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ORIGINAL PAPER

Moving to Crime Opportunity

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Abstract

Objectives Research has established that offenders are often generalists who commit a wide range of criminal offense types. Theoretical approaches to offending variety generally take a longitudinal perspective that tracks the variety of crimes committed over the life-course. Less theoretical work has been done at the microscopic scale of daily routines, though this is the scale at which individuals ultimately encounter and exploit criminal opportunities.

Methods This paper develops a neutral model that links fine-grained offender mobility patterns in heterogeneous crime environments to offending variety. Offender mobility is modeled as Brownian motion originating from central anchor point. Crime opportunities are exploited upon encounter in a simple random fashion.

Results The model shows mechanistically how offenders with higher mobility and/or environments with greater spatial overlap in distinct crime opportunities can display greater offending variety.

Conclusions The model provides a neutral baseline for evaluating the relationship between day-to-day mobility, crime environments, and offending variety. The relationship displays distinctive mathematical regularities that can serve as a foundation for further theoretical development.

Keywords Behavioral ecology · Crime · Mobility · Environmental psychology · Brownian motion · Random walk

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Introduction

Crime is often viewed through the lens of either offenders or the events themselves (Brantingham and Brantingham 1984; Sacco and Kennedy 2002; Wortley 2010). This partitioning is also true of attempts to study how crimes of different types co-occur. The range of crime types favored by an offender is referred to as their "offending variety" (Farrington 1973; Monahan and Piquero 2009; Sweeten 2012). While it was long thought that offenders might specialize in certain types of crime, it now appears that offenders are more commonly generalists willing to commit a wide array of crime types given the opportunity (Mazerolle et al. 2000; McGloin et al. 2009). Moreover, offending variety appears to change over the life-course, reflecting how individual preferences and opportunities to engage in crime shift both with age and social and environmental contexts (Gottfredson and Hirschi 1990; McGloin and Piquero 2010; Moffitt 1994). In general, observing an offender for a longer period will tend to reveal greater offending variety (McGloin et al. 2009, 2011; Piquero et al. 2010).

At the event level, the range of crime types found in a particular place, such as a neighborhood, might be referred to as "crime diversity" (Brantingham 2016; Lentz 2018; Quick et al. 2018). Crime diversity may be related to the opportunity characteristic of a particular place (Brantingham and Brantingham 1978; Mayhew et al. 1976), though the preferences of offenders may also matter (Bernasco and Block 2009; Townsley et al. 2015). Theory suggests that environmental cues favorable to crime can be crime general or crime specific, signaling respectively the appropriateness of multiple or singular crime types for that setting. In either case, larger areas are expected to host more cues and thus present greater crime diversity (Brantingham 2016; Khorshidi et al. 2021).

Given the conceptual similarity of offending variety and crime diversity as measures of crime it is a wonder that there have been few attempts to formally connect them (but see Song et al. 2019; Thomas et al. 2022). Certainly, the units of observation are very different—individual offenders vs geographic areas—and the theoretical traditions animating their investigation quite separate—life-course vs. environmental criminology. However, it must be the case that offending variety and crime diversity are connected to one another. After all, a criminal career is assembled through a sequence of events in which offenders search for, encounter, and exploit criminal opportunities in their environments. Similarly, the crime pattern in a particular place is ultimately a trace of the criminal repertoires of the offenders who committed crimes there. The present paper focuses on the first of these problems by developing an agent-based model where individual offending variety arises from mobility-driven encounters with crime opportunities distributed across a spatially explicit environment. The second problem, the generation of place-based crime diversity by foraging offenders, will be addressed in future work.

Our conceptual starting point for modeling mobility-driven offending variety can be traced to routine activities theory, crime pattern theory and the study of journey-to-crime distributions. Crime pattern theory focuses the key activity nodes and paths that make up offender (and non-offender) daily routines (Brantingham and Brantingham 1993). Mobility is what makes crime pattern theory a dynamic theory of offender behavior. Specifically, the repetitive nature of routine movement around and between activity nodes is thought to build awareness of available crime opportunities (Brantingham and Brantingham 1978). Whether those opportunities are exploited upon first encounter or later, mobility is the proximate mechanisms bringing offenders and targets together in space and time to trigger a crime

(Felson 2002). Journey-to-crime distributions, which plot the distances between crime locations and a key anchor point (usually home) across offenders, reveal certain regular features of offender routine mobility (Michaud 2023; Rengert 2004; but see Townsley and Sidebottom 2010; Van Koppen and De Keijser 1997). Most offenses are committed close to an offender's activity node with declining frequencies at greater distances. Some argue also for a buffer region immediately adjacent to the activity node where offending frequency is reduced (Rossmo and Wheeler 2024). A range of non-criminal factors may also influence routine mobility and journey-to-crime patterns including the structure of the physical and social environment (Kim and Hipp 2020; Summers and Johnson 2017) and the distribution of social, organizational, and institutional resources (Browning et al. 2022; Cai et al. 2024; Valasik et al. 2023).

Given this theoretical framework, prior studies point to at least two potential ways in which day-to-day mobility could drive offending variety (Bernasco and Nieuwbeerta 2005; Elffers 2004; Vandeviver et al. 2015), although with different implications for the role that target preference plays. Consistent with routine activities and crime pattern theory, offending variety might be seen simply as a byproduct of mobility. In this scenario, a more mobile offender may display greater offending variety if it generates to larger awareness space (in physical terms) and larger areas include a greater array of crime opportunity types (Brantingham 2016; Lentz 2018). Consistent with rational choice theories, we expect the generalist offender to be able to take full advantage of the larger awareness space generated by greater mobility. However, specialist offenders may not benefit as widely and instead choose to travel further for particularly attractive targets. This implies that increased mobility may not translate into greater offending variety for at least some offenders. Here we imagine a simplified model in which a mobile generalist offender engages in repeated excursions from a single, centralized anchor point. During these excursions, the offender randomly encounters and exploits static (non-depleting) crime opportunities. The question of interest concerns how offending variety—the number of unique crime opportunity types exploited—varies as a function of the mobility strategy, opportunity type preferences, and the spatial arrangement of crime opportunity types in the environment.

It is important to note that our approach is somewhat more abstract and formal than other examples of agent-based modeling in criminology (see Birks et al. 2025; Gerritsen and Elffers 2020). The model is best thought of as a neutral model (Gotelli and Graves 1996). It appeals to a minimum set of mechanisms necessary model the problem at hand and then assumes that these mechanisms operate with as few ad hoc assumptions as possible, which generally means that the mechanisms intentionally follow stochastically neutral rules. Influential neutral models in ecology, for example, start by assuming that all species have the exact same birth, death, immigration and emigration rates, and then proceed to simulate (and derive) major ecological patterns such as species-area relationships or species extinction rates using the rules of probability (Hubbell 2001; Morrow 2024). Similar neutral models lie at the heart of the contemporary study of molecular evolution (Galtier 2024; Kimura 1983). The agent-based model developed here is neutral in two important ways. First, the model envisions an offender who undertakes repeated excursions from a single anchor point or node according to Brownian motion. It offers a simplified vision of "the geometry of crime" consisting of just one node and thus no directed paths between nodes (Brantingham and Brantingham 1993). Brownian motion is a neutral mobility strategy in the sense that the direction and distance of each incremental move is a statistically independent event, while the position of the process in space at the next instant is dependent only upon the current position (i.e., it is a Markov process). Thus, modeling offender mobility as Brownian motion is equivalent to assuming that movement occurs without planning or any specific goal in mind (e.g., to encounter a particular criminal opportunity). Second, the offender exploits criminal opportunities in a simple random fashion. If more than one criminal opportunity is encountered, then just one of them is exploited without regard to the opportunity type. This model of target selection is neutral in the sense that the offender does not exercise any target type preference. Rather, we simply expect abundant opportunity types to be exploited with higher probability than rare opportunity types.

Such a simple, abstract model is clearly not aimed at replicating empirical reality. A lack of realism, however, does not mean that a model cannot be useful (Morrow 2024). Here we leverage model simplicity to hopefully bring clarity to the problem of how baseline mobility processes can interact with heterogeneous crime environments to generate offending variety. Our purpose is to identify possible law-like regularities and express these in formal mathematical terms.

Model

Consider an environment consisting of crime opportunities and a single mobile offender. The $i=1, 2, \ldots, N$ crime opportunities are drawn from $k=1, 2, \ldots, M$ unique crime opportunity types. Each opportunity i of type k is tied to a point location x_{ik}, y_{ik} in continuous space. We leave unspecified exactly what crime opportunity types are modeled but have in mind that each type is defined by situational conditions, not just the criminal code classification (see Clarke 1995). For example, a convenience store stickup and one highschooler strong-arming another for their cell phone are both robberies but they are ecologically distinct events that arise in very distinct settings (Haberman et al. 2022; Kuang et al. 2017). There is no prohibition against two or more unique opportunity types occupying the same location. For example, a dealer at a local street corner represents an opportunity to buy drugs but also an opportunity to rob him of his drugs or cash (Jacobs 2017). Thus, it is possible to say that each unique opportunity is tied to a singular location, but also that a single unique location may be tied to any number of unique crime opportunity types (including none). As a practical matter, a location that supports more than one unique crime opportunity type may be thought of as presenting crime-general cues (Brantingham 2016; Brantingham and Brantingham 1978), the degree of generality dependent upon the number of discrete opportunity types found there. Occasionally, we use the notation N_k to denote the number of opportunities that are of type k.

The opportunity types do not change on the time scales of importance to offender decision making. In other words, the situational cues present in a place are assumed to be static and stationary. For example, a residential burglary opportunity is tied the unique features of a house that remain largely the same from day to day (Vandeviver and Bernasco 2020). A strong-arm robbery opportunity on a key pathway home from school does not vary perceptibly because the setting attracts suitable victims daily (i.e., the opportunity does not move with victims) (Hatten and Piza 2022).

To characterize the crime environment further we need to model how crime opportunities are spatially structured, both within and between crime opportunity types. In theory, there are M^N different ways in which *M* unique opportunity types can be allocated (independently) across *N* spatially non-overlapping opportunities locations. If unique opportunity types co-occur in the same location, then this number could be considerably smaller. Nevertheless, even before we consider the specifics of space, the potential variability in crime opportunity structures is vast; in the extreme case, for example, with just $N = 10$ non-overlapping crime opportunity locations and $M = 4$ unique opportunity types, there are 10,000 potentially unique opportunity structures. For a one-dimensional environment, the lists [1, 1, 1, 1, 1, 1, 1, 1, 1, 1] and [1, 1, 1, 2, 2, 2, 3, 3, 4, 4] are but two of the 10,000 possible structures.

The ways in which opportunities might be distributed across space add to the complexity. We consider four cases to help illuminate some of the potential processes at play. In the simplest case, crime opportunities are distributed randomly with opportunity types allocated independently (see Brantingham 2016). The random case is unrealistic but theoretically interesting as an example of a counterfactual world wherein there is no concentration of crime opportunity types (Weisburd 2015). More complex (and realistic) situations occur where opportunities are clustered by type to form resource patches (Naveh and Lieberman 2013). Unique crime opportunity types may be more or less concentrated within patches, while patches may also be differentially concentrated across the environment (Ludwig and Tongway 1995).

Figure 1 illustrates one random crime environment, two regularly clustered crime environments and one patch-concentrated crime environment, all residing in an abstract two-dimensional space where all distance measures are all in arbitrary units. The space is technically infinite, meaning that we do not need to worry about spatial boundary conditions. We focus our attention a square region in the center of the environment that is roughly 80×80 units in size, large enough to contain all the dynamics of interest. In this local region, there are around $M{=}80$ unique crime opportunity types. In Fig. 1A, 1 and 1 each opportunity type is represented by around $N_k = 50$ locations. In Fig. 1D, the number of opportunities is exponentially distributed across types (see below). In all cases, the total number of crime opportunities in the environment is approximately $M \times N_k = 4{,}000$. The fully random case was generated using a two-step process. Spatial locations were determined by simulating a two-dimensional spatial Poisson process, which takes as an argument the rate or density λ of points per unit area. Here an average density of approximately $\lambda = 0.625$ opportunities per unit area was used (i.e., opportunities / area$=4000/80^2$) (Fig. 1A). Crime opportunity types were then randomly allocated to each location. This is a neutral counterfactual crime environment where we can be assured that any observed pattern in offending variety is *not* the product of spatial autocorrelation in opportunity location or type. The two regularly clustered cases were generated by placing $N_k = 50$ points from two-dimensional normal distributions $\mathcal{N}[p, s]$ centered in patches across the environment. Patch centroids were regularly spaced 10 units apart along cardinal directions ($\sqrt{200}$ on the diagonal). Within any one patch, the N_k opportunities were distributed isotropically ($p = 0$) around the centroid, while the variance (s) determined the degree of within-patch opportunity type concentration as well as the degree to which adjacent patches overlap. In Fig. 1B, the variance in the spatial distribution of each opportunity type was equivalent to the (cardinal) patch spacing (i.e., $s = 10$) resulting in patches that minimally overlap. In Fig. 1C, the variance was three times larger than the (cardinal) patch spacing (i.e., $s = 30$) resulting in patches that overlap to a substantial degree. In contrast to the random case, the clustered crime environments introduce substantial spatial structure that may impact offending variety. Finally,

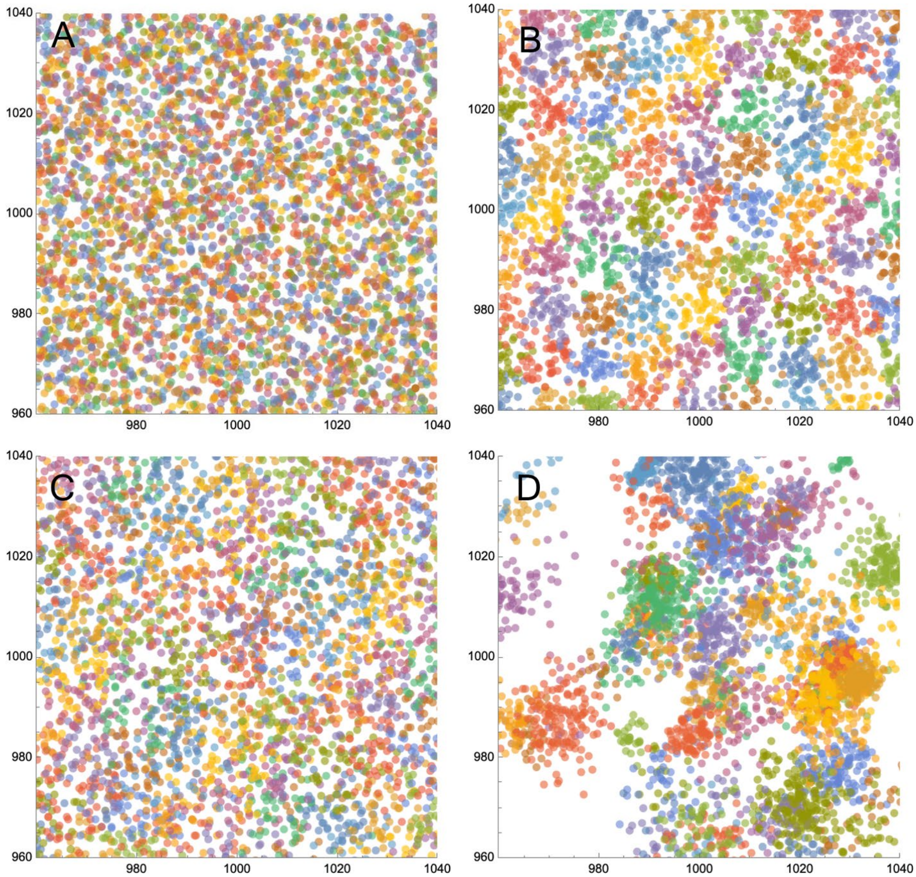

Fig. 1 Distribution of N crime opportunities of M distinct types in an arbitrary crime environment. (**A**) Opportunity locations are Poisson random in space and opportunity types are spatially independent. (**B**) Opportunity types are approximately equally spaced, but clustered into patches with minimal overlap. (**C**) Opportunity types are approximately equally spaced, but clustered into patches with substantial overlap. (**D**) Opportunity types are clustered into randomly spaced patches that vary in concentration. In A, B and C case there are around $M=80$ unique crime opportunity types and around $N_k=50$ opportunities per type for a total of around M x $N_k \sim 4{,}000$ opportunities. In D, opportunity types vary in frequency from a maximum of $N_k=163$ to a minimum of $N_k=2$ according to an exponential distribution. The total number of opportunities is also around M x $N_k \sim 4{,}000$

Fig. 1D, represents a case where patch centroids are uniform randomly distributed across space and the number of opportunities of each type is exponentially distributed according to the formula $p(N_k = n) = e^{-0.02n}$. The exponential function is chosen as a simple model for a few very common crime opportunity types and many rare opportunity types. Within patches, opportunities are arrayed around the patch centroid using the two-dimensional normal $\mathcal{N}[p, s]$ from above. In the case illustrated, unique opportunity types vary in frequency from a maximum of $N_k=163$ to a minimum of $N_k=2$. The total number of opportunity types is also M x $N_k \sim 4{,}000$. The crime environment in Fig. 1D exhibits regions where there is substantial concentration of opportunities adjacent to regions devoid of opportunities. Opportunity concentration occurs both because opportunity patches may randomly overlap and because some opportunity types are numerically much more common than others. Arguably, the landscape represented by Fig. 1D is the most realistic from the point of view of known crime patterns. We emphasize, however, that the point is not to simulate any one real-world environment, but rather to examine how the spatial structure of crime environments influences offending variety at a theoretical level.

The mobile offender operates within this environment of crime opportunities. Offender mobility is defined by the direction, distance, frequency, and duration of moves across space (Bernasco and Board 2012; Brantingham and Tita 2008). To be clear, the mobility modeled here concerns the daily movement around an environment, not "residential mobility" that operates over longer time scales (e.g., Sampson and Groves 1989). The simplest model for day-to-day mobility is to treat the offender as a discrete random walker on a two-dimension lattice or grid (Brantingham and Tita 2008). However, since the crime environment defined above is continuous in two-dimensional space, the mobile offender in our case is modeled as an agent engaged in continuous-in-time and continuous-in-space Brownian motion (Johnson 2014; Turchin 1998). In intuitive terms, our offender starts at a home location but can move in any direction, unconstrained by features of the built or social environment, and can move over both short and long distances, every few minutes, before returning home at after several hours. Brownian motion is mathematically described as a stochastic Wiener process $W_{x,y}[\mu_{x,y}, \sigma_{x,y}]$, which includes drift $\mu_{x,y}$ and volatility $\sigma_{x,y}$ terms. The drift term controls whether there is any directional bias to the agent's motion. The volatility term controls the magnitude of fluctuations in the distance moved at any moment in time. The subscripts indicate that drift and volatility operate independently in the x and y dimensions. Two-dimensional Brownian motion is the combination of two independent one-dimensional processes. Focusing on just one-dimension, the expected direction and distance of motion (relative to the current location) at any point in time is normally distributed as $\mathcal{N}[\mu_x \Delta t, \sigma_x \sqrt{\Delta t}]$, where $\mu_x \Delta t$ and $\sigma_x \sqrt{\Delta t}$ can be understood, respectively, as the mean and standard deviation of the distribution measured over some interval of time Δt (time-step size). In principle, we can measure Brownian motion at any scale (from within-household to city-wide and more) by our choice of Δt. Motion will be self-similar (i.e., fractal) across scales. To simplify presentation, we choose $\Delta t = 1$, meaning that we sample Brownian motion paths every one time-step. These are defined as the turning points where criminal opportunities can be exploited (see below). We also define a total duration T over which an agent is engaged in motion during a single day. Specifically, a single excursion or mobility path begins from an anchor point (e.g., home) (Brantingham and Brantingham 1993), and ends after T time steps somewhere in space. While the time scale of the model is abstract and arbitrary, it may be useful to think of one step as equivalent to approximately 15 min and that a full day of foraging over $T = 200$ time steps is equivalent to around 13.3 h. The relationship between the time spent foraging and the displacement or distance from the anchor point is explored below.

Figure 2 illustrates some of the potential variability in offender mobility proscribed by the model. Figure 2A shows twenty-five mobility paths following a Wiener process with $W_{x,y}[0,1]$ sampled every $\Delta t = 1$ time step. Although the paths are stochastic realizations of the general process, it is evident that the ensemble is similarly distributed in all directions (i.e., isotropic) around the anchor point. This is understandable since $\mu_{x,y} = 0$, meaning there is no drift in either the x or y dimension. By contrast, Fig. 2B simulates twenty-five realized paths with $W_{x,y}$ [0.1,1]. Here, the arbitrary value of $\mu_{x,y} = 0.1$ leads to a clear drift in the ensemble paths towards the northeast of the environment. The bias $\mu_{x,y} = 0.1$ is in both

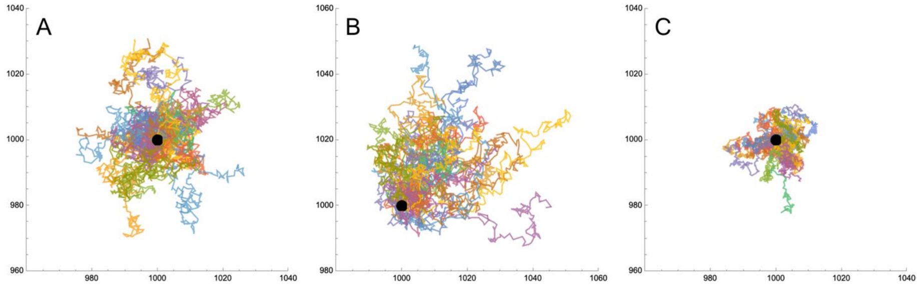

Fig. 2 Examples of repeated excursions by an offender using a Brownian motion mobility strategy. (**A**) Unbiased excursions from an anchor point following a Wiener process $W[0,1]$. (**B**) Directionally biased excursions following a Wiener process $W[0.1,1]$. (**C**) Unbiased excursions following a Wiener process $W[0,0.5]$. Shown in each case are twenty-five Brownian motion paths that begin at the origin (black dot) and terminate after $T = 200$ time steps. Note that panel (B) is re-centered to show the northeast bias in mobility paths

in the x and y dimensions but is expected to move each path a positive diagonal distance $\sqrt{0.1^2 + 0.1^2} = 0.141421$ at each sampled time step. The difference between Fig. 2A and 2 may be thought of as capturing at an abstract level offender mobility an environment with no crime attractors (Fig. 2A) versus mobility in an environment with one crime attractor in the northeast (Fig. 2B) (Frank et al. 2011). The magnitude of the bias $\mu_{x,y}$ in some sense captures the strength of the attractor. Figure 2C, by contrast, shows the consequences of reducing the volatility of the underlying Weiner process $W[0,0.5]$ to half that shown in Fig. 2A. Here the ensemble of paths is isotropic, as in Fig. 2A, but is concentrated in a more compact region around the anchor point. Indeed, the region covered by the paths in Fig. 2C is approximately half the size of that in Fig. 2A. The difference between Fig. 2A and 2 might be thought of as capturing at an abstract level different modes of mobility (e.g., car vs. on-foot). While real-world mobility paths of offenders often mix mobility modes and are almost always directionally biased (Daele and Bernasco 2012), in the following we choose to model offender mobility as isotropic Brownian motion $W[0,1]$ and concentrate on the impact of varying the duration T of excursions. The goal is to understand at a theoretical level the impact of mobility magnitude (displacement from an anchor point) on offending variety, without the confounding effects of directional biases in mobility. More complex models might consider non-Brownian mobility regimes such as Lévy random walks (Brantingham 2006; Johnson 2014) and mobility organized around more than one anchor point (Brantingham and Tita 2008).

We can intuit that the mobility paths like shown in Fig. 2 will place motivated offenders near crime opportunities like those shown in Fig. 1. We therefore need to specify how such encounters lead to offenses and how we count those offenses towards a measure of offending variety. We assume that the mobile offender can sense crime opportunities at each turning point along their mobility path. Sensing occurs within some radius ρ of their current position. Since the model environment is entirely abstract, we assume for convenience that $\rho = 1$. If more than one crime opportunity is sensed within radius ρ, then only one of those opportunities is chosen at random and exploited. For simplicity, we assume that choices are independent across time and that opportunity types are not depleted by exploitation. Thus, the type of the last opportunity exploited does not influence the offender's current choice and she may exploit the same opportunity an infinite number of times in a row if her mobility path places her in a position to do so. More complex preference models that consider contagion-like effects are certainly possible (Lammers et al. 2015), a point we return to in the Discussion.

Exploited opportunities are tabulated into a measure of offending variety by comparing the type of each crime against the list of prior crimes committed by the offender along the current mobility path. If the crime committed is of a type not represented in the repertoire of previously committed crimes, the offending variety is incremented by one. If the crime committed is of the same type as a previously committed crime, the offending variety remains unchanged. Thus, repeated exploitation of a hyper-abundant opportunity counts no more towards offending variety than exploitation of a rare opportunity (Sweeten 2012). Note that this measure is a "path-wise" offending variety rather than life-course offending variety. Since the type of crime committed is strictly dependent upon opportunity type, the crime environment ultimately constrains offending variety. Thus, if the environment consists of just one crime opportunity type, then it is necessarily the case that there will be no offending variety. If the environment consists of many opportunity types, then offending variety may be much greater. However, the extent to which offenders will have diverse crime repertoires is connected to both the structure of the crime environment and their mobility strategy. It is this mechanism that we now examine.

Analysis

The following analysis proceeds in several steps. We first examine the properties of offender mobility, concentrating on the relationship between time spent moving and distance travelled by the offender relative to their anchor point. We then examine the variability in offending variety within any one mobility regime given changes in the crime opportunity environment. Finally, we examine the relationship between increasing mobility and offending variety, focusing on the mathematical form of the relationship as a basis for empirical predictions.

All the analyses presented below are restricted to a small range of environmental conditions and mobility regimes. We only explore the crime environments shown in Fig. 1. All mobility regimes involve isotropic (unbiased) Brownian motion given by a Wiener process $W[0,1]$. The only parameter that is varied is the duration T an offender spends in motion. In essence, how many hours in a day the offender spends foraging. For any given parameter set, a total of 1,000 mobility paths are simulated to capture the mean and variance in outcomes. All simulations are run with the same random number seed so that crime environments remain stationary as mobility is allowed to vary.

Journey Time & Displacement

Brownian motion provides an intriguing model for offender mobility. A key property of isotropic (unbiased) mobility is that the average or expected position of an agent over time remains its point of origin. The result is a Gaussian probability density function (PDF) for the expected position of the agent that is symmetrical (in two-dimensions) about the origin. The PDF simply flattens out over time, reflecting a probabilistic diffusive spread.

Here we are concerned not with the expected position of a mobile offender, but the distance traveled relative to the anchor point or origin over the course of an excursion. Specifically, we define the displacement of the offender as the Euclidean distance between where the forager is in two-dimensional space and their anchor point at time t. Recognize that displacement is different from the total distance travelled since Brownian motion is not prevented from revisiting the same locations. Recall then that the Wiener process that underlies Brownian motion is defined by its drift $\mu_{x,y}$, its volatility $\sigma_{x,y}$, and the duration T over which the offender is in motion. Intuitively, the longer an offender is in motion the greater the potential displacement from the originating anchor point. The relationship is highly regular. Figure 3 shows frequency distributions of displacement distances for 1,000 mobility paths originating at a single anchor point. The ensembles each may be thought of as observations of many independent offenders originating from the same point or, equivalently, repeated observations of excursions made by the same offender. In either case, the results in each panel differ only in the duration spent in motion T in any one mobility bout (path).

The distributional form seen in Fig. 3 was first suggested by Rayleigh (1905) and is characterized by an internal mode δ and a heavy tail (right skew) (Fig. 3). The mode of the distribution represents the most probable distance traveled relative to the anchor point, which is also known formally as the mean squared displacement (MSD). Theory gives the mean square displacement as

$$\delta = \sqrt{T} \tag{1}$$

This quantity may also be estimated by fitting a Rayleigh distribution to observed or simulated data on displacement distances. Figure 3 shows both theoretical (δ) and empirically

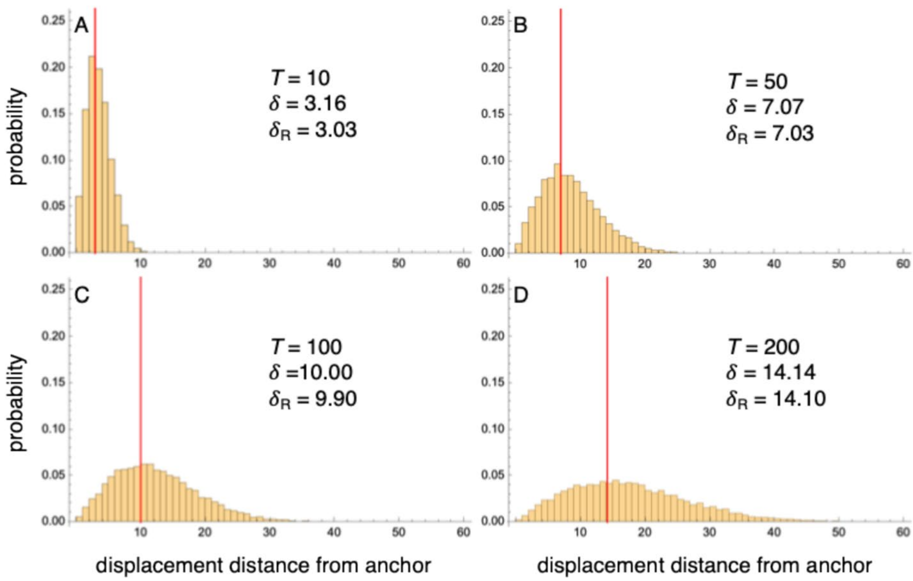

Fig. 3 Frequency distributions of displacement distance from an anchor point by 1,000 mobile offenders after T time steps. The mean squared displacement—most probable distance—is shown as a red line with δ computed from theory and δ_R estimated by fitting a Rayleigh distribution to the simulated distribution

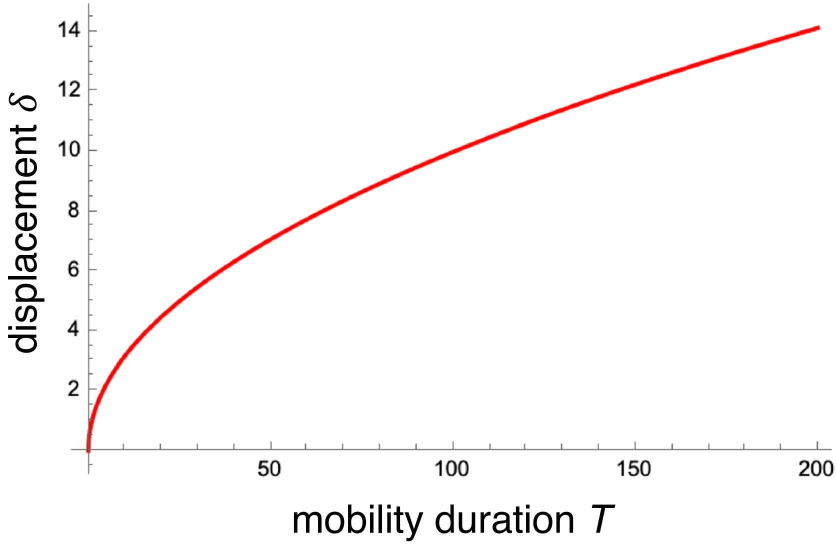

Fig. 4 The relationship between the most probable distance traveled (mean square displacement) and the time spent engaged in motion given unbiased Brownian motion

estimated (δ_R, "Rayleigh") values for the mode for each distribution, which is the MSD in each case. The displacement increases as the duration of mobility increases, while the variance (i.e., distributional spread) also increases.

Figure 4 plots Eq. 1 over values of T ranging from 0 to 200 time-steps. Displacement does increase linearly as mobility duration increases but rather is decelerating. In other words, extending the maximum duration of excursions from $T=10$ to $T=20$ has a much bigger proportional impact on displacement (+41.4%) compared with extending the duration from $T=110$ to $T=120$ (+4.5%). Equation 1 and Fig. 4 guide subsequent interpretations of changes in offending variety as a function of offender mobility.

Offending Variety

Intuition suggests that any increase in offender mobility will produce encounters with a greater variety of crime opportunity types and consequently increase individual offending variety. Figure 5 confirms this intuition and suggests that the relationship is also very regular. Each panel shows the frequency distribution of the number of unique crime types in an offender's repertoire as a function of the duration of mobility T within the crime environments shown in Fig. 1. Three different values of T are shown for each crime environment. The offending variety distribution may be interpreted as the probability of observing an offending variety v given mobility duration T and an opportunity structure. For example, with mobility duration $T=10$ and the clustered opportunity structure shown in Fig. 1B and, the most probable value for offending variety is two crime types (Fig. 5A, orange). With $T=75$ (blue), the most probable offending variety is $v=4$ unique crime types. With $T=200$ (green), the most probable offending variety is $v=8$ unique crime types. Of course, there

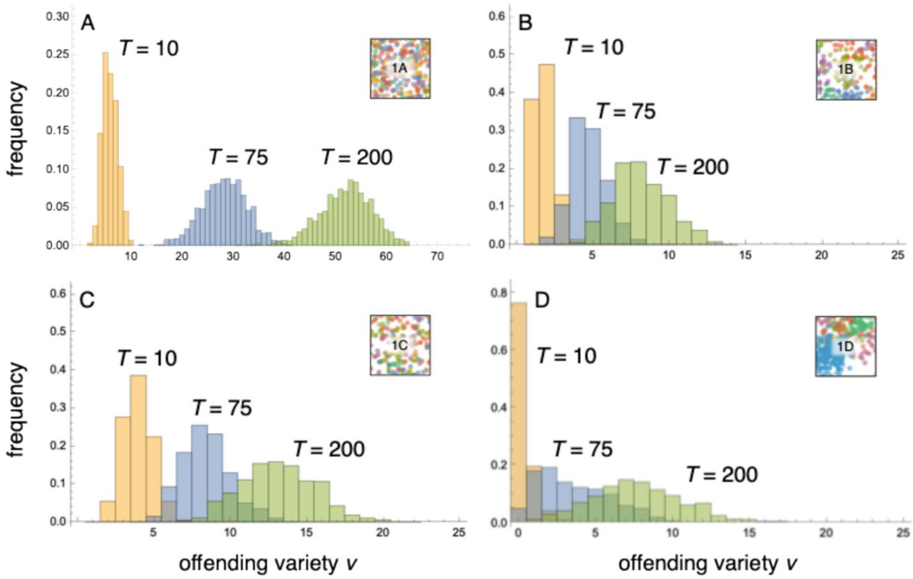

Fig. 5 Histograms of offending variety for three values of T and the four different crime opportunity structures shown in Fig. 1. (**A**) Crime opportunities are Poisson random and independent of opportunity type (see Fig. 1A). (**B**) Crime opportunity types are clustered and mostly non-overlapping (see Fig. 1B). (**C**) Crime opportunities are clustered but overlap substantially (see Fig. 1C). (**D**) Opportunities are clustered into randomly spaced patches that vary in concentration (see Fig. 1D). Y-axis scaling is different in A and D

is variation around each of these expectations, which stems from variation in the distances covered by mobile offenders and the nature of the opportunity structure. For example, with $T=75$ and the clustered opportunity structure from Fig. 1B, the minimum offending variety is $v=2$ and the maximum is $v=8$ (Fig. 5A, blue).

Changing the opportunity structure has visible impact on offending variety. Figure 5B also represents clustered opportunity types, but this time with substantial overlap in patches (see Fig. 1C). This shift in opportunity structure increases offending variety for each of the mobility regimes ($T=10$, $T=75$, $T=200$). For example, with $T=10$, the most probable value for offending variety shifts from one unique crime type to four unique crime types. The mechanism at play is easy to intuit. Mobility interacts with the spacing of opportunity patches to restrict offending variety. For example, in the non-overlapping patch case (Fig. 1B), $T=10$ typically produces short travel distances $\delta = 3.16$ (by Eq. 1). But, since patch centroids are spaced 10 units apart, most excursions remain contained inside the patch where the offender is based, and she therefore encounters only a single crime type opportunity. When patches overlap (see Fig. 1C), unique opportunities of several types occur adjacent to one another. Under these conditions, even short travel distances produce encounters with more unique crime opportunity types. Offending variety increases as a result. The extreme case obtains when crime opportunities are non-clustered (randomly distributed), and opportunity types are independent of one another (see Fig. 1A). Under these conditions crime opportunity types are maximally mixed and a mobile offender presents much higher offending variety (Fig. 5C). For example, with $T=10$ the most probable value for offending variety increases to seven unique crime types.

Mobility & Offending Variety Relationship

Figure 5 suggests that increases in mobility lead to increases in offending variety against a stationary backdrop of crime opportunities. Figure 6 reveals that the relationship is indeed very regular. Shown are the mean and variance in offending variety v over 1,000 simulated paths as mobility duration is varied smoothly from $T=2$ to $T=200$. Visual comparison with Fig. 4 suggests that the functional relationship is closely related to Eq. (1) giving the most probable distance travelled or MSD by an offender engaged in Brownian motion. The functional relationship between offending variety and mobility duration is modeled by:

$$v = \beta_0 + \beta_1\sqrt{T} \tag{2}$$

where β_0 and β_1 depend on the crime opportunity structure. The first parameter β_0 is related to the number of unique crime opportunity types in the immediate vicinity of the offender's anchor point. These are the opportunities that can be exploited within the offender's field of vision ρ without movement. The second parameter β_1 represents an accumulation rate for new opportunity types. Except for very short duration excursions (see below), the proposed functional form is nearly a perfect match ($r^2>0.99$) across the full range of crime environments considered. Mobility controls the qualitative shape of the function—compare Figs. 4 and 6. The crime environment controls the quantitative outcomes. In general, the more mixed the crime opportunity types are in the environment the faster offending variety is

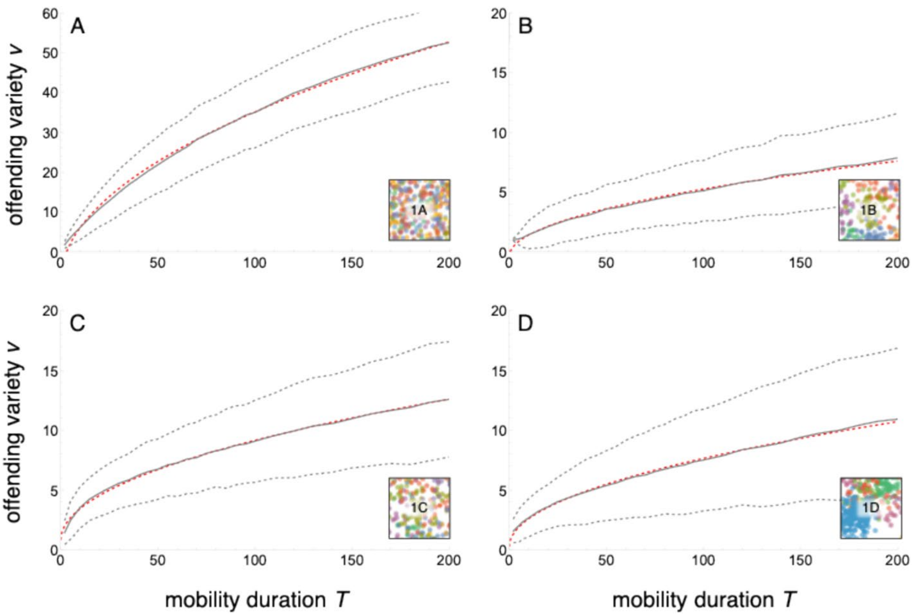

Fig. 6 Relationship between offending variety and mobility duration for the opportunity structures shown in Fig. 1. (**A**) Poisson random opportunities (see Fig. 1A). (**B**) Clustered, non-overlapping opportunity patches (Fig. 1B). (**C**) Clustered, overlapping opportunity patches (see Fig. 1C). (**D**) Opportunities are clustered into randomly spaced patches that vary in concentration (see Fig. 1D). Simulated mean (black, solid line) and 95% CI (black, dashed) in offending variety for 1,000 Brownian motion paths at each mobility duration. Predicted functional relationship (red, dashed). Y-axis scaling different in A

accumulated. For example, in Fig. 6, with mobility paths lasting $T=100$ time steps the clustered, non-overlapping environment (see Fig. 1B) produces a mean offending variety of $v=5.6$ unique crime types, the clustered, overlapping environment (see Fig. 1C) produces $v=9.6$, and the random environment produces $v=31.1$ (see Fig. 1A). The clustered randomly spaced patched produces $v=7.5$ (see Fig. 1D).

The relationship shown in Fig. 6 is important to understand from a theoretical point of view, but mobility duration (i.e., the time offenders spend in motion) is unlikely to be observed under most real-world circumstances. More practically, we can substitute Eq. 1 into Eq. 2 yielding

$$v = \beta_0 + \beta_1 \delta \tag{3}$$

Equation 3 indicates that offending variety is a linear function of the most probable distance travelled by offenders (MSD) δ, which is something we might hope to observe empirically through journey-to-crime (or distance-to-crime) distributions (see Discussion) (Bernasco and Board 2012; Kent et al. 2006; Rengert 2004). Figure 7 plots the same simulated data shown in Fig. 6 against simulated mean travel distances. The functional relationship given by Eq. 3 is also shown. The theoretical model fits the simulated pattern extremely well except at very short travel distances in two of the three cases. The potential for a poor fit of Eq. 1 to short duration Brownian motion excursions was recognized by Rayleigh (1905). This limitation appears to carry over to Eq. 3 when predicting offending variety for offenders with short range mobility regimes ($\sim T<4$, or $\delta<2$). The poor fit does not appear to hold for the clustered, overlapping patches. The reason for this difference is not immediately clear.

Model Extensions

The baseline model brings to the foreground certain theoretical observations about mobility and offending variety but is unrealistic in several important respects (see also Discussion). Specifically, the offender does not discriminate among opportunity types and exploits those opportunities whenever they are given the chance. Here we relax the second of these assumptions by restricting exploitation of crime opportunities to a single location along one foraging path. We examine offending variety with respect to both MSD for the strategy overall and a journey-to-crime measure.

Controlling the Number of Crimes Committed

In the baseline model, simulated mobility strategies vary substantially in their duration and therefore their displacement Mobility strategies that are short in duration may consist of just a few turning points while those long in duration can consist of hundreds of turning points over the course of a simulated day. Because the baseline model assumes that crimes occur at sampled turning points, short duration paths generate far fewer crimes than long duration paths. It is perhaps not surprising then that offending variety increases with mobility duration T since this is correlated with increased sample size (see also Brantingham 2016; Ugland et al. 2003). It is more realistic to assume, however, that each foraging path

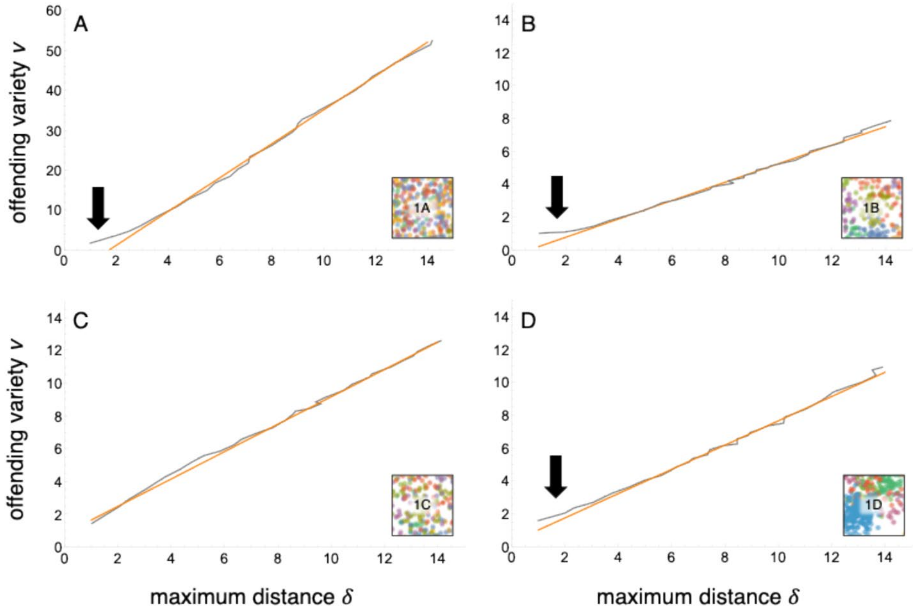

Fig. 7 Relationship between offending variety and mean squared displacement for the opportunity structures shown in Fig. 1. (**A**) Poisson random opportunities (see Fig. 1A). (**B**) Clustered, non-overlapping opportunity patches (Fig. 1B). (**C**) Clustered, overlapping opportunity patches (see Fig. 1C). (**D**) Opportunities are clustered into randomly spaced patches that vary in concentration (see Fig. 1D). Simulated mean (black, solid line) offending variety for 1,000 Brownian motion paths at each mean squared displacement. Predicted functional relationship (orange, solid). Y-axis scaling different in A. The deviation in between simulated offending variety and the expected functional form at short distances is marked in A, B and D

produces a single crime. Offending variety is therefore assembled over many such path-event pairs. The advantage of this extended model is that mobility strategies different in duration T and displacement δ generate the same number of crimes, more clearly isolating the effects of mobility on offending variety.

Figure 8 presents simulations using two different assumptions about how single crime events are related to single mobility paths. Figure 8A shows one mobility path for one offender. The anchor point is shown in white. The red point represents the case where the offender exploits an opportunity at the exact endpoint of the mobility path, which occurs at $t = T$ time units. The blue point represents the case where the offender randomly exploits an opportunity at some point along the mobility path, which occurs at $0 \leq t \leq T$ time units. For convenience, the red and blue points are shown on a single mobility path, but in our simulations each mobility path at most generates one exploited crime opportunity. The MSD of this path (and any path for this offender) is a fixed quantity defined by T. The journey-to-crime distance to each event relative to the anchor point is also shown as dashed red and blue lines for the exploited endpoint and random point, respectively (see below). Figure 8B shows the simulated relationship between offending variety v and the MSD for offenders committing endpoint crimes (red) and random point crimes (blue). Offending variety increases linearly with increased mobility in both cases. The difference in slope between endpoint and random point crimes is a result of path censoring. For the same MSD, endpoint

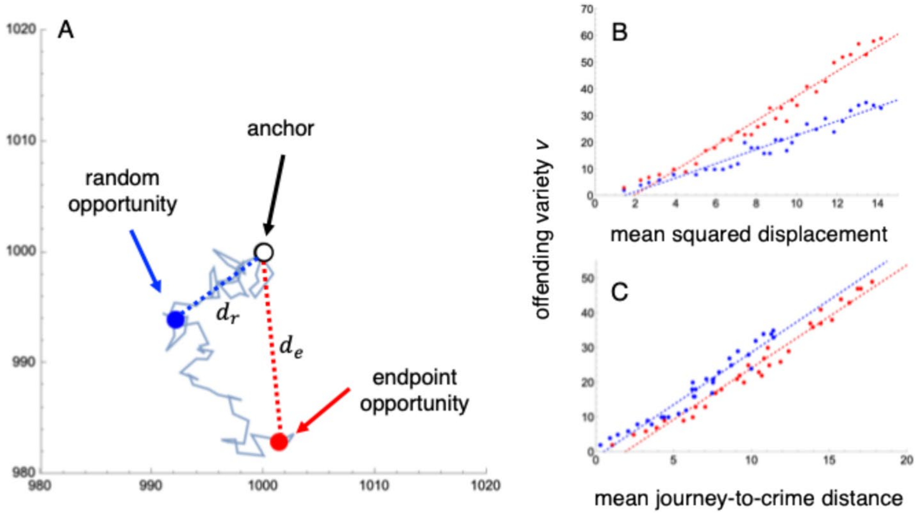

Fig. 8 Simulated journey-to-crime processes and its impact on offending variety. (**A**) One daily mobility path showing the anchor point (white point) and examples two types of event-path relationships. The red point illustrates an opportunity exploited at the endpoint of each Brownian motion path. The blue point represents an opportunity exploited at a random point along the path. The red and blue dashed lines show how journey-to-crime distances would be measured for each exploited crime opportunity. (**B**) Offending variety resulting from exploitation of only endpoint and random opportunities plotted against the mean squared displacement. (**C**) Offending variety resulting from exploitation of endpoint and random opportunities plotted against the journey-to-crime distance for each crime committed by offenders with a strategy defined by T. Each simulation consists of 1,000 paths by an offender over mobility durations lasting from T=2 through T=200, corresponding to expected mean squared displacement between $\delta = 1.41$ and $\delta = 14.14$ units from the anchor point. Each path results in only one exploited opportunity. Offending variety is aggregated over the 1,000 simulated paths per displacement distance band

offending allows greater exploitation of opportunities that are farther from the anchor point based on journey-to-crime distances (Fig. 9A). Random point offending, by contrast, will tend to censor longer paths and thus concentrate more exploitation among opportunities closer to the anchor point. As seen in the baseline model, a greater foraging range drives encounters with more unique crime opportunity types and thus greater offending variety. Random point offending reduces the effective foraging range of the same underlying mobility strategy defined by equivalent MSD values. Nevertheless, it is important to recognize that the functional relationship between offending variety and MSD is qualitatively similar to the baseline model in both path-event cases (see Fig. 7). This suggests that the functional forms that emerge from the baseline model are relatively robust to sample size differences. That is, whether we are dealing with offenders who commit many crimes in a spree-like fashion or those who commit just one crime at the endpoint or random point over many paths, we should expect higher offending variety for more mobile offenders.

Figure 8C addresses a separate issue related to measuring the magnitude of mobility. In the baseline model (and Fig. 8B), offending variety is plotted against MSD, which is an "offender-centric" summary measure of the mobility strategy. For example, an offender who engages in foraging bouts lasting exactly $T = 100$ time steps has an MSD of $\delta = 10$, although individual paths within the strategy may end up closer or farther from the anchor point than this summary value (see Fig. 3). Journey-to-crime, by contrast, is an "event-

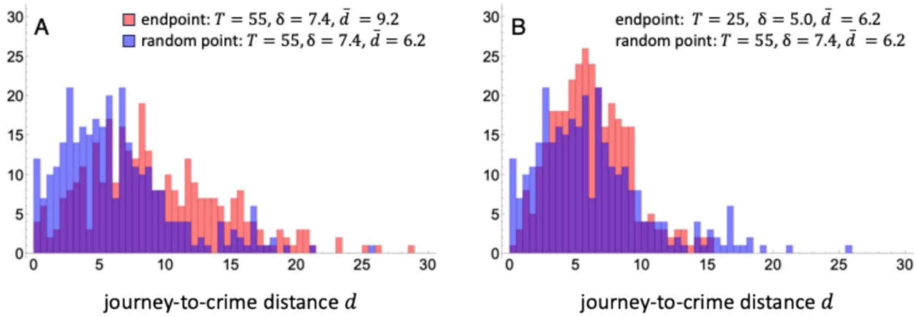

Fig. 9 Journey-to-crime distances for endpoint (red) and random point (blue) crimes matched by MSD and mean journey-to-crime distance. (**A**) For the same underlying MSD $\delta = 7.4$ ($T = 55$), the mean journey-to-crime distance is shorter for random point crimes ($\bar{d}_r = 6.2$ vs. $\bar{d}_e = 9.2$) and a thinner distribution tail compared to endpoint crimes. (**B**) For the same mean journey-to-crime distance $\bar{d} = 6.2$, the underlying MSD is greater for random point crimes ($\delta_r = 7.4$ vs $\delta_e = 5.0$) and the distribution has a longer, fatter tail compared to endpoint crimes

centric" measure that tracks the linear distance (i.e., displacement) between a crime event and the offender's anchor point (usually home). Here we turn this event-centric measure into a general mobility measure by computing the mean journey-to-crime distance over the collection of crimes committed by an offender. Offending variety is computed across the same set of crimes used to calculate the mean journey-to-crime distance for each offender. As seen in Fig. 8C, offending variety also rises with mean journey-to-crime distance in a linear fashion consistent with baseline model. The mean journey-to-crime distance for endpoint exploitation is farther from the anchor point compared to the corresponding MSD; e.g., the rightmost red point in Fig. 8C has a mean journey-to-crime distance of around $\bar{d}_e = 17.0$, while the corresponding point in Fig. 8B has an MSD of $\delta_e = 14.14$ (i.e., $T = 200$). The mean journey-to-crime distance for random point exploitation is slightly less than the corresponding MSD (i.e., $d_r = 11.2$ vs. $\delta_r = 14.14$ for the rightmost blue point) because of path censoring. Endpoint and random point offending closely parallel one another (equivalent slopes: $t = 0.41, p = 0.68$). Yet, random point exploitation produces small, but significantly greater offending variety at the same mean journey-to-crime distance (significantly different intercepts: $t = -2.73$, $p < 0.01$). For the same mean journey-to-crime distance, the distribution of journey-to-crime distances is more skewed, producing individual journey-to-crime distances that are farther from the anchor point (i.e., longer, fatter tail) (Fig. 9B). This pattern reflects that the underlying mobility strategy for the random point crimes has a higher MSD despite the equivalent mean journey-to-crime distances. These longer journeys allow random point exploitation to produce higher offending variety despite path censoring.

Discussion

This paper has sought to develop baseline theory for the relationship between offender mobility and offending variety. The central proposition is that mobile offenders should be exposed to a range of crime opportunity types as they move around their environment. As a result, more mobile offenders should display greater offending variety. The approach taken was to strip away many ethnographic-scale details to get at the core features of crime environments and behavioral routines that may interact to produce offending variety. Crime environments were modeled as arbitrary spatial regions with different opportunity types treated as discrete point locations. Offender mobility was modeled as individuals engaged in isotropic (unbiased) Brownian motion. Over the course of movement, offenders sense opportunities and exploit them when encountered. The model tracked encounters with new opportunity types over time to produce a measure of offending variety. The central finding was that increased mobility can plausibly lead to increased offending variety. It was also shown that greater spatial overlap in crime opportunity types has a similar effect to increased mobility. These observations hold both for the baseline model, where offenders exploit opportunities whenever encountered, and for a journey-to-crime model where offenders commit just one crime along any one mobility path.

A key focus of this paper was on the mathematical specification (Eq. 1) of the relationship between mobility duration (T) and spatial displacement of the forager (δ). To be clear, this is by no means a "new" result as the mathematical properties of Brownian motion (and random walks as the discrete counterpart) have been investigated for more than 100 years (Pearson 1905; Rayleigh 1905). What is new is the extension of these fundamental mathematical properties to the study of offending variety. The analysis suggests a relatively simple mathematical relationship based on Brownian motion (Eqs. 2 and 3) may describe the way in which crime environments can interact with offender mobility to produce offending variety, at least under the stylized conditions established here.

The analysis leads to two predictions and suggests at least one way in which they might be empirically tested. The qualitative prediction is that offending variety should be higher for offenders with greater mobility. To be clear, greater mobility in this case means greater distance travelled relative to an anchor point (i.e., displacement) during daily movement bouts, not greater residential mobility. The quantitative prediction is that the increase in offending variety should be linear as a function of displacement distance. The latter prediction is connected directly to Eq. 3.

Empirical testing of the model presented here could proceed at several levels of complexity. At one extreme, we could look to individual-level survey data that includes self-reported dominant transportation mode used (e.g., foot, bicycle, public transit, private car) (Bichler et al. 2011) and "how many from this list" measures of offending variety (Farrington 1973; Sweeten 2012). Provided that a uniform time measurement can be established (e.g., "in the last 12 months…")(Monahan and Piquero 2009), we expect to see offending variety to increase with dominant transportation mode, ordered by expected displacement (see Anderson and Hughes 2009; Snook 2004). If the ordering of displacement was by a scalar (continuous) value such as kilometers, then the functional form should be linear, consistent with both the baseline and journey-to-crime models presented here (see Figs. 7 and 8). At the other extreme, fine-grained movement data based on cell-tower or GPS tracking could allow direct examination of how offending variety is assembled over bouts of routine mobility (e.g., Zhou et al. 2025). However, such data are likely to remain highly restricted under most circumstances. Of intermediate complexity, data recording journey-to-crime distances from key anchor points paired with crime type information could be aggregated across offenders to examine offending variety as a function of mean journey-to-crime distances. Most studies on journey-to-crime focus on single crime types or classes (see Bichler et al. 2011). Since most offenders are thought to be generalists, however, constructing journey-to-crime data sets that including all crime types should already be possible. The expectation is that offending variety will increase with increasing mobility, consistent with our journey-to-crime models. Of course, we expect that other covariates will matter alongside direct and indirect measures of mobility including but not limited to offender age (Monahan and Piquero 2009), routine activity patterns (Hoeben et al. 2021), co-offending networks (McGloin and Piquero 2010), and the distribution of other social and economic resources (Browning et al. 2022; Cai et al. 2024).

Several limitations to the present approach are worth mentioning. First, there is a degree of ambiguity about direction of causality linking mobility and offending variety. The present model assumes a “forward process” wherein mobility drives encounters with crime opportunities which translates into offending variety, when measured over many observed mobility paths. However, it is also possible that individuals start with different preferences to be “low variety”, “medium variety” or “high variety” offenders (actually, anywhere along the continuum) and choose mobility strategies to satisfy those preferences. Assuming that crime opportunities are dispersed in space, then “high variety” offenders would necessarily develop long-range mobility strategies, while “low variety” would have short-range mobility strategies. The statistical patterns for offending variety against displacement or mean journey-to-crime distances would be like those simulated here, but the causal arrow would point from offending variety to mobility rather than mobility to offending variety. While there is no easy solution to this problem (but see Bernasco and Board 2012), we can at least argue that a model where mobility drives offending variety is theoretically preferrable to the alternative since it does not make assumptions about offender preferences (i.e., appealing to Occam’s razor). The task, then, is to reject the simpler model before proceeding to more complex alternatives. This is where abstract, simple models—and especially neutral models—can shine as tool for surfacing core theoretical insights (Gotelli and McGill 2006).

Nevertheless, the reader might assume that simple model presented here should be easy to reject and therefore wonder what the next steps might be. A few incremental extensions are discussed here. First, biased Brownian motion and non-Brownian motion mobility strategies might be investigated. While isotropic Brownian motion is a useful theoretical starting point, under most circumstances it seems reasonable to expect that offender mobility is anisotropic (e.g., Frank et al. 2011), and non-diffusive (e.g., Vandeviver et al. 2015). The models presented are sufficient to investigate at a theoretical level the impact of biased motion (see Fig. 2B). Other studies have shown how Brownian motion is a special class of Lévy motion, which allows clusters of short-range excursions separated by long-distance “flights” (e.g., Brantingham 2006; Johnson 2014; Viswanathan et al. 1996). Second, it may be important to develop simulations of offender mobility in real-world environments (Davies and Bishop 2013; Groff 2007). The barriers and corridors created by street networks and other topographic or social features of the landscape (e.g., Bernasco and Block 2011; Smith et al. 2012) almost certainly impact how mobility strategies play out in the real world. Similarly, the models could be extended to examine mobility against real-world distributions of both crime opportunities and other social and economic resources that motivate movement across the urban landscape (Browning et al. 2022; Cai et al. 2024). However, there are significant definitional and measurement challenges to developing more complex and realistic models. While it may be obvious how to map residential burglary opportunities, it is less clear how to define and spatially delineate boundaries for other crime types such as assault, or robbery where victim mobility also matters (Luo et al. 2021).

Incorporating offender preferences in ways that might reverse the direction of causation should also present interesting challenges. It should not be a surprise if we assume that offenders prefer certain crime types and then find that those crime types are part of the offending variety generated by a simulation model. To avoid circular reasoning it is perhaps best to proceed in an incremental fashion. For example, one step up in complexity from the baseline neutral model would be to assume that unique opportunity types are associated with different stationary probabilities of exploitation upon encounter. Low preference types would still be part of offending variety if they are abundant enough in the environment, while high preference types might not appear if they are too rare. We could then explore how preferences and opportunities are balanced via Brownian motion mobility strategies, maintaining that key part of the baseline neutral model. A further step up in complexity might assume that that there are contagion-like effects akin to near-repeat victimization (e.g., Lammers et al. 2015). For example, in addition to different stationary probabilities across opportunity types, that preferences are also "self-exciting" (Mohler et al. 2011). An encounter with opportunity type k causes a spike in the preference for that opportunity type increases the probability that it is exploited if encountered again in a relatively short period of time. If it is not encountered again, then the heightened preference decays back towards the baseline probability. Here, understanding the interactions between baseline preferences, self-excitation and Brownian motion mobility would be of interest. We leave these alternatives for future work.

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Declarations

Competing interests On behalf of all authors, the corresponding author states that there is no conflict of interest.

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