motivated citizens perceive the guardianship capability of other citizen agents. P_C is a uniform number between –5 and 5.[8] Motivation in the victimization score is the criminal propensity of the motivated citizen, as discussed. The riskiness of location is a risk score assigned to each grid cell in space (x, y) and is incorporated into the motivated citizen's likelihood of committing a robbery by adding the riskiness value of the grid cell on which the motivated citizen is located to the overall victimization score. When more than one citizen meets the criteria for being both an offender and a victim, the role is assigned at random. Once a robbery occurs, the offender and victim return to their home grid cells (see also Verma, Ramyaa, and Marru, 2013). Neither can become victims of robbery until the next time they leave their respective home grid cell.

EVALUATING THE BASE MODEL

Model validation is a critical area for ABMs because it involves measuring how well the model represents the target phenomena in the real world (Gilbert, 2008). We ran the model with random police patrol within assigned patrol beats 100 times and used the outcomes to evaluate the veracity of the model for testing the impact of police patrol. Our goal was to verify that the bottom-up interactions of agents were generatively sufficient to produce known patterns in robbery data. As Groff and Birks (2008) noted, there are several general challenges to validating model outcomes. Some apply to all simulation models, such as a paucity of standardization related to building and analyzing models, a lack of model replication, and the possibility that different mechanisms can produce similar results (Batty and Torrens, 2005; Manson, 2001; O'Sullivan, 2004). Another has to do with whether empirical data exist that can be used to validate the results. Particularly relevant to models of crime events are the well-known problems with official crime data (Maguire, 2002), which means we do not have a reliable metric with which to compare the results of ABMs (Birks, Donkin, and Wellsmith, 2008; Eck and Liu, 2008; Groff, 2007a, 2007b; Groff and Birks, 2008; Townsley and Birks, 2008). In other words, the number of reported crimes in empirical data is a subset of crime that occurs, but the results of an ABM include all crimes. As a result, modelers have used an alternative method for validation that involves identifying well-known patterns in crime data and using those patterns

8. We tried to choose a value range that could potentially change the outcome of a decision without this parameter included. See the section on sensitivity testing for more information.

to validate models (Birks, Townsley, and Stewart, 2012, 2014; Groff, 2007a, 2007b; Wang, Liu, and Eck, 2008).

The base model developed here is of street robbery on a landscape that represents the population density and citizen-to-officer ratio found by averaging empirical data for the top 20 largest cities in the United States. Whether our model produced a realistic number and spatial pattern of simulated robbery events provides the most relevant criteria to assess its performance.[9] We do not have a precise estimate of actual robbery rates for the top 20 largest cities. The best data on actual robbery rates would be provided by the National Crime Victimization Survey (NCVS), but it does not report on robbery rates by specific cities or for urban areas. At the same time, it provides a national estimate that approximately 60 percent of robberies are reported to the police (U.S. Department of Justice, 2015). If we apply that estimate to robbery rates in the 20 largest cities as reported by the Uniform Crime Reports (UCR) program, we gain a robbery rate of about 428 per 100,000 (UCR average of 256.90; U.S. Department of Justice, 2014). Taking the top 20 cities with a population of greater than 250,000 with the highest robbery rate, we obtain a robbery rate of 859 (UCR average of 515.54 per 100,000 population; U.S. Department of Justice, 2014). The base model in the sensitivity analyses produced a robbery rate of 548.50 per 100,000. By using these estimates as a guide, we think our model produced realistic estimates for robbery rates in a large urban area.

We examine our output robbery data using three well-known patterns in crime data: 1) the concentration of crime in the form of hot spots, 2) repeat victimization of people and places, and 3) highly motivated offenders are responsible for approximately half of the crime (see tables S.2 and S.3 in the online supporting information). The distribution of robberies in the borough displays statistically significant clustering (Moran's $I = .06$; $z = 16.29$; $p < .001$). Our model also produces a high rate of repeat victimization, with a base model average of almost four robberies per victim. We find chronic offenders, representing just 5 percent of motivated citizens, produce almost half of the robberies in the base model. This examination provides evidence that the model is generatively sufficient (Epstein, 1999) to produce street robbery patterns with these signature elements.

SENSITIVITY TESTING

Before proceeding to the test of policing strategies, we also undertook a robust set of sensitivity tests to explore the effect of changing the values of key parameters on overall numbers of robberies (see appendix S.1 in the online supporting information). Sensitivity testing provides important information regarding the robustness of model results given changes in the parameters used. For example, if we increase or decrease the number of police, does the outcome of the model change dramatically and are the conclusions changed (Gilbert, 2008; Grimm and Railsback, 2005; Manson, 2001)? The process of conducting the tests also provides insights into how changes in parameter values affect model dynamics (Gilbert, 2008). The observed effects should be in line with theoretical expectations.

9. The hot spots targeted by police in the experiments are depicted in figures S.2 and S.3. Even though the likelihood of robbery is higher on risky grid cells, robberies still occur on grid cells with a risky value of 0 (see table S.4 in the online supporting information).

We systematically varied a set of 12 critical parameters, one at a time, across a spectrum of values (see tables S.2 and S.3 in the online supporting information). We ran multiple simulations of each set of parameters and averaged the results across all runs. Sensitivity analyses were conducted on the following parameters: initial seed number; the number of days until reoffending; the number of police officers; the probability of going to home grid cell; the location of activity grid cells; the spatial distribution of riskiness values; stochastic element in the decision to offend; beat boundaries; attractiveness and guardianship scores; the deterrence radius of the police; and the number of grid cells agents move per tick. For each parameter tested, the outcome changed in a plausible manner and in the expected direction (see tables S.2 and S.3 in the online supporting information for details). For example, robbery rates increase when the number of days until reoffending is reduced or the number of police officers is decreased. There are increases in robbery when riskiness values are increased or when guardianship values are decreased.

HYPOTHESES AND EXPERIMENTS

To examine the effect of hot spots policing on crime in the larger urban context within which such strategies are implemented, we run two separate experiments using our robbery ABM:

1. *Low-Intensity Hot Spots Policing Implementation*: Two thirds of the police officers patrol randomly, whereas the other one third is assigned to provide approximately 50 percent of their time at the top five hot spots in each beat.[10]
2. *High-Intensity Hot Spots Policing Implementation*: Roughly half of the police officers in each beat patrol randomly, whereas the other half is assigned 100 percent of their time to the top five hot spots in each beat.[11]

We chose these allocations of hot spots policing because they represent lower and upper bounds of the hot spots policing model. Some minimal commitment of patrol forces would be necessary to expect a large-area impact. In experiment 1, police patrol follows the traditional random patrol model. Nevertheless, one third of the force spends half of their time on hot spots patrol. In experiment 2, half of the patrol force carries out hot spots policing strategies. This investment is large but realistic. Estimates of unallocated police time vary between 25 and 50 percent of patrol time and even more in some cases (Famega, Frank, and Mazerolle, 2005; Frank, Brandl, and Watkins, 1997; Kelling et al., 1974; Mastrofski et al., 1998; Weisburd et al., 2015; Whitaker, 1982). This suggests that a major reallocation of patrol could be carried out in police agencies if they wanted to adopt a hot spots patrol approach across their jurisdictions.

Each of these experimental conditions is compared to two scenarios, one in which 1) all patrol officers operate under a random patrol model all of the time and 2) there are no

10. Hot spots patrol officers begin the simulation at either a randomly selected target grid cell within their beat or a randomly selected grid cell in a designated hot spot within their beat.
11. Hot spots patrol officers are assigned to this hot spot for 1,440 ticks (1 day) and move to a new grid cell within this assigned hot spot every 15 ticks (15 minutes) (Koper, 1995). Officers are assigned to a new hot spot after 1,440 ticks. There is always at least one officer assigned to each hot spot at any given time. The diameter of the hot spot at times exceeds the deterrence radius of the officer, so even when a police officer is present at a hot spot, a robbery may still occur at the location depending on where the officer is located.

police officers at all. Although the relevant model for assessing the benefits of hot spots policing is in comparison with the random patrol model, the "no police patrol" model provides an interesting baseline for our work. Perhaps, for example, it does not make a difference whether the police patrol at all.

We ran the model with random police patrol 100 times and used the outcome distribution across all 100 runs to identify hot spot areas. This procedure is similar to the way many police departments create their hot spot maps from crime patterns. Hot spot areas comprise 1,366 grid cells in the borough, with an average of 69 grid cells per hot spot. The maximum hot spot diameter is 19.3 grid cells (907 feet). We considered using an environment in which there were no police for identifying hot spots, but we decided against that because there is never a real-world situation in modern Western cities in which there are no police. We identified the hot spots by averaging the number of crimes on each grid cell across all 100 runs of the base model. We used a local indictor of spatial autocorrelation (LISA) statistic to identify cells with high average robberies that are surrounded by other cells with high average robberies. We collapsed hot spots that were within one grid cell of one another into a single, larger hot spot. At the end of the process, we had delineated 20 hot spots (5 hot spots in each police beat).

For each experiment, we ran the street robbery model 100 times and reported the average of the trials as the outcome. We then aggregated the robbery event data to several different units of analysis including hot spots, police beats, and the borough to test the following hypotheses:

1. The adoption of hot spots policing will reduce robbery rates in the associated hot spot.
2. The adoption of hot spots policing will reduce robbery rates in the associated police beat.
3. The adoption of hot spots policing will reduce robbery rates in the associated borough.

ANALYSIS

The effect of hot spots policing is analyzed with descriptive statistics obtained for each model condition. We use *t* tests and analyses of variance to examine various geographic units of analysis and to identify the duration of time at which hot spots patrol becomes effective at a larger geographic unit of analysis over the 365-day period. Immediate spatial displacement of robbery outside the hot spot is also examined (7 and 14 grid cell buffer around each hot spot). It is also possible that crime displaces to other high-opportunity areas further away that motivated citizens encounter during their daily routine activities. The reallocation of officers to hot spots may also reduce police presence at other high-opportunity areas. To assess spatial displacement that may occur farther away from the targeted hot spots, we explored trends in robbery on grid cells with a risky location value greater than zero that were not located in a hot spot targeted by police.

RESULTS

Table 3 presents the mean overall number of robberies by condition. These findings suggest that there is a significant difference over the 1-year period in the mean number

Table 3. Mean Number of Robberies by Unit of Analysis and Condition

	No. Officers		Random Patrol		Low-Intensity Hot Spots Policing (#1)		High-Intensity Hot Spots Policing (#2)		
Area	**M**	**(SD)**	**M**	**(SD)**	**M**	**(SD)**	**M**	**(SD)**	***F***
Borough	301.04	(45.58)	268.98	(40.86)	262.46	(36.20)	237.49	(22.84)	49.07***
Police Beat	74.40	(11.31)	66.41	(10.10)	64.92	(11.31)	58.79	(5.62)	48.11***
Hot Spots	2.37	(.43)	2.55	(.46)	2.07	(.39)	.58	(.17)	561.56***

NOTE: $df = 399$.
ABBREVIATION: M = mean; SD = standard deviation.
***$p < .001$.

of robberies among conditions at the hot spot [$F(3, 396) = 561.56$; $p < .001$], police beat [$F(3, 396) = 48.11$; $p < .001$], and borough [$F(3, 396) = 49.07$; $p < .001$] levels. Both no police patrol and random police patrol models had a higher overall number of robberies across all geographic units in comparison with the hot spots policing strategies. The high-intensity hot spots policing implementation had a lower overall number of robberies at all geographic levels in comparison with the low-intensity hot spots policing implementation. Importantly, this model also suggests that random police patrol does produce a benefit for larger geographic areas above that of no police, and a comparison between these two conditions confirms that these differences are statistically significant, $t(99) = -7.26$; $p < .001$. This finding is consistent with nonexperimental studies that have been conducted when police are on strike (for a summary, see Sherman and Eck, 2002).

Table 4 presents the results of experiments 1 and 2 by condition in more detail. The first hypothesis tests whether hot spots policing strategies reduce robbery rates across geographic units in comparison with no police patrol. Low-intensity hot spots policing reduces the incidence of robbery by 12.8 percent at the borough level, 12.7 percent at the police-beat level, and 12.7 percent at the hot spot level. High-intensity hot spots policing reduces the incidence of robbery by 21.1 percent at the borough level, 21.0 percent at the police-beat level, and 75.5 percent at the hot spot level in comparison with a borough without police patrol. The second hypothesis tests whether hot spots policing strategies reduce robbery rates across geographic units of analysis in comparison with random police patrol.[12] Low-intensity hot spots policing reduces the incidence of robbery by 2.4 percent at the borough level, 2.2 percent at the police-beat level, and 18.8 percent at the hot spot level as compared with the full random patrol model. High-intensity hot spots policing reduces the incidence of robbery by 11.7 percent at the borough level, 11.5 percent at the police-beat level, and 77.3 percent at the hot spot level in comparison with a borough in which all police patrol randomly.

Figure 2 presents the mean number of cumulative robberies at the borough level across the four conditions that emerge over the 365-day period. When comparing conditions for experiment 2, significant differences in the mean number of borough robberies emerges between the no-police-patrol implementation and both low- [$t(99) = 2.11$; $p < .05$)] and high- [$t(99) = 2.61$, $p \leq .01$] intensity, hot spots policing implementations by day 5. There is an average of 2.13 robberies (SD = 1.43) across simulations on day 5 for the no-police-patrol implementation as compared with 1.70 robberies (SD = 1.45) for low-intensity hot spots policing and 1.64 robberies (SD = 1.19) for high-intensity hot spots policing. When comparing conditions for experiment 2, significant differences in the mean number of borough robberies emerges between the random-police-patrol implementation and low- [$t(99) = 2.12$; $p < .05$] and high- [$t(99) = 2.46$; $p < .05$] intensity hot spots policing and by day 200 and 35, respectively. There is an average of 143.94 robberies (SD = 21.91) across simulations on day 200 with random patrol as compared with 140.32 robberies (SD = 21.62) with low-intensity hot spots policing. Furthermore,

12. The size of crime-reduction impacts at the hot spot level estimated in our simulations are consistent with crime reductions noted in several hot spots policing evaluations (Braga, Papachristos, and Hureau, 2012, 2014). Similar to the high-intensity implementation in our simulation, some crime reductions were large (e.g., DiTella and Schargrodsky, 2004; Sherman and Rogan, 1995; Weisburd et al., 2006). Other hot spots policing evaluation findings were more consistent with the low-intensity hot spots policing implementation (e.g., Sherman and Weisburd, 1995).

Table 4. Paired Sample *t* Tests for Number of Robberies

Experiment 1

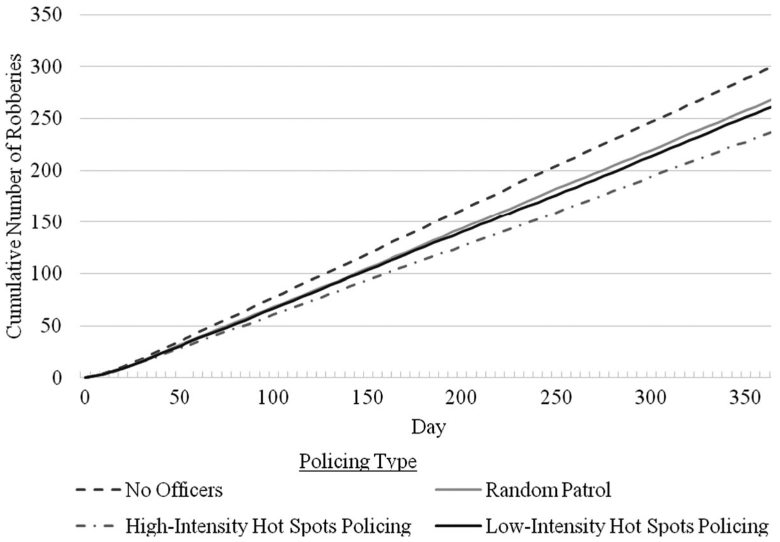
	Low-Intensity Hot Spots Policing vs. No Officers						High-Intensity Hot Spots Policing vs. No Officers					
		Paired Δ						Paired Δ				
Area	% Change	M	(SD)	95% CI of Paired Δ		*t* value	% Change	M	(SD)	95% CI of Paired Δ		*t* value
Borough	–12.8%	–38.58	(37.98)	–46.12	–31.04	–10.16***	–21.1%	–63.55	(39.21)	–71.33	–55.77	–16.21***
Police Beat	–12.7%	–9.48	(9.38)	–11.34	–7.62	–10.11***	–21.0%	–15.61	(9.74)	–17.54	–13.67	–16.02***
Hot Spots	–12.7%	–.31	(.48)	–.41	–.22	–6.50***	–75.5%	–1.80	(.46)	–1.89	–1.71	–38.95***

Experiment 2

	Low-Intensity Hot Spots Policing vs. Random Patrol						High-Intensity Hot Spots Policing vs. Random Patrol					
		Paired Δ						Paired Δ				
Area	% Change	M	(SD)	95% CI of Paired Δ		*t* value	% Change	M	(SD)	95% CI of Paired Δ		*t* value
Borough	–2.4%	–6.52	(24.15)	–11.31	–1.73	–2.70***	–11.7%	–31.49	(33.03)	–38.04	–24.93	–9.53***
Police Beat	–2.2%	–1.51	(6.01)	–2.70	–.32	–2.51*	–11.5%	–7.63	(8.29)	–9.28	–5.99	–9.21***
Hot Spots	–18.8%	–0.48	(.04)	–.56	–.39	–11.18***	–77.3%	–1.96	(0.45)	–2.05	–1.87	–43.25***

NOTES: $df = 99$ and Δ = differences paired by random seed.
ABBREVIATION: CI = confidence interval; M = mean; SD = standard deviation.
$^{*}p = .014$; $^{***}p < .001$.

Figure 2. Trends in the Mean Cumulative Number of Robberies by Condition at the Borough Level



NOTE: Trends reflect the mean robberies at the borough level across 100 simulations (models report total number of robberies every 5 days for the 365-day period).

there is an average of 20.01 robberies (SD = 4.98) across simulations on day 35 with random patrol as compared with 18.51 robberies (SD = 4.41) with high-intensity hot spots policing.

Findings from both experiments 1 and 2 suggest that the adoption of hot spots policing reduces robbery rates in the associated hot spot, police beat, and borough. An examination of the immediate areas that surround the target sites reveals that hot spots policing strategies yield significant reductions in robbery across geography levels without displacing robberies to nearby areas (table 5). Relative to random patrol conditions, both sets of buffer zones surrounding targeted places with high-intensity hot spots policing experienced much lower levels of robberies, whereas buffer zones surrounding targeted places with low-intensity hot spots policing did not. The simulation results suggest that hot spots policing with a high dosage of police presence in target areas is likely to result in a diffusion of crime-control benefits immediately around the hot spot. This is consistent with empirical findings (e.g., see Clarke and Weisburd, 1994; Weisburd et al., 2006).

Next, we explore trends in robbery at grid cells with a risky location value greater than zero that were not located in a hot spot targeted by police (table 5). The mean sum of robberies occurring in these high-opportunity areas is higher with low- (M = 149.89; SD = 15.51) and high- (M = 147.60; SD = 20.98) intensity hot spots policing in comparison with random patrol (M = 142.31; SD = 23.93). This finding reveals that crime may displace to areas motivated offenders encounter during their routine activities outside the immediate area of targeted hot spots. Nevertheless, in both hot spots policing models, the spatial displacement to more distal areas was small and did not outweigh the crime-control benefits gained.

Table 5. Examination of Spatial Displacement by Mean Robberies

Area	No Officers		Random Patrol		Low-Intensity Hot Spots Policing		High-Intensity Hot Spots Policing		
	M	(SD)	M	(SD)	M	(SD)	M	(SD)	*F*
Immediate Spatial Displacement:									
Catchment Area #1 (7 Grid cells/329 ft buffer)	57.83	(11.30)	51.32	(11.12)	50.99	(9.54)	40.59	(8.08)	49.87***
Catchment Area #2 (14 Grid cells/658 ft buffer)	131.42	(21.71)	112.51	(19.78)	112.75	(18.04)	109.32	(13.93)	28.18***
Immediate and Distal Spatial Displacement:									
Risky Locations (non-hot spots)	169.77	(26.87)	142.31	(23.93)	149.89	(15.51)	147.60	(20.98)	29.22***

NOTE: $df = 399$.
ABBREVIATION: M = mean; SD = standard deviation.
***$p < .001$.

DISCUSSION

The aim of our study was to examine whether hot spots policing strategies can have effects on crime in the larger urban areas within which such strategies are implemented. By using an ABM approach, we found strong and significant large-area effects for hot spots policing beyond both a random patrol model and a landscape without police. One interesting outcome of our ABM is that random preventive patrol reduces robbery in comparison with an environment where there is no police. In some sense, this result is not surprising given prior studies of cities in which police have been withdrawn or go on strike. Nagin and Weisburd (2013) argued that some of the most convincing quasi-experimental evidence on the effects of police presence on crime has come from accounts of the impact of an event unrelated to the crime rate that results in the complete withdrawal of police presence: For example, in September 1944, German soldiers occupying Denmark arrested the entire Danish police force. According to an account by Andenaes (1974), crime rates rose immediately but not uniformly. The frequency of street crimes such as robbery, whose control depends heavily on visible police presence, rose sharply. By contrast, crimes such as fraud were less affected. Sherman and Eck (2002) summarized studies showing similar impacts of the withdrawal of police presence as a result of strikes.

Of course, the key question is not whether random patrol within beats is better than no patrol at all but whether hot spots policing provides greater crime-prevention benefits than do traditional random patrol strategies. The answer in our simulations is that hot spots policing provides strong benefits for the larger urban area in which hot spots policing is applied, especially when applied at higher dosages. In the model in which roughly half of the patrol force is devoted to hot spots policing, robberies declined more than 10 percent in the beats and borough where this focused approach was being used as compared with the random patrol model. This is a substantial reduction in crime.

If we assume that our findings in a borough including four beats can be extrapolated to urban areas more generally, large crime-prevention gains would be expected. The Federal Bureau of Investigation (FBI) estimated in 2010 that there were 119 robberies per 100,000 citizens (U.S. Department of Justice, 2010). If we assumed that there were approximately 600 robberies on average in cities of 500,000 population, the adoption of a high-intensity hot spots policing model as in our ABM would lead to a reduction of approximately 60 robberies per year. The benefit of a low-intensity hot spots policing model is much smaller, an estimated 2 percent, or 12 robberies a year in a city with 500,000 population. In cities with serious crime problems, the benefits would be much larger. For example, Baltimore has a population of approximately 600,000, but there were 3,734 robberies in Baltimore in 2013 (U.S. Department of Justice, 2013). High-intensity hot spots policing, such as the one we present, would lead to a decline of almost 400 robberies in Baltimore according to our model. Even low-intensity hot spots policing would lead to a decline of 75 robberies. Moreover, our models used a static approach to defining crime hot spots. With the development of predictive policing approaches, which allow a dynamic definition of hot spots that would be sensitive to variability in shorter time spans, we might expect these impacts to be larger (e.g., see Mohler et al., 2015).

Although our findings suggest that hot spots policing does not lead to crime displacement in the areas immediately surrounding the targeted hot spot, our models show that robberies are displacing to locations that are more distal. The finding of little immediate areal displacement is consistent with a series of experimental and quasi-experimental studies of hot spots policing (Braga, Papachristos, and Hureau, 2012, 2014; Clarke and Weisburd, 1994; Weisburd et al., 2004). As noted by Weisburd et al. (2006), moving "around the corner" is not a simple choice for offenders who have developed a familiarity with and knowledge of the crime hot spot. Moving sites may entail significant danger either because of competition from other offenders or lack of familiarity with people who live in the area who might, for example, call the police in response to their activities. Moreover, areas nearby may not offer the same opportunities for crime as those of the crime hot spot. For example, a crime hot spot may be located at a mall or bar, and the areas nearby may be residential streets. This is represented in our model by different levels of attractiveness of specific grid cells.

At the same time, although the results of field studies have not revealed this outcome, we might expect that some offenders would be willing to increase efforts and risk to continue their criminal activity despite these barriers to displacement. Brantingham and Brantingham (2003) argued that when highly motivated offenders are confronted with blocked opportunities at one location, they will look to the nearest location with adequate crime opportunities (Brantingham and Brantingham, 2003). We suspect that this search for new opportunities is tempered by the risk and effort involved in moving crime locations (Weisburd et al., 2006). At the same time, it seems reasonable that some highly motivated offenders will search out and take advantage of new sites that offer high levels of criminal opportunities. Our data reflect this, but they also reinforce the idea that this distal displacement is much smaller than the crime-prevention benefits of the concentration of police patrol at crime hot spots. We think this intriguing finding deserves more attention both in future simulations and in field studies of hot spots policing.

But are the levels of hot spots policing we have tested in our models realistic? And do these findings suggest that the widespread adoption of hot spots policing over the last decade of the twentieth century (Weisburd and Lum, 2005) could be responsible for a meaningful part of the crime drop observed in the United States during that period (Wallman and Blumstein, 2006; Weisburd and Braga, 2006; Zimring, 2012)? It certainly seems reasonable that a police agency can allocate one third of its police force to hot spots policing duties. If estimates that put free time on patrol at levels higher than 50 percent are correct (Famega, 2009; Matrix Consulting Group, 2009, 2011), then this type of commitment is certainly not difficult to achieve. Even if the amount of free time is 25 or 30 percent of patrol time (Weisburd et al., 2015), this level of dosage should be reasonable. But is it reasonable to expect police to devote attention to hot spots when demand for police more generally is highest in a city? It is important to remember that in peak hours, hot spots of crime are also likely to be at their highest level of activity. The top 1 percent of streets produces 25 percent of crime and even higher rates in smaller cities (Weisburd, 2015). Given this, hot spots of crime during hours of peak demand will likely get high levels of police patrol simply because a good deal of the action of crime occurs there.

Although available data are lacking to evaluate this, when police agencies have implemented hot spots policing, they seem to have done so at dosage levels closer to our lower intensity intervention experiment. Therefore, based on our estimates from ABM, we suspect that the influence of hot spots policing on crime in cities has in practice been more modest. Many cities have adopted the idea of hot spots patrol as one focus of its efforts, but they have not abandoned their more general commitment to staffing minimum amounts of preventive patrol across larger geographic areas. Weisburd (2008) argued that the concentration of crime at micro-geographic hot spots in a city calls for a restructuring of patrol resources from large geographies to crime hot spots. The traditional police approach to spreading resources across large geographies, even when there is little evidence of crime in those areas, makes it almost impossible to achieve the highest dosage of hot spots patrol we test (see Weisburd et al., 2015). Our simulations suggest that if robbery hot spots became the major focus of unallocated patrol time in the city, and the rapid response philosophy was tempered to a greater degree by the need to focus on hot spots, hot spots patrol could be implemented at levels that would have large impacts on robbery levels in the city.

Of course, our assumptions here are based on a simulated borough and caution should be used in drawing conclusions (Gilbert and Troitzsch, 2005; Groff, 2007a, 2007b). We built our simulation to test hot spots policing in one urban borough divided into four police beats with a population density and citizen–police ratio that are consistent with the averages for the top 20 populated cities in the United States rather than an entire city, which would include boroughs with lower and higher levels of robbery. Unfortunately, even with the batch processing we used in this simulation, it would be extremely difficult to estimate an ABM applied to a larger number of boroughs. Given contemporary computer computing constraints, we decided to conduct our hot spots policing simulation in a single representative borough with robbery rates that were similar to citywide trends. There is no reason to believe that our results would not apply more generally given our use of base parameters that mimicked larger city characteristics.[13] We take this position because the current simulation is of a representative landscape, with a representative population density and a representative police–citizen ratio. So simply scaling it up by including more geographic units should produce an estimate that is still representative. Nonetheless, it is important for scholars to develop larger simulations as such applications become more feasible to examine whether our assumptions would hold in a similar manner.

Not only is this simulated borough limited by the geography that we chose, but also the values of the parameters in our model are determined by what we know about hot spots policing, crime, and robbery offending behavior. That knowledge is certainly imperfect, and accordingly, our models must be evaluated with that uncertainty in mind. Nonetheless, this is what knowledge today suggests regarding the agents in our models. Moreover, whenever possible, our models draw from empirical evidence further supporting the conclusions we reach. But still, these are simply simulations of the real world and they cannot provide the certainty of studies in the field designed to be used by researchers to answer these questions.

Two other modeling decisions deserve further exploration: inclusion of street networks and the nature of police behavior toward citizens at crime hot spots. We used an approach that divided our borough into grid cells. But several scholars, including some authors of this article, have argued that street networks may impact human activity and, as a consequence, the pattern of crime events (Davies and Johnson, 2015; Groff, 2007b; Weisburd, Groff, and Yang, 2012). Future ABM applications should be used to explore the

13. Bosse, Elffers, and Gerritsen (2010) examined directly whether small-scale ABM models produce results similar to larger simulations. These authors doubled the size of their model and noted, "[T]he effect of scaling up the size of the society [on crime] turned out to be small" (p. 63).

potential impact of varying street networks on the results we have gained. Future applications should also be used to consider to a greater extent the impacts of officer behavior in hot spots on the crime outcomes observed. Tom Tyler and colleagues have argued that when the police behave in ways that encourage police legitimacy, crime-control gains are likely to be enhanced (e.g., Tyler, Jackson, and Mentovitch, 2015). Although empirical studies are still emerging on this issue, as they are developed, it will be important to add them to models to gain more accurate estimates of the impacts of hot spots policing.

In the end, we cannot simply rely on existing empirical evidence indicating the crime reduction achieved by police at hot spots to know whether hot spots policing reduces crime in larger geographic areas and entire jurisdictions. We need carefully designed field studies to focus in on this question. This will require multijurisdictional experiments, or at least ones that divide cities into areas that are assigned to hot spots policing and those that are not. Our article illustrates the potential for using ABM more broadly in the development of such studies. ABM can help us define clearly the level of dosage that would be optimal to test, as well as the ways in which patrol should be allocated across time and space. Field experiments are expensive and hard to develop. Our article suggests that ABM can help in designing such field experiments in ways that maximize outcomes.

CONCLUSION

The design of our ABM allowed for us to create a simulated counterfactual for hot spots policing in the larger urban context within which such strategies are implemented. Based on our results, hot spots policing strategies do have large-area impacts on simulated robberies. Therefore, by building on the available scientific evidence showing crime-control effectiveness (Braga, Papachristos, and Hureau, 2012, 2014) and the results of this analysis suggesting borough-level implementation can influence area-wide crime trends, we believe a prima facie case can be made that the emergence of hot spots policing played a role in the crime drop of the 1990s that continued through the 2000s. Crime mapping technologies (McEwen and Taxman, 1995; Weisburd and Lum, 2005) and Compstat performance management accountability systems (Weisburd et al., 2003) rapidly diffused across U.S. police departments during the 1990s and early 2000s. At the least, these innovations better positioned police departments to "put cops on dots" (Maple and Mitchell, 1999: 128), with some jurisdictions implementing more strategic applications of the hot spots policing approach (Braga et al., 1999, Sherman and Rogan, 1995; Sherman and Weisburd, 1995; Weisburd and Green, 1995). Hot spots policing rapidly became a standard crime-control strategy in the policing profession (Police Executive Research Forum, 2008). Correlation clearly does not confirm causation; nevertheless, the coincidental timing of widespread adoption of hot spots policing and the surprising 1990s crime decline does support the nomination of the approach as a particular kind of police innovation that may have contributed to the puzzling crime drop.

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SUPPORTING INFORMATION

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

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