

CRIME DIVERSITY*

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Large geographic areas should host a greater diversity of crime compared with small geographic areas. This proposition is reasonable given that larger geographic areas should not only support more crime but also contain a greater diversity of criminogenic settings. This article uses a neutral model to characterize crime richness as a function of area. The model starts with two neutral assumptions: 1) that all environments are statistically equivalent and exert no influence on what types of crimes occur there; and 2) that different crime types occur independently of one another. The model produces rigorous predictions for the mean and variance in crime richness with increasing area. Tests of the model against a sample of 172,055 crimes occurring in Los Angeles during the year 2013 are qualitatively consistent with neutral expectations. The model is made quantitatively consistent by constant scaling. Resampling experiments show that at most 20 percent of the mean crime richness is attributable to nonrandom clustering and assortment of crime types. A modified neutral model allowing for variation crime concentration is consistent with observed variance in crime richness. The results suggest that very general and largely neutral laws may be driving crime diversity in space.

Environmental criminology is based broadly on the idea that the crime manifest in a place is closely connected to the environmental conditions of that place (Brantingham and Brantingham, 1978, 1981; Eck and Weisburd, 1995). Considerable ambiguity still exists, however, surrounding the mechanisms that give rise to such connections, especially when examining the occurrence of unique crime types in the context of place. In a manner paralleling the debate over offender specialization (Blumstein et al., 1988; Deane, Armstrong, and Felson, 2005; McGloin et al., 2011; Osgood and Schreck, 2007), the tie between a unique crime type and an environment may be explained as offender decision-making in response to either very general or very specific environmental cues or opportunities (Brantingham and Brantingham, 1978, 1981; Weisburd et al., 1992; Wikström et al., 2012). In the former case, general environmental cues are necessary for the occurrence of crime, but these cues place few constraints on exactly what type of crime might occur there (Keizer, Lindenberg, and Steg, 2008; Kinney et al., 2008). In the latter case, environmental cues are not only necessary for the occurrence of crime

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but also narrowly specify which crime types are possible (Clarke and Cornish, 1985). Here it is assumed that there is a close fit between the requirements to complete a particular type of crime and the opportunities presented by the environment (Taylor and Gottfredson, 1986). Indeed, the absence of a specific environmental cue or opportunity may be sufficient to exclude some crime types from occurring at all.

Which of these mechanisms is more plausible, or whether some mixture of generalized and specialized environmental cues drives crime, is of great importance both theoretically and as a matter of policy and practice. Again paralleling the debate over offender specialization (Osgood and Schreck, 2007), offending in response to very generalized environmental cues suggests that generic, universal models may be sufficient to explain the spatial patterning of any crime type across all environments (Weisburd, 2015). By contrast, if crimes are tied to environments in intricate and mutually dependent ways, then generalizations beyond individual crime types or even the individual events and the places where they occur may be problematic (Cornish and Clarke, 1986; Weisburd et al., 1992). On the policy front, generalized connections between crime and place suggest that generic environmental interventions may be both widely applicable and scalable (Jeffery, 1977). On the other hand, if unique crime types are committed in ways that are closely calibrated to a unique set of environmental cues or opportunities, then situational, problem-oriented solutions may be required for each environmental setting (Clarke, 1997; Eck and Spelman, 1988; Goldstein, 1979). The idea of problem-oriented policing may be widely applicable, but actual interventions do not readily scale.

The proposition that crime types are well fit to the environment holds important microscopic implications about the decision-making of offenders (e.g., Bernasco and Nieuwebeerta, 2005; Townsley et al., 2015; Wikström et al., 2012). It also leads to novel macroscopic predictions (e.g., Schreck, McGloin, and Kirk, 2009). Specifically, larger geographic areas should be expected to host a more diverse set of crime types compared with smaller geographic areas. Such macroscopic patterning can arise both if the environmental cues that support crime are very general and if they are very specific. If general environmental cues drive crime, then larger geographic areas should contain more unique crime types simply by virtue of the size of the area sampled. By contrast, if specific environmental cues drive crime, then larger geographic areas should also contain more unique crime types because larger areas will generally encompass a more heterogeneous mixture of environmental settings. The primary goal of this article is to document empirically macroscopic patterns of crime diversity and provide a mathematically grounded explanation for these patterns.

The situation outlined earlier parallels closely one well known in ecology. The attributes of organisms are thought to be well fit to the environments they inhabit, with evolution by means of natural selection being the primary mechanism whereby adaptations develop (Bock, 1980). Whether adaptations develop in response to general environmental conditions such as temperature, or specific resources such as an essential nutrient, large areas are expected to contain more unique species than are small areas. In contrast to the case with crime diversity, however, strong empirical evidence describes patterns of biodiversity across spatial scales. Decades of research in ecology have shown not only that species diversity increases as a function of the size of the geographic area sampled but also that this pattern of increase is very regular, although usually nonlinear (Arrhenius, 1921; Fisher, Corbet, and Williams, 1943; He and Hubbell, 2011; Hubbell,

2001; Huston, 1979; MacArthur and Wilson, 1967; Simberloff, 1974). This so-called “species–area relationship” is observed in almost all environments and across radically different functional groups of organisms (Ferenc et al., 2014; Hobbs et al., 2012; Murgui, 2007; Pedrós-Alió, 2012). Indeed, species–area relationships are one of a small handful of universal patterns in ecology that hint at fundamental laws regulating biodiversity (Hubbell, 2001; Leibold et al., 2004). Here I find many of the same regularities in crime-type–area relationships, raising the possibility that similarly broad mechanisms are at play in regulating the diversity of crime (see also Weisburd, 2015). The findings have important implications not only for the study of crime and place but also for broader issues in crime pattern theory and environmental criminology.

The structure of this article is as follows. The first section defines what is meant by crime diversity and why it may be important. The approach I take deviates from existing methods in criminology in considering patterns expressed across a wide spectrum of crime types. By following practice in ecology, I distinguish between crime *richness*, which is simply a count of the number of unique crime types found in a sample, and crime *evenness*, which refers the patterns of abundance among different unique crime types (see Piquero et al., 1999). Here the focus is on crime richness. As a target measure, richness is blind to detailed characteristics of specific crime types. The co-occurrence of homicide and theft is counted in the same way as the co-occurrence of narcotics violations and theft, even though theory might suggest there is a stronger functional connection between narcotics violations and theft than that between homicide and theft (Anglin and Speckart, 1988; Wright and Decker, 1994). It is argued that crime richness is relevant to ecosystem function, with areas supporting a greater range of crime types being functionally worse off.

The second section places crime diversity in the context of crime pattern theory (Brantingham and Brantingham, 1978, 1981, 1984; see also Wikström et al., 2012). Crime pattern theory posits that the spatial occurrence of crime stems from motivated offenders deploying a multistage decision process in response to environmental cues or opportunities. Those cues can be either very general or very specific and, thus, place few or many constraints on the types of crime that might occur, respectively. Both general and specific cues might underlie patterns of increasing crime diversity as a function of the size of the area observed. The third section seeks to disentangle the role of general and specific environmental cues or opportunities by drawing on models from theoretical ecology for guidance. The approach taken is explicitly neutral (Gotelli and Graves, 1996; Hubbell, 2001). This section starts by introducing key assumptions underlying neutral modeling. These assumptions are likely to be met with considerable outrage (see Rosindell, Hubbell, and Etienne, 2011), although the goal is to improve explanation (Weisburd and Piquero, 2008). The fourth section follows with a formal mathematical model for characterizing crime diversity generated by neutral processes (Arrhenius, 1921; Coleman, 1981; Connor and McCoy, 1979). The passive sampling model, as it is termed, assumes that crime types are placed randomly and independently in space. The occurrence of a crime type in any given area is determined only by the relative size of that area and the global abundance of that crime type. No dependencies between crime types or crime types and environments are assumed. Patterns of crime diversity as a function of area are modeled as the result of neutral stochastic processes alone. The neutral approach is used to set rigorous mathematical expectations for crime diversity patterns that should be easy to reject if the model is a poor fit for the processes at hand.

The fifth section turns to a consideration of empirical patterns of crime diversity. The case study focuses on the full spectrum of crime types that occurred within the city of Los Angeles during the year 2013. The general relationships between crime richness and crime-type abundance are presented. The sixth section presents the core results. I examine the richness of crime types in repeated samples of areas of the same fixed size. The resulting patterns are regular in form, suggesting that law-like processes underlie crime richness at any given spatial scale. I then characterize the way in which crime richness changes with increasing size of the area sampled. The relationship between crime richness and area is compared with expectations from the passive sampling model. The relationship is again surprisingly regular, and the match between theory and empirical patterns is striking. The mean and variance in crime richness as a function of the size of the area sampled qualitatively match theoretical expectations and are made quantitatively accurate by constant scaling. The implication is that the passive sampling model provides a good first approximation of the law-like process driving crime diversity in space. In practical terms, the evidence suggests that the diversity of crime within an area is far more random than is typically assumed.

The seventh section seeks to explain how and why the empirical evidence requires scaling to become quantitatively accurate. Resampling and simulation methods provide an alternative means of characterizing the results. I find that small modifications to the passive sampling model, especially to account for variations in crime clustering or concentration across space, are sufficient to explain observed deviations from theory. The results raise questions about the closeness of the fit between crime types and environments. The simplest explanation is that widely distributed general environmental cues or opportunities play a dominant role in driving crime diversity. The article closes with a discussion of the limitations of the study and future research goals.

DEFINING CRIME DIVERSITY

Studies focusing on crime and place for single crime types have been common (e.g., Bernasco and Block, 2009; Mair et al., 2013; Rengert, Ratcliffe, and Chakravorty, 2005). Far fewer studies have examined the spatial occurrence of multiple crime types. Sherman and Weisburd (1995) and Weisburd, Groff, and Yang (2012) did not differentiate among crime types when defining crime hotspots, although they did link variations in crime concentration across space to environmental conditions. Weisburd et al. (1992) and Andresen and Linning (2012) investigated a spectrum of crimes and their spatial patterning, finding not only that there is strong tendency toward micro-geographic concentration for each crime type but also that hotspots for different crime types do not necessarily coincide. The sources of such differences are not entirely clear, although Weisburd (2015) suggested that both persistent social and physical environmental processes warrant attention (see also Braga and Clarke, 2014). Schreck, McGloin, and Kirk (2009) used latent measures of violent and property crime to show that different neighborhoods have divergent crime profiles. Some neighborhoods have distinctively higher rates of violent crime relative to property crime, which they linked back to place-based differences in social disorganization. These studies suggested that a specialized fit between crime types and specific environmental conditions plays a role in driving the diversity of crime.

Crime diversity is perhaps an unfamiliar concept in criminology, although not one entirely without precedent (e.g., Britt, 1996; Jeuniaux et al., 2015; Piquero et al., 1999).

By borrowing ideas from the ecological study of biodiversity (Magurran, 2004), the diversity of crime can be characterized by two related measures. The first, referred to simply as crime richness, is a raw count of the number of unique crime types present in a sample. For example, if we observe a sample of 100 crimes and tabulate one or more instances of theft, burglary, robbery, and homicide, then the richness of the sample is four unique crime types. Richness is to be contrasted with crime evenness, which refers to the absolute or relative abundances of incidents across different crime types in a sample. For example, the previous sample of 100 crimes might include 65 thefts, 25 burglaries, 9 robberies, and 1 homicide. This type of breakdown would represent an uneven distribution of crime.

Richness and evenness are conceptually related, but they offer different pictures of diversity. High (low) richness, qualitatively, is a sample that contains a large (small) number of unique crime types. Richness measures can be made quantitative with reference to either the maximum possible richness for a sample, if it is known, or the size of the sample under observation along a rarefaction curve (Gotelli and Colwell, 2001). The issue here is conceptually similar to describing offender specialization with reference to the rate of offending (see Osgood and Schreck, 2007: 281). High evenness, by contrast, is a quantitative measure describing a situation where each crime type is represented by an equal number of incidents. Low evenness, therefore, describes a situation where a few crime types represent many incidents, whereas many crime types represent few incidents. The diversity index used by Piquero et al. (1999) and others in their characterization of offense specialization is a common metric for computing evenness. The location quotient accomplishes a similar task with respect to crime-type evenness across spatial units of analysis (Andresen, 2009; Brantingham and Brantingham, 1997).

The focus of this article is on patterns of crime richness as a function of the size of the geographic area observed. Before proceeding to specific issues of modeling and measurement, an important question to address is whether we should care if an area hosts a high or a low number of unique crime types. To the extent that we consider crime a component of community dynamics (Boessen and Hipp, 2015), a greater array of crime types in an area may both be a symptom of and a contributor to increased community dysfunction. A greater array of crime types may imply an increased abundance and range of crime generators and attractors (Brantingham and Brantingham, 1995) or, more pointedly, risky facilities in the local environment (Eck, Clarke, and Guerette, 2007). More unique crime types may also imply that mechanisms of formal and informal guardianship fail severely in more settings (Braga and Clarke, 2014). Areas experiencing a greater array of unique crime types are also subject to a wider range of bureaucratic challenges. The police are forced to deal with reporting and evidence handling for a much greater array of problems (Malm et al., 2005). The public must also be prepared to navigate many different formal and informal courses of action depending on the crime to which they fall victim. The challenges of crime prevention may be exacerbated where crime is more diverse. Strategies to deal with one type of crime, say domestic violence, may have no impact on another crime type, such as shoplifting. Perhaps a unique prevention strategy is needed for each crime type represented in an area (Clarke and Cornish, 1985), a prospect that becomes more daunting with increasing crime richness. The argument here is that community function is not just about the total volume of crime. Rather, the range of crime types also matters. I reemphasize, however, that richness is a measure of diversity

blind to the specific differences between crime types. As with the diversity index used by Piquero et al. (1999), richness captures information about the degree to which an area hosts a wide range of crime types or few. Thus, two areas might display equivalent high crime richness without sharing a single crime type in common. Such a measure is useful in testing predictions about general processes driving crime diversity, although not necessarily why the two areas contain these different mixtures of crimes (see Osgood and Schreck 2007: 280).

PATTERN THEORY OF CRIME DIVERSITY

Crime pattern theory provides a general framework for understanding how crime-area diversity patterns might arise (Brantingham and Brantingham, 1978, 1981). In this framework, motivated offenders are assumed to be naturally present in the environment. Although motivation may be multifaceted and variable in intensity from offender to offender (Townsend et al., 2015), this variation matters less than the decision process in response to environmental cues or opportunities. Importantly, these environmental cues or opportunities may be rooted in both the physical features of the environment or the local social conditions, including the degree of community cohesion (Baudains, Braithwaite, and Johnson, 2013; Braga and Clarke, 2014; Johnson and Summers, 2015). Offenders learn which individual cues, or clusters of cues, mark suitable targets or victims (Taylor and Gottfredson, 1986), quickly arriving at a target template that can be acted on in an autonomic or scripted fashion (Cornish, 1994; Coyne and Eck, 2014; Katz, 1988). Routine activities play a role in the initial learning of target templates and the subsequent repeated contact between offenders and victims, but it is the decision-making process in response to environmental cues that ultimately underlies the act of offending. This emphasis is developed in situational action theory (Wikström et al., 2012).

In the context of crime pattern theory, the spatial distribution of environmental cues and opportunities plays a central role in regulating crime diversity, much more so than the distribution of offenders (Brantingham and Brantingham, 1978, 1981; Weisburd et al., 1992). Assume for the moment that the decision-making process for each crime type is tied to a mutually exclusive environmental cue or opportunity. If this is the case, then we can imagine a location that is sufficiently small that it contains just that one environmental cue. This limited environment will support only the one unique crime type tied to that cue. Now imagine that we expand the observational area outward from this singular location. As the area increases, the number of unique environmental cues also grows. The number of unique crime types should increase accordingly. Large areas may contain a complex, heterogeneous mixture of environmental settings, which support a heterogeneous mixture of crime types. This richness pattern is expected because of the close fit between crime types and environmental cues or opportunities. Area, in this sense, is proxy for the heterogeneity of environmental settings.

Area may set only an upper limit on the number of environmental settings, however. It does not necessitate the co-occurrence of multiple cues or opportunities. Indeed, a very large area might be environmentally homogeneous and therefore support very few unique crime types, assuming crime types are closely tied to those environmental cues. Thus, under pattern theory, small areas are constrained to host very few unique crime types, whereas large areas might host many unique crime types or very few. We may expect crime richness on average will be greater in larger areas compared with

small areas, but how crime richness increases as a function of area is dependent on how environmental heterogeneity increases with area.

Pattern theory also creates the possibility that the diversity of crime in an area is tied to generalized crime cues (Brantingham and Brantingham, 1978, 1981). Many different crime types might occur in response to exposure to those generalized cues. An area that is sufficiently small will support very low crime richness simply because the number of crimes that can occur there is highly restricted. In effect, the lower limit on crime richness is one as the number of crimes that occur in a location approaches one. As the area around this small location increases, more crimes can occur, which means that more types of crime can occur. Crime richness in such an area is likely to be higher, although the specific mixture of crimes may prove to be random, a point to which I will return in greater detail.

In principle, one need only measure environmental heterogeneity in the field to disentangle the impacts of general and specific environmental cues on crime diversity (e.g., Braga and Clarke, 2014; Kennedy, Caplan, and Piza, 2011). In practice, however, measuring environmental heterogeneity is not at all easy and, more importantly, how exactly environments influence crime is still problematic to establish beyond coarse limits. It is not surprising that residential burglaries cannot occur in areas that have no residences (Clarke and Cornish, 1985). Yet, in areas where there are residences, it is often surprising why some houses are victimized and others are not (Taylor and Gottfredson, 1986; Wright and Decker, 1994; Wright, Logie, and Decker, 1995). Problem-oriented, situational, and discrete choice approaches (Clarke, 1995; Goldstein, 1990; Townsley et al., 2015) point in a direction where each setting may need to be characterized to understand why a specific crime type occurs there. This direction of study raises serious questions about generalization of processes across settings.

NEUTRAL THEORY OF CRIME DIVERSITY

Neutral theories provide a way around some of the thorny problems mentioned earlier by setting baseline theoretical expectations for empirical patterns. Neutral theories make no appeal to functional processes tied to seemingly unique attributes or components of the system (see Gotelli and Graves, 1996; Hubbell, 2001). Rather, neutral theories see empirical patterns as solely the result of stochastic or drift-like processes. In the language of experimental criminology, neutral models provide a type of extreme counterfactual suggesting what would be possible if everything operates completely at random.

In some instances, neutral theories have become essential to the modern character of a discipline. In genomics, for example, the neutral theory of molecular evolution has not only come to be accepted as an accurate picture of genetic processes (Nei, Suzuki, and Nozawa, 2010), but it also has provided a robust mathematical structure for studying those processes (Kimura, 1983). In other instances, neutral theories continue to be highly controversial. In ecology, for example, a starting assumption that all organisms are equivalent in their birth, death, and emigration and immigration rates (see Caswell, 1976; Gotelli and Graves, 1996; Hubbell, 2001) has been a lightning rod for critique. Yet, it is not the assumptions *per se* that fuel the controversy. Rather, neutral theories have been difficult to reject given the empirical evidence at hand. The possibility that favored ecological mechanisms are not as important as often thought is deeply unpopular (Rosindell, Hubbell, and Etienne, 2011). In some sectors of ecology, however, neutral

models are a core part of the discipline (e.g., in estimating extinction risk; He and Hubbell, 2011; Kadmon and Benjamini, 2006; but see Moullot et al., 2013).

Here I leverage a neutral model to set baseline expectations for crime-richness–area relationships. I start with two neutral propositions: 1) All environments are statistically identical to one another and exert no influence on what types of crimes occur there; and 2) different crime types occur independently of one another. Area is important only to the extent that it imposes finite sample size effects (Azalee, Cornell, and Kunin, 2011; Raudys and Jain, 1991). Consider briefly how radical these propositions truly are. The first proposition effectively says that any associations between specific crime types and specific environments arise only by chance. The second proposition says that any patterns of co-occurrence between two or more crime types arise only by chance. In the language of crime pattern theory, these two propositions assert that environmental cues are always general and universally distributed.

An inclination to reject such propositions outright is understandable. If ecology is any guide, however, the rejection of simple neutral propositions like those earlier is much harder than we imagine. As a matter of scientific principle, we should favor the simplest possible model that withstands empirical testing as the best candidate explanation. If such neutral theories are truly incapable of capturing the form or dynamics of a system, they should be easy to reject. In this way, neutral theories may lead to more complex theories and provide a complementary source of explanations to randomized controlled trials and observational studies. In practice, such models are often discarded prematurely because they do not fit with our preconception of the world as a complex place (Pearl, 1978; Popper, 2005).

PASSIVE SAMPLING MODEL

A useful formal characterization of the earlier neutral propositions views the environment as passively sampling crime types (Arrhenius, 1921; Coleman, 1981; Connor and McCoy, 1979). An analogy adapted from Gotelli and Graves (1996) helps to characterize the problem at hand. Imagine a jurisdiction as a dart board with the board divided into nonoverlapping regions of different sizes. Imagine individual crimes as a bag of darts, where the color of the dart corresponds to crime type. The different color darts need not occur in equal frequencies in the bag. We reach into the bag and draw out a dart at random. The dart is thrown randomly at the board. This process is repeated until all the darts are gone. Because darts are drawn at random, the colors are exchangeable in any one selection, although they are not independent if the total number of darts is small. Because the darts are thrown randomly at the dart board, where a dart lands is independent of all previous darts. The number of darts a region of the dart board contains is dependent only on the size of the area and, critically, has nothing to do with the color of the darts.

To translate this analogy into mathematical form, assume that S distinct crime types occur in some complete two-dimensional region R (Coleman, 1981). Assume also that we can count the number of crimes n_i representing each crime type $i = 1, 2, \dots, S$ that occur in R . Finally, assume that the total region R is divided into a series of nonoverlapping two-dimensional subregions r_k , where $k = 1, 2, \dots, K$ is an index labeling each subregion. The relative area of any subregion is $\alpha_k = r_k/R$. It is then the case that $\sum r_k = R$ and $\sum \alpha_k = 1$.

Imagine now that we draw a crime from the list of historically known crimes that occurred in region R . This crime is of a particular type i . Under neutral assumptions, the probability that this crime of type i does *not* occur in a subregion r_k is $1 - \alpha_k$. The probability is regulated by the relative area α_k of the subregion only. The smaller the subregion, the less likely the crime is to occur there. Now we pull each and every crime of type i from the list. The probability that two independently drawn crimes of type i do not occur in a subregion of relative area α_k is $(1 - \alpha_k)(1 - \alpha_k)$. The probability that three crimes of type i do not occur in a subregion of relative area α_k is $(1 - \alpha_k)(1 - \alpha_k)(1 - \alpha_k)$. Then after extending the pattern, the probability that none of the n_i crimes of type i occur in a subregion of relative area α_k is:

$$q_i = (1 - \alpha_k)^{n_i} \quad (1)$$

The complement of equation (1) is the probability that *at least one* instance of crime type i is represented in a subregion of relative area α_k :

$$p_i = 1 - (1 - \alpha_k)^{n_i}. \quad (2)$$

If the relative area α_k of subregion k is small, then equations (1) and (2) can be rewritten in exponential form $q_i = e^{-\alpha_k n_i}$ and $p_i = 1 - e^{-\alpha_k n_i}$, which helps illustrate two key points (figure 1a). First, as the abundance of a crime type n_i increases, the probability that i is *not* observed in an area α_k decreases exponentially. Second, the probability that a crime type is absent declines much faster for larger areas.

Equations (1) and (2) describe neutral expectations for the probability of occurrence of a single crime type i as a function of the relative size of the area observed and the global abundance of that crime type. Via the Binomial Theorem, we can calculate the mean $\bar{s}(\alpha)$ and variance $\sigma^2(\alpha)$ in the number of unique crime types in any region of area α (Coleman, 1981):

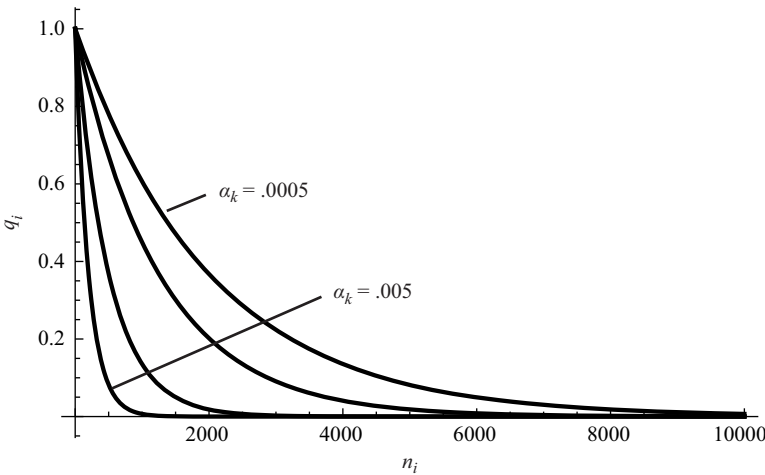
$$\bar{s}(\alpha) = \sum_{i=1}^S 1 - (1 - \alpha)^{n_i} = S - \sum_{i=1}^S (1 - \alpha)^{n_i} \quad (3)$$

$$\sigma^2(\alpha) = \sum_{i=1}^S (1 - \alpha)^{n_i} - \sum_{i=1}^S (1 - \alpha)^{2n_i} \quad (4)$$

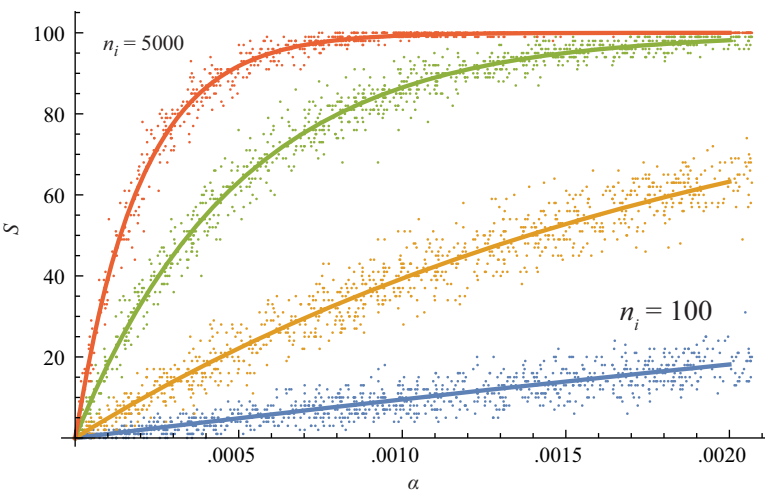
Equation (3) is closely related to equation (1) with the appearance of $(1 - \alpha)^{n_i}$ in the summation. Equation (3) states that the mean crime richness in an area of size α is the maximum richness S minus the probability that a crime type is absent summed over each crime type. For extremely small areas, the term inside the parentheses approaches unity. The summation approaches S , whereas the mean richness approaches zero. As area increases, the term inside the parentheses approaches zero. The summation will also approach zero, and the mean richness will approach the maximum richness S . Both patterns are visible for a range of crime abundance situations shown through Monte Carlo simulations (figure 1b). When each crime type occurs in equal frequency but low overall abundance (e.g., $n_i = n_j = 100$), crime richness appears to increase linearly with the

Figure 1. Expected Crime Diversity Patterns in the Passive Sampling Model

a Probability q_i that a crime of type i is *not* observed in a region α as a function of the global abundance of that crime n_i



b Number of unique crime types S observed as a function of the relative area α



NOTES: (a) Curves are calculated directly from equation (1). (b) Monte Carlo simulations of crime richness over 1,000 uniformly distributed area sizes. Solid lines show expected richness $\bar{s}(\alpha)$ calculated directly from equation (3).

increasing area of sampled subregions. At higher crime type abundances (e.g., $n_i = n_j = 500$ and $n_i = n_j = 1000$), crime richness clearly increases nonlinearly with area.

Equation (4) suggests that the variance in crime richness as a function of area is also controlled by the probability that each crime type is absent but with second-order effects. In small areas, most crime types will be absent. In this case, the first and second terms

in equation (4) both approach the maximum richness S but cancel one another out. The variance in crime richness will be close to zero. Similarly, for very large areas, most crime types will be present and both the first and second terms are close to zero. The variance again approaches zero. It is between these extremes where the second term in equation (4) decreases faster than the first term and the variance approaches a maximum. The maximum variance in crime richness at intermediate area sizes is clearly visible in the scatter of observations in Monte Carlo simulations (figure 1b). The simulation iterates equation (2) for each area of size α given a uniform abundance n_i for each crime type i . The presence or absence of a crime type in an area is assigned stochastically at each iteration using the probability determined from equation (2).

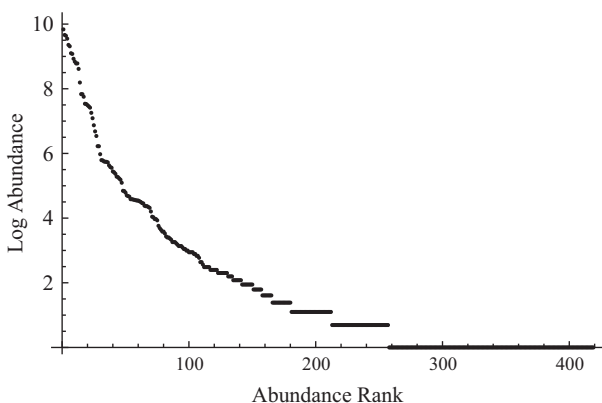
LOS ANGELES CRIME PATTERNS

The passive sampling model provides a simple, yet rigorous set of expectations for the relationship between crime richness and area that can be tested with empirical data. The goal of the following section is to establish whether the passive sampling model can be rejected as a null model for the origin of any observed crime–area relationships.

Empirical data for the purposes of this study were provided by the Los Angeles Police Department (LAPD). The LAPD serves approximately 3.8 million people distributed over an area of 503 square miles (1,300 km²). Los Angeles is extremely diverse in both human and physical terrain characteristics at all spatial scales. Given its size, Los Angeles also experiences ample crime representing a wide array of crime types. The focus here is on recorded crimes occurring within the LAPD jurisdiction during 2013. Excluded from analysis are sex crimes and crimes against children at the request of the LAPD. Because the spatial location of occurrence is important to analysis, I excluded from analysis crimes that failed to geocode or had reported time ranges exceeding the annual period. Finally, I excluded crimes with a recorded incident address corresponding to any of the 21 LAPD police stations and LAPD police headquarters. Station addresses are often used when the true location of a crime incident is not known. The final sample from 2013 includes 172,055 recorded crimes.

The LAPD uses its own coding system for identifying crime types. The classification system includes 226 recognized crime types. This is more finely resolved than either the Uniform Crime Reports (7 Part I and 21 Part II offenses) or the National Incident Based Reporting System (49 Group A and 90 Group B offenses). For example, aggravated assault as a crime type is associated with four unique codes, including assault with a deadly weapon (LAPD-CC 230), assault with a deadly weapon against a police officer (LAPD-CC 231), shots fired at a moving vehicle (LAPD-CC 250), and shots fired at a dwelling (LAPD-CC 251). Not all of the available crime codes are used in practice, however. An important feature of the LAPD crime coding system is that it allows combinations of codes to produce novel compound classifications. For example, aggravated assault is associated with an additional 105 unique code combinations, including assault with a deadly weapon plus shots fired at a dwelling (LAPD-CC 230 251), assault with a deadly weapon plus petty theft (LAPD-CC 230 440), and assault with a deadly weapon plus attempted vehicle theft plus vehicle recovered (LAPD-230 520 521). I choose to treat any unique combination of crime codes as unique crime types. Thus, an event that is coded as assault with a deadly weapon alone (LAPD-CC 230) is counted as different from assault with a deadly weapon plus petty theft (LAPD-CC 230 440). The assumption

Figure 2. Crime Rank Abundance (Whittaker) Plot Showing the Log of the Number of Events Against Its Rank Order



NOTES: The most abundant crime type is assigned rank 1, the second most abundant crime type is rank 2, and so on. Crime types with log abundance of zero occur exactly once in the entire collection of crimes.

is that the recording officers applied classification codes to help ensure that any one event is sufficiently distinguished from other events. By following these counting procedures, the 172,055 crimes recorded in Los Angeles in 2013 represent 419 unique crime types.

Measuring crime diversity also involves defining clearly how samples are chosen. The work here is consistent with a shift away from the offender as the unit of analysis toward the physical space where crime events occur (Brantingham and Brantingham, 1978; Weisburd et al., 1992, 2016). The question at hand is the relationship between crime richness and the places in which those crimes occur. A crime place might be defined as a single street address, street segment, or some other larger scale spatial unit such as neighborhoods or cities (Boessen and Hipp, 2015; Brantingham, Brantingham, Vajihollahi, and Wuschke, 2009; Roncek and Bell, 1981; Weisburd, Groff, and Yang, 2012). Here I examine bounded two-dimensional areas spanning a range of subcity spatial scales. Such bounded areas might be defined in two different ways. Arbitrary areas such as quadrats are sampling units of defined absolute or relative size whose geometry, size, and pattern of placement is functionally independent of the target of study (Dale and Fortin, 2014; Hayek and Buzas, 1997). These contrast with nonarbitrary areas such as census tracts, police divisions, or police reporting districts. The structure and organization of such official reporting areas are often tied to the target of study in some way. Nonarbitrary spatial sampling units can introduce significant biases into observations (Dale and Fortin, 2014). Only arbitrary sample areas will be investigated here. Specifically, the richness of crime will be assessed among repeated random samples of circular areas or disks of arbitrary, but varying size.

RESULTS

A first-order question concerns the distribution of crimes across crime types. Figure 2 shows a rank abundance (Whittaker) plot for the 419 unique crime types observed in the

Table 1. Rank, Count, and Cumulative Percentage for the Top 25 Most Common Crime Types in Los Angeles in 2013

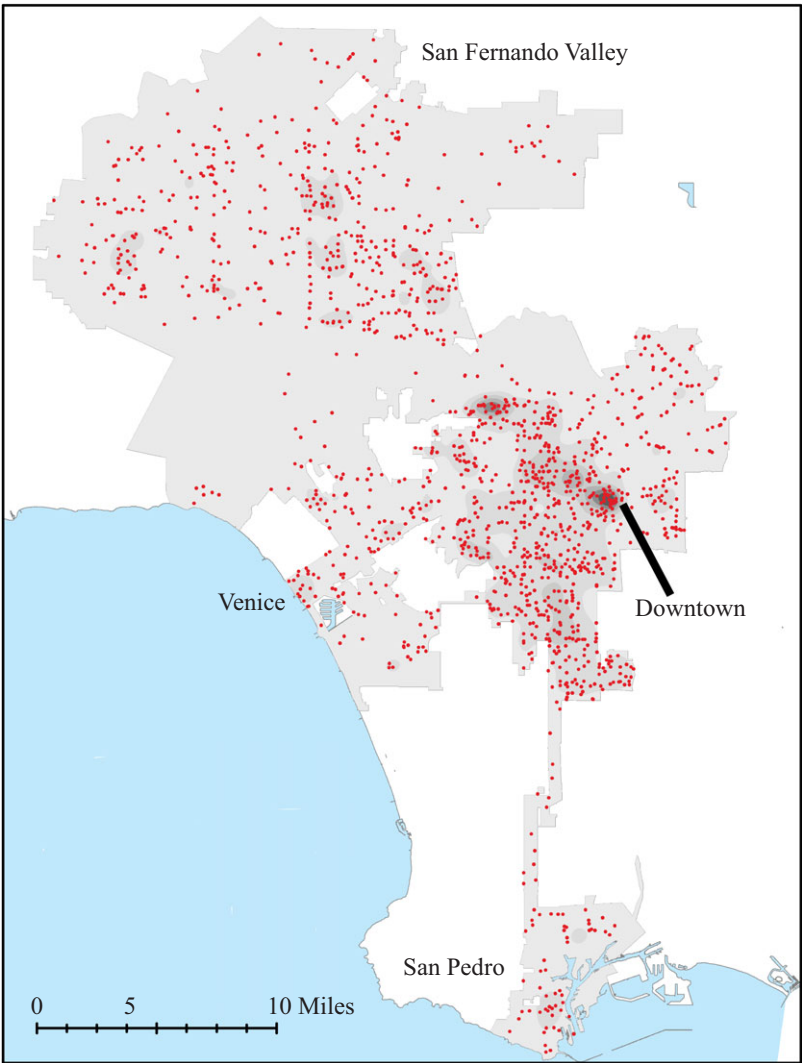
Crime Type	Rank	Count	Cumulative Percent
Battery	1	18,696	10.9
Petty Theft	2	15,734	20.0
Burglary From Vehicle	3	15,349	28.9
Burglary	4	14,042	37.1
Identity Theft	5	11,572	43.8
Vehicle Stolen + Recovered	6	11,094	50.3
Vandalism Under \$400	7	8,944	55.5
Vandalism Over \$400	8	8,762	60.6
Petty Theft From Vehicle	9	7,536	64.9
Assault With Deadly Weapon	10	6,899	68.9
Grand Theft	11	6,531	72.7
Robbery	12	6,530	76.5
Criminal Threats	13	5,510	79.7
Shoplifting	14	3,615	81.8
Document, Forged or Stolen	15	2,525	83.3
Grand Theft From Vehicle	16	2,521	84.8
Vehicle Stolen	17	2,331	86.1
Violation of Court Order	18	1,874	87.2
Annoying/Lewd/Obscene Calls/Letter	19	1,861	88.3
Other Miscellaneous Crime	20	1,795	89.3
Violation of Restraining Order	21	1,729	90.3
Trespassing	22	1,663	91.3
Theft From Person	23	1,416	92.1
Attempted Burglary	24	1,199	92.8
Attempted Robbery	25	964	93.4

NOTE: Cumulative percent is calculated with respect to the total sample size of 172,055 crimes.

2013 LAPD data, whereas table 1 reports abundances for the top 25 most common crimes city wide. Only a few crime types account for most events. For example, battery is the most common crime type (rank 1) and accounts for 10.9 percent of all observed crimes. The top six crime types (rank 1–6) account for 50.3 percent of all observed crime. The top 25 crime types (rank 1–25) account for 93.4 percent of all observed crime. By contrast, rare crime types account for most of the diversity in crime. For example, the remaining 394 crime types (rank 26–419) account for only 6.6 percent of all observed crime by volume. Fully 162 crime types are represented by only single events. These so-called “singletons” include crimes such as bigamy (LAPD-CC 948), grand theft from a coin machine (LAPD-CC 473), and auto repair grand theft (LAPD-CC 349). Singletons are not an aberration of sampling or classification. They are a common feature of diversity in biological, geological, and linguistic systems (e.g., Baayen, 2001; Hystad et al., 2015; Lim, Balke, and Meier, 2011). When measuring diversity, rarity is common.

I now examine the role that space plays in controlling crime diversity. Crime is not uniformly distributed across space (figure 3), but it is concentrated into hotspots recognizable at a range of spatial scales (Boessen and Hipp, 2015; Brantingham and Brantingham, 1984; Brantingham et al., 2009; Eck et al., 2005). In general, a small number of spatial locations in any environment harbors a disproportionate amount of crime. The phenomenon is so widely recognized and so regular as to invoke a law of crime concentration (Weisburd, 2015). Similar regularities characterize the richness of crime types as a function of the area sampled. Figure 4 presents frequency histograms of crime-type

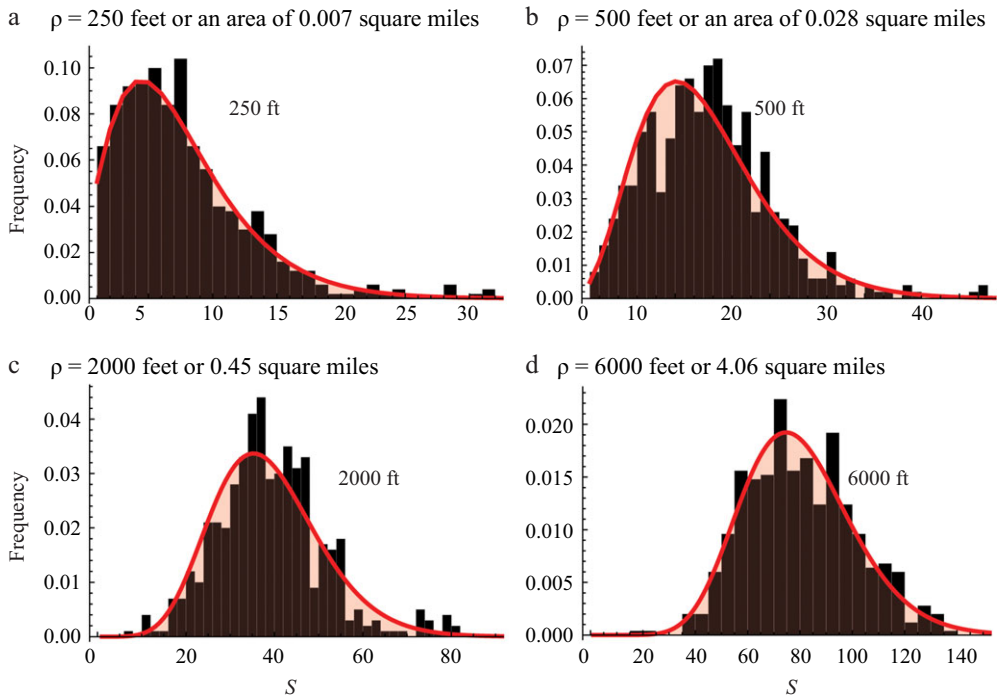
Figure 3. Spatial Distribution of Crime in Los Angeles in 2013



NOTE: Shown is a random sample of 1,500 crimes across all crime types superimposed on a density map of all 172,055 crimes.

richness in repeated random samples of areas of the same size. The sampling procedure involves drawing a location at random without replacement from the list of 172,055 crimes. The randomly selected location was treated as the centroid of a two-dimensional circular area or disk of radius ρ . The number of unique crime types falling strictly inside the disk was scored. The process was then repeated 500 times generating a range of richness values for each value of ρ . At relatively small area sizes ($\rho = 250$ ft or 0.007 square miles), mean crime-type richness is low, whereas the overall distribution displays a strong right skew (figure 4a). With increasing area size, the modal richness shifts progressively to the right. Low-richness areas appear less and less frequently in the samples,

Figure 4. Frequency Histograms of the Number of Unique Crime Types S , or Crime-Type Richness in Repeated Random Samples of Fixed Area Sizes



NOTES: Five hundred locations were drawn at random without replacement from the list of 2013 crimes. For each randomly selected location, the number of unique crime types S within a disk of radius ρ is scored. Crime-type richness follows a negative binomial distribution (red curve) that shifts to the right with increasing area of the sampled region.

and the right skew becomes less pronounced (figure 4b–d). Nevertheless, the overall pattern is well fit by a negative binomial distribution (table 2), which is not unexpected when there is spatial clumping within types (He and Gaston, 2000; He and Legendre, 2002).

The regularity observed in crime-richness distributions for fixed-area sizes implies a regular functional relationship across multiple spatial scales. This expectation is borne out in figure 5, which compares empirical patterns with the theoretical expectations of the passive sampling model. The sampling procedure used here is the same as the one used earlier. Figure 5a plots empirical crime richness S as a function of area for sample regions ranging from 0.007 to 6.34 square miles, which corresponds to circular sampling areas with radii ρ ranging from 250 to 7500 feet, respectively. Consistent with the earlier analysis, sample areas at all sizes display a range of richness values with even large areas sometimes containing only a handful of unique crime types and small areas sometimes containing a large number of unique crime types. The mean trend is very orderly, however. Crime richness increases rapidly from very small sampling areas. As sampling area grows, crime richness accumulates more gradually. Note, however, that

Table 2. Sample Characteristics and Negative Binominal Model Fit to Richness Distributions From Fixed Sample Area Sizes

Radius ρ (ft)	Area (sq mi)	Sample Size	Mean S	Sd S	Range	n	p	Pearson χ^2	P-Value
250	.007	500	7.1	5.0	28	3.125	.300	9.877	.827
500	.028	500	13.5	6.6	42	5.433	.294	24.846	.166
1,000	.113	500	23.6	8.9	57	9.796	.293	39.468	.018
2,000	.451	500	37.9	13.4	78	13.467	.258	30.324	.174
4,000	1.803	500	61.5	18.9	93	11.806	.169	20.143	.689
6,000	4.057	500	79.1	22.0	118	17.103	.176	15.059	.919
7,500	6.339	500	90.8	22.0	114	17.459	.161	69.744	<.001

NOTES: S is the number of unique crime types present in different sample area sizes; r and p are parameters of the standard negative binomial distribution $NB(r, p)$ estimated from the fitted curve.

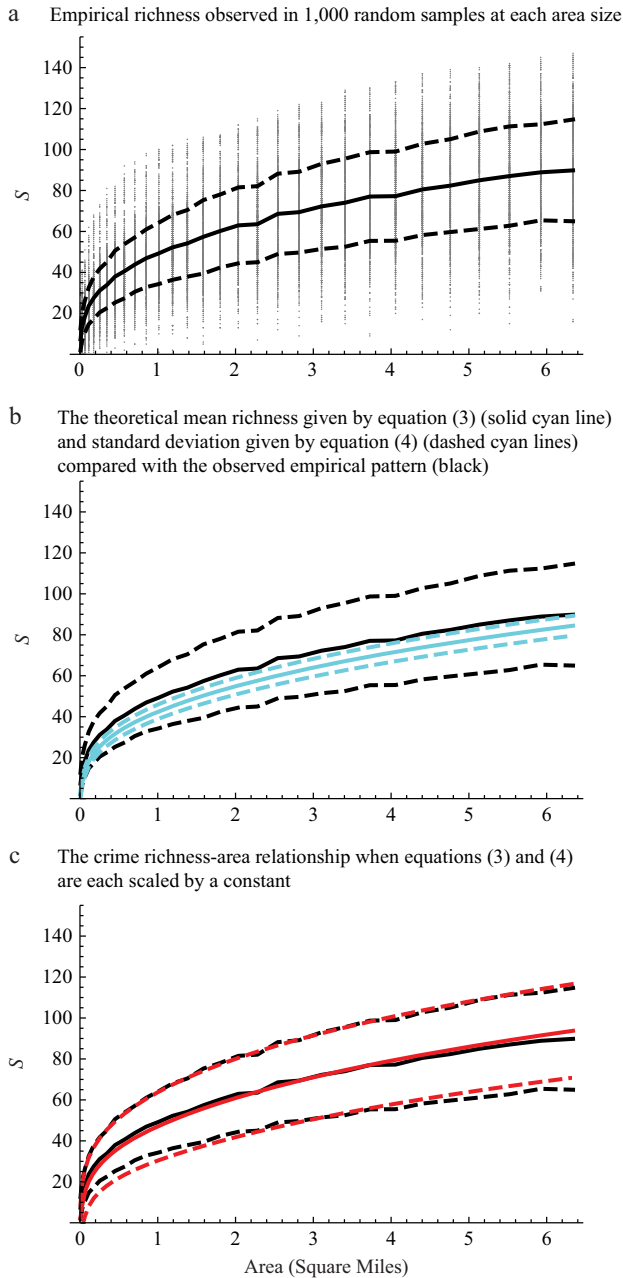
the variance in crime richness as a function of crime area is not constant. Rather, with increasing sampling area size, the variance in richness also increases.

Figure 5b plots the empirical mean and 1 standard deviation (SD) for crime richness as a function of area alongside the mean and 1 SD in richness predicted by the passive sampling model. Observed frequencies of each crime type n_i in the city-wide sample of 172,055 crimes are used to calculate the theoretical mean $\bar{s}(\alpha)$ and theoretical variance $\sigma^2(\alpha)$ in richness using equations (3) and (4), respectively (table 2). Recall that $\alpha = r/R$, and here the total area of Los Angeles is taken to be $R = 503$ square miles. Results are rescaled into square miles for presentation. The theoretical expectations from the passive sampling model are qualitatively similar to the empirical pattern. In the theoretical case, mean richness increases rapidly at first and then slows with increasing area. The mean trends parallel one another closely. The theoretical variance also increases with increasing sample area size, but here the increase in variance is muted compared with the empirical case. Figure 5c shows that the similarities between the observed data and theoretical expectations are strong. Here I have applied constant scaling factors to equations (3) and (4) yielding a scaled mean $c_1\bar{s}(\alpha)$ and scaled standard deviation $c_2\sigma(\alpha)$. With $c_1 = 1.11051$ and $c_2 = 4.72795$, the theoretical expectations from the passive sampling model are statistically indistinguishable from the empirical curves (Kolmogorov–Smirnov $D = 2$, $p = 1.0$ for comparisons of the mean, +1 SD and –1 SD individually). In other words, the empirical pattern differs from the pure theoretical expectation by only a constant basis.

EXPLAINING THE RESULTS

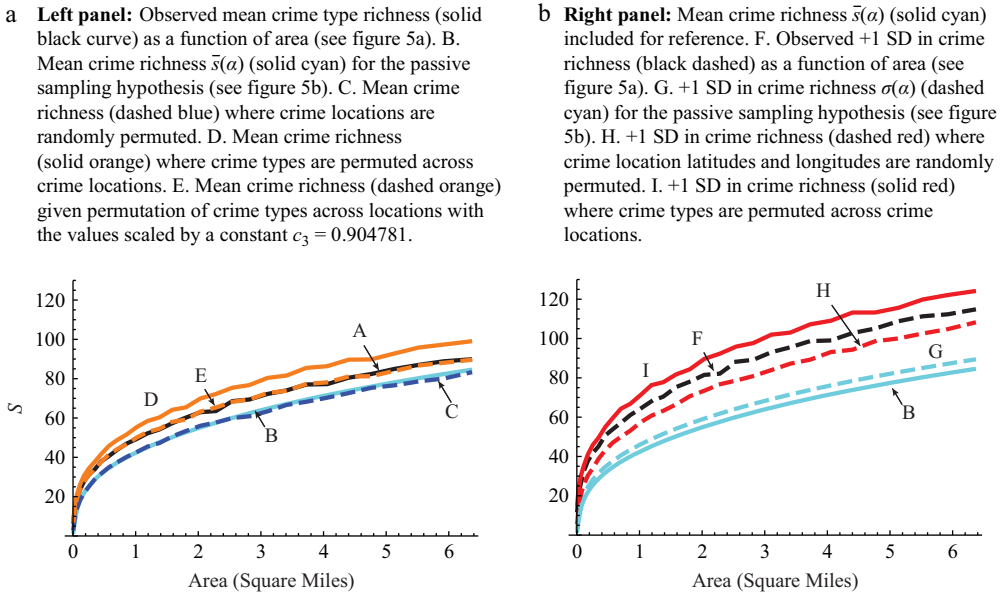
As a first approximation, the passive sampling model provides a good description of the observed relationship between crime richness and area. The unmodified passive model is qualitatively very similar to the empirical pattern. When the mean and standard deviation predicted by theory are each scaled by a constant, yielding $c_1\bar{s}(\alpha)$ and $c_2\sigma(\alpha)$, the passive sampling model becomes quantitatively accurate. This result is surprising given that the passive sampling model jettisons much of what we think is important about crime and place. Indeed, the passive sampling model seems to describe the qualitative and quantitative increase in crime types as a function of area without having to invoke any notion that crimes are well fit to their environments. This conclusion requires some additional scrutiny. It is necessary to explain why the unmodified passive sampling model is qualitatively accurate but requires scaling to become quantitatively accurate.

Figure 5. Crime Richness S as a Function of the Area in Square Miles of Randomly Sampled Regions in the City of Los Angeles



NOTES: The richness of each sample is shown as a gray point. The empirically observed mean richness (solid black line) and ± 1 SD (dashed black line) are shown in each panel. The scaled theoretical mean (solid red line) and scaled standard deviations (dashed red lines) are statistically equivalent to the observed empirical pattern. Richness is scored for all 172,055 crimes recorded in 2013.

Figure 6. Random Permutation of Crime Locations and Crime Types in the Empirical Record Compared With the Expected Mean and Standard Deviation in Crime Richness



RESAMPLING EXPERIMENTS

Figure 6 presents results of resampling experiments that shed light on the role that crime clustering in space and positive assortment within crime types have on the crime-richness–area relationship. By starting with all 172,055 crimes in the 2013 database, I perform permutations of key target variables. Random permutation of the latitude and longitude of crime locations in the raw data, independently for each, destroys nonrandom clustering in crime and breaks correlations between location and crime type. Measurement of the spatially permuted data is expected to reveal what crime richness would look like in Los Angeles if crimes were randomly distributed in space as required by the passive sampling model. By contrast, random permutation of crime types, leaving crime locations as they are in the raw data, retains the effects of crime clustering, while breaking correlations between crime type and location. Measurement under these conditions is expected to reveal what crime richness would look like if crime is nonrandomly distributed in space but clustering is truly independent of crime type.

The left most panel in figure 6 presents several crime-richness area curves for the mean crime richness. Curve A (solid black) shows the empirical mean crime richness as a function of area and is identical to that shown in figure 5a. Curve B (solid cyan) is the theoretical mean richness $\bar{s}(\alpha)$ calculated directly from equation (3) and is identical to that shown in figure 5b. Curve C (dashed blue) shows the mean richness given random permutation of the latitude and longitude of crime locations in the raw data. The resampled curve follows exactly the expectation of the passive sampling model for $\bar{s}(\alpha)$ (Kolmogorov–Smirnov $D = 2, p = 1.0$). Because random permutation of locations in the raw data reduces mean

crime richness relative to the observed empirical pattern across all area sizes, I conclude that nonrandom spatial clustering of crime inherent to the Los Angeles crime data serves to increase crime richness above the passive baseline. The more densely crime is clustered, the more opportunities there are to observe unique crime types for a given fixed-area size.

An effect in the opposite direction is observed for nonrandom assortment of crime types. Curve D (solid orange) shows the results of random permutation of crime types leaving crime locations in the raw data untouched. Because random permutation of crime types increases mean crime richness relative to the empirical pattern across all area sizes, I conclude that nonrandom assortment within unique crime types serves to lower crime richness overall. The assortment is positive within crime types but negative across crime types. In a sense, the occurrence of a crime of one type increases the likelihood that more crimes of that type will occur in close proximity and decreases the likelihood that crimes of another type will occur in that same area. Mean crime richness is lower as a result. Consistent with the analyses presented in Figure 5, there is a simple relationship between the permuted crime type pattern and the raw empirical pattern. Let $\bar{s}_{\tilde{c}}(\alpha)$ be the mean crime richness for crime type permuted data $\tilde{c}$. For reference, $\bar{s}_{\tilde{c}}(\alpha)$ corresponds to curve D (solid orange) in figure 6. The crime-type permuted data are made statistically indistinguishable from the empirical data through multiplication by a constant scaling factor $c_3 \bar{s}_{\tilde{c}}(\alpha)$ (Kolmogorov–Smirnov $D = 2$, $p = 1.0$; curve E, dashed orange). In this case, the scaling factor is $c_3 = 0.904781$.

The structure of the relationships between scaled and unscaled predictions suggests a procedure to calculate the relative magnitude of nonrandom effects on mean crime richness. Specifically, the percentage difference in richness between the empirically observed data and its theoretical alternatives is calculated as $(c_i \bar{s}(\alpha) - \bar{s}(\alpha)) / \bar{s}(\alpha)$, where c_i is the scaling factor for theoretical alternative i . For any theoretical richness value $\bar{s}(\alpha)$, the previous equation simplifies to $c_i - 1$. Recall that the scaling factor sufficient to match mean crime richness in the passive sampling model to the empirical pattern is $c_1 = 1.11051$. Therefore, the percentage increase in measured richness attributable to nonrandom clustering of crime in space is 11.05 percent (i.e., $c_1 - 1 = 1.11051 - 1 = 0.110513$). The scaling factor sufficient to match mean crime richness in the crime type permuted data to the empirical pattern is $c_3 = 0.904781$. Therefore, the percentage reduction in measured richness attributable to nonrandom assortment within crime types is –9.5 percent (i.e., $c_3 - 1 = 0.904781 - 1 = -0.095219$). These numbers are remarkable because they leave a tremendous amount of the relationship between mean crime richness and area attributable to the neutral process specified by the passive sampling model. When additive absolute effects are assumed, nearly 80 percent of the observed empirical relationship is consistent with passive sampling.

The right panel in figure 6 shows the results of the same resampling experiments on the +1 SD in crime richness. The results are applicable to the –1 SD through symmetry. Curve B (solid cyan) in the rightmost panel of figure 6 is the mean crime richness $\bar{s}(\alpha)$ computed from the passive sampling theory. Curve B is included for comparison with figure 5a and the left panel in figure 6. Curve F (dashed black) is the empirical +1 SD shown in figure 5a. Curve G (dashed cyan) is the +1 SD computed from equation (4) and matches that shown in figure 5b. Curves H and I are then the results of random permutation of crime locations and crime types, respectively. Consistent with the results for mean crime richness, the random permutation of crime locations shown in curve H (red dashed) reduces the variance

in crime richness relative to the empirical pattern. Similarly, the permutation of crime types, leaving crime locations untouched, increases the variance in crime richness relative to the empirical pattern. Nevertheless, unlike the impact on mean richness, the variance observed after permutation of locations still greatly exceeds that expected from theory. Indeed, a scaling constant $c_4 = 1.20018$ is required to make the theoretical expectation (curve G, dashed cyan) consistent with standard deviation after random permutation of crime locations (curve H, red dashed; i.e., $c_4\sigma(\alpha) = H$). This constant multiplier represents a 20 percent gap with the outcome expected from theory (i.e., $c_4 - 1 = 0.2018$).

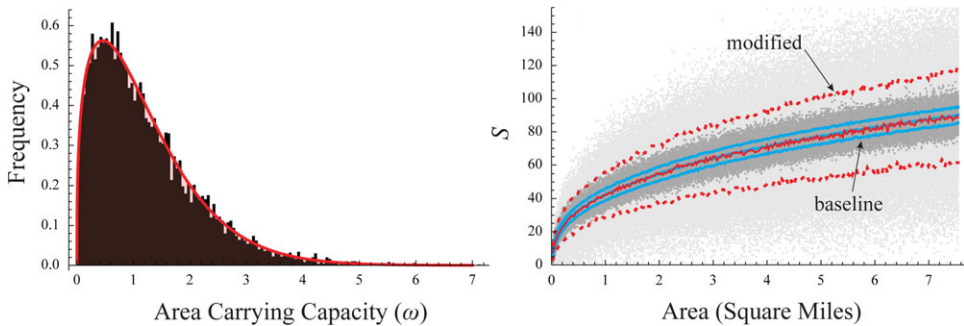
VARIATION IN CRIME CONCENTRATION

Additional mechanisms are clearly involved in driving the variance in crime richness at all spatial scales. I offer a possible explanation that allows for differences in the clustering or concentration of crime over space, while preserving the neutral character of how different crime types populate that space. Consider a variant of the passive sampling model where each subregion k under observation has a carrying capacity that determines the amount of crime it can support. In the baseline passive sampling model, the probability that a crime type i is found in a subregion of size α is $p_i = 1 - (1 - \alpha)^{n_i}$. We now rewrite equation (2) as $p_{i\omega} = 1 - (1 - \omega_k\alpha)^{n_i}$, where ω_k is a random variable for each subregion k drawn from some probability distribution, subject to the constraint $\omega_k \geq 0$. The variable ω_k captures the idea that there is natural variation from place to place in the amount of crime supported. Crimes are randomly placed with respect to their type, but now some areas of a fixed size α inherently accept more or less total crime than do others. In general, if $0 < \omega_k < 1$, then the probability that a crime of type i is represented in a subregion k is less than that expected for the baseline passive sampling model (i.e., $p_{i\omega} < p_i$). If $\omega_k = 1$, then the probability that crime type i is represented in subregion k is equivalent to the passive sampling model (i.e., $p_{i\omega} = p_i$). If $\omega_k > 1$, then the probability that crime type i is represented in subregion k is greater than expected for the baseline passive sampling model (i.e., $p_{i\omega} > p_i$). Over a large sample of subregions, each of size α , some of those subregions will support fewer unique crime types than expected (i.e., where $\omega_k\alpha < \alpha$), some will support the expected number of crime types (i.e., where $\omega_k\alpha = \alpha$), and some will support more unique crime types than expected (i.e., $\omega_k\alpha > \alpha$). Equations (3) and (4) may be rewritten to reflect variation in crime carrying capacities by replacing α with $\omega_k\alpha$. Yet, these modifications mean that it is no longer possible to compute the mean and variance in crime richness directly without first knowing the crime carrying capacity of each sampled subregion k .

An alternative approach is to assume that ω_k is drawn from a probability distribution that serves as a general theoretical model for the carrying capacity of crime. We seek a probability distribution for ω_k that increases the variance in crime richness over a sample of areas of size α , without impacting mean crime richness as specified by the baseline passive sampling model. In other words, we seek a probability distribution for ω_k where $\bar{\sigma}(\omega_k\alpha) = \bar{\sigma}(\alpha)$ but $\sigma(\omega_k\alpha) > \sigma(\alpha)$. Any probability distribution for ω_k that has a median of one is sufficient to meet the first criterion, subject to the constraint that $\omega_k \geq 0$. In concrete terms, a probability distribution with a median of one means that 50 percent of the sampled areas will have a crime richness below and 50 percent above the richness expected from the baseline passive sampling model. The mean richness will remain

Figure 7. Impact of Variable Crime Carrying Capacity on the Variance in Crime Richness as a Function of Area

- a Crime carrying capacity is modeled as a Weibull distribution with a median of one
- b Expected crime richness as a function of area where the crime carrying capacity for each sampled area of size α is drawn at random from the distribution shown in (a)



NOTES: Dark gray points are samples from the baseline passive sampling model. Light gray points are samples from the modified model. Mean and ± 1 SD for the baseline passive sampling model are shown as solid cyan curves. Mean crime richness from the modified model is the solid red curve. The ± 1 SD in crime richness from the modified model (dashed red lines) quantitatively match observed data. Baseline expectations (cyan lines) are consistent with the modified model to a constant scaling factor of $c_5 = 4.80497$.

consistent with the baseline model. The shape and scale of the probability distribution for ω_k controls whether the second condition requiring greater richness variance than the baseline model also is met.

Figure 7a models the carrying capacity of crime across areas of size α as a Weibull distribution. The two-parameter Weibull probability density function is given as $f(\omega|\theta, \lambda) = \omega^{\theta-1} e^{-(\omega/\lambda)^\theta}$, where θ is a shape parameter and λ is a scale parameter. The Weibull distribution is commonly used to examine survival data, but it is here chosen for its flexibility in capturing a range of different distribution shapes ranging from exponential (when $0 < \theta \leq 1$) to log-normal (when $\theta = 2$), normal (when $3 < \theta \leq 4$), and left-skewed (when $\theta > 4$). The shape and scale parameters also can be chosen to enforce the condition that the distribution has a median of 1, which occurs when $\theta \ln(2)^{-\lambda} = 1$. The distribution in figure 7a meets this criterion with $\theta = 1.33$ (shape) and $\lambda = 1.305$ (scale), which places the distribution close to a log-normal form. The exact parameter values for the distribution shown in figure 7a are of no immediate behavioral significance, beyond providing a best fit for observed crime richness patterns as a function of area. The qualitative characteristics of the distribution in figure 7a will be considered in the discussion.

Figure 7b illustrates the impact of introducing crime carrying capacities on the mean and variance in crime richness. Here I iterate the baseline version of equation (2), namely, $p_i = 1 - (1 - \alpha)^{n_i}$ and its extension $p_{i\omega} = 1 - (1 - \omega_k \alpha)^{n_i}$. Five hundred samples are generated at each area size ranging from 0.007 square miles (a disk with radius $\rho = 250$ feet) to 6.34 square miles ($\rho = 7,500$ feet). In each sample, the probability that crime type i is present in α is computed using the observed frequency n_i of crime type i in the 2013 LAPD data, whereas ω_k is drawn for each disk from the Weibull distribution shown in figure 7a. Iteration of equation (2) yields the expected theoretical mean and

standard deviation in crime richness as a function of area (compare figure 7b cyan curves with figure 5b). The iteration of $p_{i\omega}$ does not alter the mean richness (solid red curve), but it does amplify the variance in exactly the manner observed with the empirical data (dashed red curves). Indeed, the expected +1 SD in crime richness is equivalent to the theoretical +1 SD to a constant scaling factor $c_5 = 4.77396$, which is statistically equivalent to the observed scaling $c_2 = 4.72795$ (figure 5c). Alternative parameterizations of the Weibull distribution have a predictable impact on the variance in richness. When $\theta \leq 1$, for example, the distribution of crime carrying capacities ω_k is exponential and the variance in richness at all spatial scales is much greater than that shown in figure 7b. When $\theta > 3$, the distribution of ω_k is normal or left-skewed and the variance in richness is indistinguishable from the passive sampling model.

Overall, the variance in crime richness is dependent on more than area alone. Richness responds to differences in the amount of crime that those areas can support. Nevertheless, these variations in crime carrying capacity do not necessarily override neutral processes with respect to crime types. Stated explicitly, the capacity to support crime differs from area to area, but the placement of crime seems to occur independently of crime type. Areas that have a lower capacity to support crime have correspondingly lower diversity of randomly placed crime, whereas areas that have a higher capacity have correspondingly higher diversity of randomly placed crime. This observation holds across the full spectrum of spatial scales examined here.

DISCUSSION

Environmental cues or opportunities play a key role in controlling crime. The results presented here suggest, however, that this role may not be as deterministic as we typically assume. Rather, a large fraction of the diversity in crime that we see in an area may be modulated by random processes independent of both the crime types and the specific environmental characteristics present in that area. This observation holds closely for patterns of mean crime richness as a function of area. It also holds for the variance in crime richness but only after differences in the capacity of local areas to support crime are taken into account. The results present several interesting possibilities when seeking to understand the dynamics of crime and place.

NEUTRAL PROCESSES AND CRIME CONCENTRATION

The first possibility concerns how crimes are linked to environmental conditions. At one extreme, environments may simply provide space for crime to occur and little else. In terms of crime pattern theory, this is equivalent to stating that environmental cues are always general and universally present. As the size of an observed space grows, more types of crime occur simply as a result of the larger area involved. If the observed richness data were to match quantitatively the theoretical predictions in both mean and variance, then it would be difficult to argue that anything other than random, neutral processes define the relationship between environment and crime. It is safe to say that we can reject the neutral model in this purest form. Yet, observed patterns of mean crime richness as a function of area do not deviate far from the neutral expectation. At a minimum, the results favor the view that generalized crime cues or opportunities outweigh specific cues or opportunities in driving the mean crime richness of an area. These generalized cues place fewer

constraints on what types of crimes can occur, and therefore, the diversity of crime in an area might be assembled through largely random processes. Random neutral processes are not the only thing at play, but they are potentially a dominant force. Something more is clearly involved in driving the observed variance in crime richness. Indeed, to explain the variance in crime richness as a function of area, it is necessary to abandon the baseline neutral model. In its place is a slightly more complex model that allows areas to differ in the amount of crime they support, while placing few constraints on what crime types can occur in any given environment. In this extended model, crime in general is tightly coupled to place (Weisburd, Groff, and Yang, 2012), but specific crime types seem to be less so.

The connections between the crime-richness patterns investigated here and the law-like patterns of crime concentration introduced by Weisburd (2015) are notable. Weisburd made a compelling case that a small fraction of street segments is responsible for a large fraction of overall crime and that such patterns of crime concentration are universal (see also Roncek and Bell, 1981; Weisburd, Groff, and Yang, 2012), paralleling a similar observation for offenders and crime (Wolfgang, Figlio, and Sellin, 1987). The analyses presented in figure 7 reinforce the law-like status of this conclusion because the variance in crime richness is parsimoniously explained by invoking a regular statistical distribution by which crime concentration varies from place to place. Specifically, figure 7a represents a candidate distribution for the law-like way in which areas of comparable size vary probabilistically in crime concentration. The distribution here is closely related to a log-normal distribution. The internal peak of the distribution implies that most sampled areas will show low crime clustering or concentration, with completely crime-free areas rare compared with areas with some crime. The long tail of the distribution implies that a small number of sampled areas will show very high crime clustering or concentration. The log-normal form of the distribution suggests, although does not prove, that the cues or opportunities underlying variation in crime concentration combine via a multiplicative process (Mitzenmacher, 2004). Specifically, if we imagine that a large number of environmental cues each contributes a random quantity Ω_j to the overall carrying capacity in a subregion k , then these quantities are combined as $\omega_k = \prod \Omega_j$. The distribution of carrying capacities across multiple subregions is expected to be well approximated by a log-normal form. Additive contributions would be expected to produce a normal distribution of crime carrying capacity via the Central Limit Theorem.

Somewhat contrary to Weisburd's (2015) view, however, the impact of variation in crime concentration on richness is here observed across spatial scales. That is, the candidate distribution shown in figure 7a describes the variation in the capacity of the environment to support crime both when the observed areas are extremely small (e.g., 0.007 square miles) and when they are quite large (e.g., 6.37 square miles). When viewing micro-geographic units such as street segments, it is clearly the case that a small handful of those is responsible for the majority of crime. But it is also the case that larger spatial units also display such law-like patterns of concentration. Variation in crime concentration at each spatial scale translates into regular patterns of variation in crime richness at that scale. This observation raises very important questions about how the level of data aggregation impacts the patterns we detect and the explanations offered for those patterns (Andresen and Linning, 2012; Groff, Weisburd, and Morris, 2009; Openshaw and Taylor, 1979). It is certainly not the case, however, that only one scale of pattern and process matters.

CRIME CLASSIFICATION AND REPORTING

The analyses presented here certainly have limitations. The first concerns matters of measurement. It must be acknowledged that it is no simple matter to delineate what constitutes a unique crime type. On the one hand, a legal perspective would seem to necessitate that each codified violation of the law is a unique crime type. On the other, one might attempt to identify clusters of behavior that define broad latent crime types that might cross-cut specific legal codes (Osgood and Schreck, 2007; Schreck, McGloin, and Kirk, 2009). It is possible to detect patterns within both particulate and aggregate crime classification systems. Indeed, we can contrast Weisburd et al. (1992), who found both divergent and convergent patterns in calls for service related to a large list of different crime types, with Weisburd, Groff, and Yang (2012), who detected patterns when there was no distinction whatsoever between crime types. In the present case, it hampers our ability to speak about crime diversity if we limit the analysis to only a very small number of latent crime types. A similar point was raised in relation to the study of offender specialization (Blumstein et al., 1988: 310). It is also not clear that combining crime types is always statistically warranted, especially for spatial analyses (Andresen and Linning, 2012; see also Groff, Weisburd, and Morris, 2009). The approach taken here, therefore, hews closely to the particulate or fine-grained empirical classification system used by the LAPD. These behavioral distinctions are employed by LAPD officers when dealing with crime in the field. The full list of crime types may be unique to Los Angeles, but this does not preclude comparison with crime diversity patterns in other locations. Biodiversity is regularly compared across environments even though species inventories do not overlap at all (Gaston, 2000). Crime-richness patterns tell us something about crime–environment dynamics without looking in detail at what those crimes or environments are. Nevertheless, future work should seek to examine how different procedures for aggregating crime types, based on behavioral, social, spatial, or legal criteria, impacts measurement of crime diversity.

Even if we agree on a classification system for unique crime types, potential problems can arise through the real-world use of that system. Indeed, several potential sources of error stem from the detection of and reporting of crime. The underreporting of crime is widespread, and it is well known that underreporting rates differ across crime types (Hough and Mayhew, 1983; Skogan, 1977). Such differences can impact our understanding of crime diversity in the sense that crime types with lower reporting rates will show up less frequently in samples based on official statistics. Heavily underreported crimes may fail to register at all in very small samples. This bias could be of significant concern were it the case that underreporting rates changed on short time scales or differed dramatically from one local place to another. In such a case, two samples collected at two different times or in two different places could look quite different in terms of crime richness (and evenness) simply as a matter of differences in underreporting rates. Although changes in law, public attitudes toward certain crime types, and trust in the police may alter reporting rates (Bachman, 1998; Sunshine and Tyler, 2003), most crime types have experienced only small incremental shifts in reporting over time (e.g., Xie, 2012). Here I simply assume that reporting biases are stationary at the temporal and spatial scales under consideration.

Closely related to problems of underreporting are potential biases arising from misidentification of crimes. Crimes reported to police may be misclassified because of

true uncertainty about the nature of the crime or because some discretionary process leads a crime of one definitive type to be intentionally identified as another definitive type. The effects of uncertainty and discretion can arise in the actions of both individuals reporting a crime and individuals compiling a crime report. A victim might not have sufficient information to classify a crime correctly, or the victim might intentionally misclassify a crime to downplay or exaggerate the seriousness of the crime (Klinger and Bridges, 1997). Similarly, someone collecting a crime report might unintentionally or intentionally misclassify a crime because of a lack of information or to achieve some desired outcome (Seidman and Couzens, 1974). The Uniform Crime Reports hierarchy rule might be thought of as a special case of classificatory discretion that seeks to avoid the problems of multiple recorded crimes occurring in a single event (Lynch and Addington, 2006). Ecological studies of biological diversity are not immune to classificatory problems, where the rate of species misidentification can reach 5 percent (Scott and Hallam, 2003). In these cases, rare species are more likely to be misidentified and species present inside richer assemblages are more likely to be misidentified (Archaux et al., 2009). Similar problems may pertain to the classification of crime. Nevertheless, it might also be the case that rare crimes demand more careful attention and therefore end up being more accurately classified. Future work should seek to assess the degree to which classification and sample size biases impact measures of crime diversity and what statistical protocols might be most appropriate in controlling for such biases.

CRIME RICHNESS AND HARM INDICIES

In this context, one thing that is clearly missing from the analyses is some notion of crime severity or harm (see also Blumstein et al., 1988; Ratcliffe, 2015; Sherman, 2011). Here unique crime types are treated as equivalent or simply as arbitrary labels. This assumption should not be taken as a statement that different crime types produce equivalent harm. On the contrary, the assumption is a deliberate analytical strategy. How relative harm impacts the dynamics of crime is poorly understood as it has primarily been studied as a policy issue. Under such circumstances, it is useful to assume that there are no differences among crime types. Nevertheless, one could imagine that the picture of crime richness across Los Angeles or any other city would be quite different if crime types were weighted by their relative severity or harm. An area with low overall crime richness might still score very high on some harm-weighted diversity metric if even a few crime types are considered “high harm.” Conversely, an area with high overall crime richness might still score low on this harm-weighted diversity metric if all crime types present are considered “low harm.” I leave these possibilities and their interpretation for future investigation.

EXPLANATION VIA NEUTRAL MODELS

Questions of process are just as important as questions of measurement. That neutral processes are suggested to play a significant role in crime diversity does not disprove the hypothesis that specific crimes are tied in deterministic ways to the environments in which they occur. In theory, environmental settings themselves could be randomly distributed in space, allowing crime types to be simultaneously well fit to specific environmental conditions *and* randomly distributed in space. Imagine, for the sake of argument, that

there are exactly 419 unique environmental cues, one for each unique crime type in the LAPD data set. Each of those 419 cues could be randomly and independently drawn and placed in the environment according to the passive sampling process. The probability of observing any one cue in an area α would be described by an analog to equation (2), whereas the mean and variance in the number of unique cues found in an area of size α would be described by analogs of equations (3) and (4). Crime types could then be distributed in space in a completely deterministic way, with each crime type lining up exactly with its corresponding cue. This scenario would preserve a key feature of crime pattern theory and its close relatives in problem-oriented policing. We would then be confronted, however, with the challenge of explaining why different criminogenic cues are randomly distributed in space.

Even with these caveats, the results presented here do seem hard to accept given the number of studies over the decades that have linked crime types to particular environmental characteristics. One unnerving possibility is that the inferred connections between unique crime types and the attributes of particular settings reflect the effects of confirmation bias. To wit, for a crime that occurs in a specific location, we start by assuming that there must be an environmental cue or opportunity that was a critical driver of the event. With complex environments (i.e., those that consist of countless physical and social attributes), we are almost guaranteed to find some environmental cue or opportunity that is a plausible cause for the crime if we go looking for it. Randomized controlled experiments offer a possibility to control for the effects of confirmation bias (Garvin, Cannuscio, and Branas, 2013; Keizer, Lindenberg, and Steg, 2008). Nevertheless, randomized controlled trials focusing on environmental manipulation are currently dwarfed in number by studies looking simply at environment–crime correlations. What is causally proven and what is plausible is not entirely clear at present.

Randomized controlled experiments are, of course, not the only way to test theory. Indeed, the approach used here is one alternative. Simple mathematical models that yield rigorous predictions can be used to generate causal inferences. The methodological steps are straightforward in principle. Simple models need to be tested before more complex models. Model testing involves seeking empirical evidence sufficient to reject model assumptions in whole or in part. Causal models necessarily become more complex as the unreasonable assumptions of simple models are rejected in favor of more complex assumptions. The simplest possible model that cannot be rejected given existing data offers the best current explanation. This positivist ideal is laudable. It runs into opposition, however, when a simple model seems to do a good job of explaining a phenomenon despite ignoring favored variables and mechanisms. The simple model implies that such favored variables or mechanisms are not as important as they are held out to be. In the present case, an exceedingly simple model goes a long way toward explaining the observed relationship between crime richness and area without invoking complex crime–environment dependencies. Certainly, a more complex model could fit richness patterns just as well or perhaps even better than could the passive sampling model. Yet, as emphasized in model comparison metrics such as the Akaike Information Criterion (Akaike, 1974), models should be rewarded for their statistical fit but also penalized for their complexity.

Finally, it is worth addressing whether the results presented here should be considered unique to Los Angeles or whether they should find broad applicability. On the one hand, it is an empirical question that can be easily tested. Any jurisdiction of any size, for

which spatially resolved event data cover a spectrum of crime types, can be evaluated in reference to the passive sampling model. The passive sampling model provides a valuable baseline or starting point for evaluation of crime richness in any environment. On the other hand, it is a theoretical question that speaks directly to searching for universal laws and broad scientific theory underlying patterns in crime. Regular empirical patterning that can be described through general, but rigorous mechanistic models is essential to claims of law-like behavior. The surprising regularity of the empirical patterning observed in Los Angeles and the degree to which a basic mechanistic model succeeds in explaining this pattern raise the likelihood that very similar patterning may be found in many, if not most, other environments. This has certainly been the case in the study of biodiversity, where very similar species-richness curves are observed across radically different ecological settings. In the end, however, it may be the deviations from baseline expectations that are most informative for diagnosing the mechanisms driving crime diversity.

CONCLUSIONS

The assumption that there is a close fit between the type of crime that occurs in a place and environmental cues or opportunities present in that place is central to environmental criminology. This core assumption leads to a unique macroscopic prediction. Larger areas are expected to contain more unique environmental settings, and therefore, larger areas should host a greater variety of crimes. This empirical pattern, well known in ecology, seems to hold for crime richness, which is a measure of the number of unique crime types in a sample or area. By using data from Los Angeles, it was shown that as the area sampled increases in size, the mean number of unique crime types also increases. The pattern of increase in crime richness is very regular. Nevertheless, the exact mechanisms driving this pattern are not immediately clear. It is possible that very general environmental cues or opportunities may lead to greater diversity of crime in an area simply by virtue of the large area sampled. It seems equally plausible that larger areas will include a greater variety of environmental cues, which encourages a greater diversity of crime through direct ties between specific environmental cues and unique crime types.

By borrowing from the ecological literature, I have presented a neutral model for the crime-type area relationship called the passive sampling model. The model treats each crime type as an arbitrary label and posits that crimes are placed randomly and independently in space. The model provides clear quantitative expectations in terms of the mean and variance in richness as a function of area under the neutral assumptions. Surprisingly, the model is qualitatively consistent with that observed from Los Angeles and, with scaling by constant factors, is made quantitatively indistinguishable. The results were cross-checked with resampling experiments, which show that a fraction of the mean observed crime richness—on the order of 20 percent—is linked to nonrandom clustering crime in space and nonrandom assortment within unique crime types. The much larger fraction of the pattern for mean crime richness is consistent with the passive sampling model. Nonrandom clustering or concentration of crime seems to play a much bigger role in driving variance in crime richness. Two areas of the same absolute size may display different capacities to support crime. Those areas that support a lower overall density show lower crime richness, whereas those that support a higher overall density show

higher crime richness. Nevertheless, such a mechanism can operate alongside neutral processes whereby the specific crime types in a place occur largely at random.

Overall, these results presented here suggest that some very general rules or laws may be at play in driving crime diversity in space. That these rules or laws may be largely neutral is not that unusual when viewed from other scientific domains. It does suggest, however, that more work is needed to disentangle the causal dynamics linking crime to the environments in which it occurs.

REFERENCES

- Akaike, Hirotoga. 1974. A new look at statistical model identification. *IEEE Transactions on Automatic Control* AC 19:716–23.
- Andresen, Martin A. 2009. Crime specialization across the Canadian provinces. *Canadian Journal of Criminology and Criminal Justice* 51:31–53.
- Andresen, Martin A., and Shannon J. Linning. 2012. The (in)appropriateness of aggregating across crime types. *Applied Geography* 35:275–82.
- Anglin, M. Douglas, and George Speckart. 1988. Narcotics use and crime: A multisample, multimethod analysis. *Criminology* 26:197–233.
- Archaux, Frédéric, Sylvaine Camaret, Jean-Luc Dupouey, Erwin Ulrich, Emmanuel Corcket, Laurence Bourjot, Alain Brêthes, Richard Chevalier, Jean-Francois Dobremez, Yann Dumas, Gérard Dumé, Marie Forêt, Françoise Forgeard, Myriam Lebrete Gallet, Jean-François Picard, Franck Richard, Jean-Marie Savoie, Laurent Seytre, Jean Timbal, and Jean Touffet. 2009. Can we reliably estimate species richness with large plots? An assessment through calibration training. *Plant Ecology* 203:303–15.
- Arrhenius, Olof. 1921. Species and area. *Journal of Ecology* 9:95–9.
- Azaele, Sandro, Stephen J. Cornell, and William E. Kunin. 2011. Downscaling species occupancy from coarse spatial scales. *Ecological Applications* 22:1004–14.
- Baayen, R. Harald. 2001. *Word Frequency Distributions*, vol. 18. New York: Springer Science & Business Media.
- Bachman, Ronet. 1998. The factors related to rape reporting behavior and arrest: New evidence from the National Crime Victimization Survey. *Criminal Justice and Behavior* 25:8–29.
- Baudains, Peter, Alex Braithwaite, and Shane D. Johnson. 2013. Target choice during extreme events: A discrete spatial choice model of the 2011 London riots. *Criminology* 51:251–85.
- Bernasco, Wim, and Richard Block. 2009. Where offenders choose to attack: A discrete choice model of robberies in Chicago. *Criminology* 47:93–130.
- Bernasco, Wim, and Paul Nieuwbeerta. 2005. How do residential burglars select target areas? A new approach to the analysis of criminal location choice. *British Journal of Criminology* 45:296–315.
- Blumstein, Alfred, Jacqueline Cohen, Somnath Das, and Soumyo D. Moitra. 1988. Specialization and seriousness during adult criminal careers. *Journal of Quantitative Criminology* 4:303–45.
- Bock, Walter J. 1980. The definition and recognition of biological adaptation. *American Zoologist* 20:217–27.
- Boessen, Adam, and John R. Hipp. 2015. Close-ups and the scale of ecology: Land uses and the geography of social context and crime. *Criminology* 53:399–426.

- Braga, Anthony A., and Ronald V. Clarke. 2014. Explaining high-risk concentrations of crime in the city: Social disorganization, crime opportunities, and important next steps. *Journal of Research in Crime and Delinquency* 51:480–98.
- Brantingham, Patricia L., and Paul J. Brantingham. 1995. Criminality of place: Crime generators and crime attractors. *European Journal on Criminal Policy and Research* 3:5–26.
- Brantingham, Patricia L., and Paul J. Brantingham. 1997. Mapping crime for analytic purposes: Location quotients, counts and rates. *Crime Mapping and Crime Prevention* 8:263–88.
- Brantingham, Patricia L., Paul J. Brantingham, Mona Vajihollahi, and Kathryn Wuschke. 2009. Crime analysis at multiple scales of aggregation: A topological approach. In *Putting Crime in its Place*, eds. David Weisburd, Win Bernasco, and Gerben J. N. Bruinsma. New York: Springer.
- Brantingham, Paul J., and Patricia L. Brantingham. 1978. A theoretical model of crime site selection. In *Theoretical Perspectives on Crime and Criminal Justice*, eds. Marvin D. Krohn and Ronald L. Akers. Beverly Hills, CA: Sage.
- Brantingham, Paul J., and Patricia L. Brantingham. 1981. *Environmental Criminology*. Beverly Hills, CA: Sage.
- Brantingham, Paul J., and Patricia L. Brantingham. 1984. *Patterns in Crime*. New York: MacMillan.
- Britt, Chester L. 1996. The measurement of specialization and escalation in the criminal career: An alternative modeling strategy. *Journal of Quantitative Criminology* 12: 193–222.
- Caswell, Hal. 1976. Community structure: A neutral model analysis. *Ecological Monographs* 46:327–54.
- Clarke, Ronald V. 1995. Situational crime prevention. *Crime and Justice* 19: 91–150.
- Clarke, Ronald V. 1997. *Situational Crime Prevention*. Monsey, NY: Criminal Justice Press.
- Clarke, Ronald V., and Derek B. Cornish. 1985. Modeling offenders' decisions: A framework for research and policy. In *Crime and Justice: A Review of Research*, vol. 6, eds. Michael Tonry and Norval Morris. Chicago, IL: University of Chicago Press.
- Coleman, Bernard D. 1981. On random placement and species-area relations. *Mathematical Biosciences* 54:191–215.
- Connor, Edward F., and Earl D. McCoy. 1979. The statistics and biology of the species-area relationship. *The American Naturalist* 113:791–833.
- Cornish, Derek B. 1994. The procedural analysis of offending, and its relevance for situational prevention. In *Crime Prevention Studies*, vol. 3, eds. Ronald V. Clarke. Monsey, NY: Criminal Justice Press.
- Cornish, Derek B., and Ronald V. Clarke. 1986. *The Reasoning Criminal: Rational Choice Perspectives on Offending*. New York: Springer-Verlag.
- Coyne, Michelle A., and John E. Eck. 2014. Situational choice and crime events. *Journal of Contemporary Criminal Justice* 31:12–29.
- Dale, Mark R. T., and Marie-Josée Fortin. 2014. *Spatial Analysis: A Guide for Ecologists*. Cambridge, U.K.: Cambridge University Press.
- Deane, Glenn, David P. Armstrong, and Richard B. Felson. 2005. Examination of offense specialization using marginal logit models. *Criminology* 43:955–88.

- Eck, John E., Spencer Chainey, James G. Cameron, Michael Leitner, and Ronald E. Wilson. 2005. *Mapping Crime: Understanding Hot Spots*. Washington, DC: National Institute of Justice.
- Eck, John E., Ronald V. Clarke, and Rob T. Guerette. 2007. Risky facilities: Crime concentration in homogeneous sets of establishments and facilities. In *Crime Prevention Studies*, eds. Graham Farrell, Kate J. Bowers, Shane D. Johnson, and Michael Townsley. Cullompton, U.K.: Willan.
- Eck, John E., and William Spelman. 1988. *Problem Solving: Problem-Oriented Policing in Newport News*. Washington, DC: Police Executive Research Forum and National Institute of Justice.
- Eck, John E., and David L. Weisburd. 1995. Crime places in crime theory. In *Crime and Place*, eds. John E. Eck and David L. Weisburd. Monsey, NY: Criminal Justice Press.
- Ferenc, Michal, Ondřej Sedláček, Roman Fuchs, Marco Dinetti, Maurizio Fraissinet, and David Storch. 2014. Are cities different? Patterns of species richness and beta diversity of urban bird communities and regional species assemblages in Europe. *Global Ecology and Biogeography* 23:479–89.
- Fisher, R. A., A. Steven Corbet, and C. B. Williams. 1943. The relation between the number of species and the number of individuals in a random sample of an animal population. *Journal of Animal Ecology* 12:42–58.
- Garvin, Eugenia C., Carolyn C. Cannuscio, and Charles C. Branas. 2013. Greening vacant lots to reduce violent crime: A randomised controlled trial. *Injury Prevention* 19:198–203.
- Gaston, Kevin J. 2000. Global patterns in biodiversity. *Nature* 405:220–7.
- Goldstein, Herman. 1979. Improving policing: A problem-oriented approach. *Crime & Delinquency* 25:236–58.
- Goldstein, Herman. 1990. *Problem-Oriented Policing*. New York: McGraw Hill.
- Gotelli, Nicholas J., and Robert K. Colwell. 2001. Quantifying biodiversity: Procedures and pitfalls in the measurement and comparison of species richness. *Ecology Letters* 4:379–91.
- Gotelli, Nicholas J., and Gary R. Graves. 1996. *Null Models in Ecology*. Washington, DC: Smithsonian Institution Press.
- Groff, Elizabeth R., David L. Weisburd, and Nancy A. Morris. 2009. Where the action is at places: Examining spatio-temporal patterns of juvenile crime at places using trajectory analysis and GIS. In *Putting Crime in its Place*, eds. David L. Weisburd, Wim Bernasco, and Gerben J. N. Bruinsma. New York: Springer.
- Hayek, Lee-Ann C., and Martin A. Buzas. 1997. *Surveying Natural Populations*. New York: Columbia University Press.
- He, Fangliang, and Kevin J. Gaston. 2000. Estimating species abundance from occurrence. *The American Naturalist* 156:553–9.
- He, Fangliang, and Stephen P. Hubbell. 2011. Species-area relationships always overestimate extinction rates from habitat loss. *Nature* 473:368–71.
- He, Fangliang, and Pierre Legendre. 2002. Species diversity patterns derived from species-area models. *Ecology* 83:1185–98.
- Hobbs, Jean-Paul A., Geoffrey P. Jones, Philip L. Munday, Sean R. Connolly, and Maya Srinivasan. 2012. Biogeography and the structure of coral reef fish communities on isolated islands. *Journal of Biogeography* 39:130–9.

- Hough, Michael and Patricia Mayhew. 1983. *The British Crime Survey: First Report*. London, England: Her Majesty's Stationery Office.
- Hubbell, Stephen P. 2001. *The Unified Neutral Theory of Biodiversity and Biogeography*. Princeton, NJ: Princeton University Press.
- Huston, Michael. 1979. A general hypothesis of species diversity. *The American Naturalist* 113:81–101.
- Hystad, Grethe, Robert T. Downs, Edward S. Grew, and Robert M. Hazen. 2015. Statistical analysis of mineral diversity and distribution: Earth's mineralogy is unique. *Earth and Planetary Science Letters* 426:154–7.
- Jeffery, C. Ray. 1977. *Crime Prevention Through Environmental Design*. Beverly Hills, CA: Sage.
- Jeuniaux, Patrick P. J. M. H., Leen Dubocage, Bertrand Renard, Pierre Van Renterghem, and Vanessa Vanvooren. 2015. Establishing networks in a forensic DNA database to gain operational and strategic intelligence. *Security Journal*. epub ahead of print. doi: 10.1057/sj.2015.31.
- Johnson, Shane D., and Lucia Summers. 2015. Testing ecological theories of offender spatial decision making using a discrete choice model. *Crime & Delinquency* 61: 454–80.
- Kadmon, Ronen, and Yuval Benjamini. 2006. Effects of productivity and disturbance on species richness: A neutral model. *The American Naturalist* 167:939–46.
- Katz, Jack. 1988. *Seductions of Crime*. New York: Basic Books.
- Keizer, Kees, Siegwart Lindenbergh, and Linda Steg. 2008. The spreading of disorder. *Science* 322:1681–5.
- Kennedy, Leslie, Joel Caplan, and Eric Piza. 2011. Risk clusters, hotspots, and spatial intelligence: Risk terrain modeling as an algorithm for police resource allocation strategies. *Journal of Quantitative Criminology* 27:339–62.
- Kimura, Motoo. 1983. *The Neutral Theory of Molecular Evolution*. Cambridge, U.K.: Cambridge University Press.
- Kinney, J. Bryan, Patricia L. Brantingham, Kathryn Wuschke, Michael G. Kirk, and Paul J. Brantingham. 2008. Crime attractors, generators and detractors: Land use and urban crime opportunities. *Built Environment* 34:62–74.
- Klinger, David A., and George S. Bridges. 1997. Measurement error in calls-for-service as an indicator of crime. *Criminology* 35:705–26.
- Leibold, Matthew A., Marcel Holyoak, Nicolas Mouquet, Priyanga Amarasekare, Jonathan M. Chase, Martha F. Hoopes, Robert D. Holt, Jonathan B. Shurin, Richard Law, David Tilman, Michel Loreau, and Andrew Gonzalez. 2004. The metacommunity concept: A framework for multi-scale community ecology. *Ecology Letters* 7: 601–13.
- Lim, Gwynne S., Michael Balke, and Rudolf Meier. 2011. Determining species boundaries in a world full of rarity: Singletons, species delimitation methods. *Systematic Biology* 61:165–9.
- Lynch, James P., and Lynn A. Addington. 2006. *Understanding Crime Statistics: Revisiting the Divergence of the NCVS and the UCR*. Cambridge, U.K.: Cambridge University Press.
- MacArthur, Robert H., and Edward O. Wilson. 1967. *The Theory of Island Biogeography*. Princeton, NJ: Princeton University Press.
- Magurran, Anne E. 2004. *Measuring Biological Diversity*. Oxford, U.K.: Blackwell.

- Mair, Christina, Paul J. Gruenewald, William R. Ponicki, and Lillian Remer. 2013. Varying impacts of alcohol outlet densities on violent assaults: Explaining differences across neighborhoods. *Journal of Studies on Alcohol and Drugs* 74:50–8.
- Malm, Aili, Nahanni Pollard, Paul J. Brantingham, Paul Tinsley, Darryl Plecas, Patricia L. Brantingham, Irwin Cohen, and Bryan Kinney. 2005. *A 30 Year Analysis of Police Service Delivery and Costing: "E" Division*. Abbotsford, U.K.: Centre for Criminal Justice Research.
- McGloin, Jean Marie, Christopher J. Sullivan, Alex R. Piquero, Arjan Blokland, and Paul Nieuwbeerta. 2011. Marriage and offending specialization: Expanding the impact of turning points and the process of desistance. *European Journal of Criminology* 8: 361–76.
- Mitzenmacher, Michael. 2004. A brief history of generative models for power law and lognormal distributions. *Internet Mathematics* 1:226–51.
- Mouillot, David, Nicholas A. J. Graham, Sébastien Villéger, Norman W. H. Mason, and David R. Bellwood. 2013. A functional approach reveals community responses to disturbances. *Trends in Ecology & Evolution* 28:167–77.
- Murgui, Enrique. 2007. Effects of seasonality on the species–area relationship: A case study with birds in urban parks. *Global Ecology and Biogeography* 16:319–29.
- Nei, Masatoshi, Yoshiyuki Suzuki, and Masafumi Nozawa. 2010. The neutral theory of molecular evolution in the genomic era. *Annual Review of Genomics and Human Genetics* 11:265–89.
- Openshaw, Stan, and Peter J. Taylor. 1979. A million or so correlation coefficients: Three experiments on the modifiable areal unit problem. *Statistical Applications in the Spatial Sciences* 21:127–44.
- Osgood, D. Wayne, and Christopher J. Schreck. 2007. A new method for studying the extent, stability, and predictors of individual specialization in violence. *Criminology* 45:273–312.
- Pearl, Judea. 1978. On the connection between the complexity and credibility of inferred models. *International Journal of General Systems* 4:255–64.
- Pedrós-Alió, Carlos. 2012. The rare bacterial biosphere. *Annual Review of Marine Science* 4:449–66.
- Piquero, Alex R., Raymond Paternoster, Paul Mazerolle, Robert Brame, and Charles W. Dean. 1999. Onset age and offense specialization. *Journal of Research in Crime and Delinquency* 36:275–99.
- Popper, Karl. 2005. *The Logic of Scientific Discovery*. New York: Routledge.
- Ratcliffe, Jerry H. 2015. Towards an index for harm-focused policing. *Policing* 9:164–82.
- Raudys, Sarunas J., and Anil K. Jain. 1991. Small sample size effects in statistical pattern recognition: Recommendations for practitioners. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 13:252–64.
- Rengert, George F., Jerry H. Ratcliffe, and Sanjoy Chakravorty. 2005. *Policing Illegal Drug Markets: Geographic Approaches to Crime Reduction*. Monsey, NY: Criminal Justice Press.
- Roncek, Dennis W., and Ralph Bell. 1981. Bars, blocks, and crimes. *Journal of Environmental Systems* 11:35–47.
- Rosindell, James, Stephen P. Hubbell, and Rampal S. Etienne. 2011. The unified neutral theory of biodiversity and biogeography at age ten. *Trends in Ecology & Evolution* 26:340–8.

- Schreck, Christopher J., Jean Marie McGloin, and David S. Kirk. 2009. On the origins of the violent neighborhood: A study of the nature and predictors of crime-type differentiation across Chicago neighborhoods. *Justice Quarterly* 26:771–94.
- Scott, W. Andrew, and Caroline J. Hallam. 2003. Assessing species misidentification rates through quality assurance of vegetation monitoring. *Plant Ecology* 165:101–15.
- Seidman, David, and Michael Couzens. 1974. Getting the crime rate down: Political pressure and crime reporting. *Law & Society Review* 8:457–93.
- Sherman, Lawrence W. 2011. Al Capone, the Sword of Damocles, and the police–corrections budget ratio. *Criminology & Public Policy* 10:195–206.
- Sherman, Lawrence W., and David L. Weisburd. 1995. General deterrent effects of police patrol in crime “hot spots”: A randomized, controlled trial. *Justice Quarterly* 12: 625–48.
- Simberloff, Daniel S. 1974. Equilibrium theory of island biogeography and ecology. *Annual Review of Ecology and Systematics* 5:161–82.
- Skogan, Wesley G. 1977. Dimensions of the dark figure of unreported crime. *Crime & Delinquency* 23:41–50.
- Sunshine, Jason, and Tom R. Tyler. 2003. The role of procedural justice and legitimacy in shaping public support for policing. *Law & Society Review* 37:513–48.
- Taylor, Ralph B., and Stephen Gottfredson. 1986. Environmental design, crime, and prevention: An examination of community dynamics. In *Crime and Justice: A Review of Research*, vol. 8, ed. Michael Tonry. Chicago, IL: University of Chicago Press.
- Townsley, Michael, Daniel Birks, Stijn Ruiter, Wim Bernasco, and Gentry White. 2015. Target selection models with preference variation between offenders. *Journal of Quantitative Criminology* 32:283–304.
- Weisburd, David L. 2015. The law of crime concentration and the criminology of place. *Criminology* 53:133–57.
- Weisburd, David L., Elizabeth R. Groff, and Sue-Ming Yang. 2012. *The Criminology of Place: Street Segments and Our Understanding of the Crime Problem*. Oxford, U.K.: Oxford University Press.
- Weisburd, David L., Lisa Maher, Lawrence W. Sherman, Michael Buerger, Ellen G. Cohn, and Anthony Petrisino. 1992. Contrasting crime general and crime specific theory: The case of hot spots of crime. *Advances in Criminological Theory* 4: 45–69.
- Weisburd, David L., and Alex R. Piquero. 2008. How well do criminologists explain crime? Statistical modeling in published studies. In *Crime and Justice: A Review of Research*, vol. 37, ed. Michael Tonry. Chicago, IL: University of Chicago Press.
- Weisburd, David L., Cody W. Telep, Breanne Cave, Kate Bowers, John E. Eck, Gerben J. N. Bruinsma, Charlotte Gill, Elizabeth R. Groff, Julie Hibdon, and Joshua C. Hinkle. 2016. *Place Matters*. Cambridge, U.K.: Cambridge University Press.
- Wikström, Per-Olof H., Dietrich Oberwittler, Kyle Treiber, and Beth Hardie. 2012. *Breaking Rules: The Social and Situational Dynamics of Young People’s Urban Crime*. Oxford, U.K.: Oxford University Press.
- Wolfgang, Marvin E., Robert M. Figlio, and Thorsten Sellin. 1987. *Delinquency in a Birth Cohort*. Chicago, IL: University of Chicago Press.
- Wright, Richard T., and Scott H. Decker. 1994. *Burglars on the Job: Streetlife and Residential Breakins*. Boston, MA: Northeastern University Press.

- Wright, Richard T., Robert H. Logie, and Scott H. Decker. 1995. Criminal expertise and offender decision making: An experimental study of the target selection process in residential burglary. *Journal of Research in Crime and Delinquency* 32:39–53.
- Xie, Min. 2012. Area differences and time trends in crime reporting: Comparing New York with other metropolitan areas. *Justice Quarterly* 31:43–73.

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