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General theory of spatial crime patterns

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General theory of spatial crime patterns

Abstract

I propose a general theory for examining the spatial distribution of crime by specifically addressing and estimating the spatial distribution of the residences of offenders, targets, guardians, and their respective movement patterns across space and time. The model combines information on the locations of persons, typical spatial movement patterns, and situational characteristics of locations to create estimates of *crime potential* at various locations at various points in time and makes four key contributions. First, the equations make the ideas involved in the theory explicit, and highlight points at which our current state of empirical evidence is lacking. Second, by creating measures of spatial "potentials" of offenders, targets, and guardians, this theory provides an explicit grounding for operationalizing spatial effects in studies of place and crime. Third, the equations provide an explicit consideration of offenders and where they might travel, and therefore incorporates offenders into crime and place research. Fourth, these equations suggest ways that researchers could use simulations to predict stable patterns, as well as changes, in the levels of crime at both micro and macro scales. Finally, I provide an empirical demonstration of the added explanatory power provided by the theory to a study of place and crime.

Bio

John R. Hipp is a Professor in the departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *American Sociological Review, Criminology, Social Forces, Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

General theory of spatial crime patterns

There is a burgeoning field of research focusing on the spatial distribution of crime. One large research area emanates from the Chicago School and focuses on the ecological distribution of crime in meso units such as neighborhoods (Sampson and Groves 1989; Peterson and Krivo 2010; Hipp 2007; Browning et al. 2010; Sampson, Raudenbush, and Earls 1997). This tradition often explores these spatial patterns of crime through the lens of social disorganization theory. A second large research area has grown in more recent years and focuses on crime at micro-locations such as street segments or even smaller units such as parcels (Wikström et al. 2010; Weisburd, Groff, and Yang 2012; Weisburd et al. 2004), which most frequently employs routine activities theory or crime pattern theory in studying these micro-units. Some researchers have suggested ways to integrate both routine activities and social disorganization theories (Smith, Frazee, and Davison 2000).

In the present manuscript, I propose a spatially explicit theory that, while adopting insights from these existing ecological theories, formalizes these various insights mathematically. While elements of the theory presented here are abstract, there are several advantages to presenting these ideas in a formalized manner that mathematically defines these propositions. First, these equations make the ideas involved in the theory explicit. Second, these equations will clarify points at which our current state of empirical evidence is lacking. In what follows, there are certain equations in which we have little evidence regarding what the parameter values might be, and therefore highlight areas of needed research. Third, by creating measures of spatial “potentials” of offenders, targets, and guardians, this theory provides an explicit grounding for operationalizing spatial effects in studies of place and crime. This moves beyond the unit of analysis problem and moves beyond treating spatial effects simply as a nuisance. Fourth, the equations provide an explicit consideration of offenders and where they might travel. Existing ecological studies of crime typically ignore the presence of offenders, and this theory provides estimates of where offenders might be, and allows for empirical tests of levels of crime at micro and macro scale as a consequence. I provide an empirical demonstration of the added explanatory power to a study of place and crime. Fifth, these equations suggest ways that researchers could use simulations to predict stable patterns, as well as changes, in the levels of crime at both micro and macro scales. By utilizing these equations within a simulation framework, various predictions can be made and subsequently tested empirically (Birks, Townsley, and Stewart 2012; Groff and Mazerolle 2008).

The proposed general theory of spatial crime patterns focuses specifically on the spatial processes of crime. It explicitly takes these processes into account by formalizing them in a series of propositions and then draws out implications. This model utilizes the framework of routine activities theory (Cohen and Felson 1979) to focus on three types of persons moving about in the environment: potential offenders, targets, and guardians. Routine activities theory posits that crime events will only occur when there is a co-occurrence in time and space of a motivated offender, a suitable target, and the lack of a capable guardian. This implies the need for both offenders and targets to come together in space and time. What is needed is information on where offenders, targets, and guardians live and where they go during the day and night, which provides the starting point for this theory, and then to formalize these ideas in equations.

From one point of view, we would collect information on where offenders, targets, and guardians are located at all times of the day. With this information, we could estimate the equations that predict the amount of crime in a location based on these three key ingredients.

However, whereas existing research attempts to proxy for the presence of offenders, or the presence of targets, or the presence of guardians, or even sometimes two of these three ingredients, research almost never tries to estimate the presence of all three elements simultaneously. One example of a study attempting to measure the movement of targets and guardians utilized the locations of schools and workplaces to model the presence of students or workers at block locations during daytime hours and Census information to capture the nighttime presence of persons (Boessen 2014). Furthermore, with advances in various technologies such as GPS-enabled smart phones or cameras to record the presence of persons, it may become more feasible over time to actually measure the presence of persons at various times of day (although the challenge remains of distinguishing between offenders, guardians, and targets).

Rather than attempting to measure the locations of persons, the focus of this general theory of spatial crime patterns is to build a model explaining where people might *potentially* be at any given time. These potentials are probabilistic, allowing researchers to draw general inferences about where and how much crime might occur across spatial locations. In this model, it is important to track the movements of different types of persons throughout the day. Thus, it is important to understand the spatial patterns of potential offenders due to the fact that all crimes involve offenders. A large literature focuses on the spatial movement of offenders (for a discussion of this literature, see Rossmo 2000). Given that violent crimes involve targets who are persons, it is necessary to understand how persons move about during the day or night to understand target location. Furthermore, persons can serve as guardians, so understanding the location of potential guardians is important for both violent and property crimes as well as understanding whether these individuals are indeed willing to act as guardians at that particular location.

Three fundamental premises guide this general theory of spatial crime patterns: 1) different types of crime exhibit specific spatial patterns; 2) persons' residences are distributed in space; 3) persons exhibit general spatial patterns on where they travel during the day or night based on the preference to travel shorter rather than longer distances (Zipf 1949). This latter premise builds on the notion of energy efficiency, in which persons prefer to travel minimum distances to accomplish the same thing as could be accomplished when traveling longer distances (Zipf 1949; Mayhew and Levinger 1977; Mayhew et al. 1995). Given these three premises, the theory makes predictions regarding the spatial distribution of crime. In this paper I focus only on the most serious types of crime in developing the theory; however, this theoretical model extends readily to other types of crime, including drug crimes, vandalism, and vice crimes. Such extensions would require consideration of the possibly idiosyncratic spatial processes characteristic of any particular type of crime (mostly regarding the locations and movements of potential offenders or targets), but otherwise the model can easily be extended.

BUILDING A SPATIAL MODEL OF CRIME PATTERNS

People in the area

The general theory of spatial crime patterns focuses on the general patterns of where persons are *potentially* located at all times of the day and considers the presence of these persons in the context of the three key ingredients of crime identified by routine activities theory (Felson 2002; Cohen and Felson 1979): 1) motivated offenders; 2) suitable targets; 3) capable guardians. Although it would be simplest if each person occupied only one of these categories at any given time, that is not in fact the case. Persons may vary in the *degree* to which they occupy each of these categories, and these categories are not mutually exclusive. Note that these three characteristics do not necessarily sum to 100% and a person may effectively range from occupying none of these characteristics to occupying all three of them simultaneously. For example, a person may be extremely unwilling to ever commit a crime (essentially 0 as an offender), have no money or worldly goods and therefore have very low value as a potential target for acquisitive types of crime, and also be unwilling to ever intervene when observing a crime event (and therefore have a value close to 0 as a guardian). In contrast, persons who are willing to be offenders (value near 1) are also often more likely to be victims (Gottfredson and Hirschi 1990) (therefore a value near 1 as a target) and may even be willing to serve as a guardian in some instances and therefore have a nonzero value as a guardian (e.g., the gangs discussed in Pattillo 1998 who served as guardians within their own neighborhood during certain periods of time). The difficulty in classifying the degree to which persons fill each of these categories at a given place and time points to an ongoing challenge requiring considerably more research effort.

Key characteristics of various types of crime: crime dyads and spatial temporality

Property and violent crimes differ in the characteristics of the target, which has important spatial implications. Property crimes are notable in that the dyad involved in the crime is an offender and a non-person, and the target is typically fixed in a particular location. For motor vehicle thefts, although vehicles move about in space, they are typically stolen only when they are at a fixed point (and not occupied). Violent crimes, however, are person-on-person crimes. Both the offender and the target can move about the social environment. Finally, offenders typically prefer isolation for the commission of a crime as it reduces the potential number of witnesses.

Given these considerations, we can provide a general expression of where crime will occur spatially. The following general equation expressing the probability of a crime event at a particular location for a particular period in time based on the logic of routine activities theory. For concreteness, I consider locations to be street segments and consider a period in time to be a 10-minute period (thus each day has 144 time-periods)[1].

$$\text{(1)} \qquad \mathrm{Prob}(C_{qbt}) = f(O_{bt}, T_{bt}, G_{bt}, SIT_{bt})$$

where C is a crime event of crime type *q* in street block *b* during 10-minute period *t*, O is the number of motivated offenders on the street block during this time period, T is the number of suitable targets on the street block during this time period, G is the number of capable guardians on the street block during this time period, and SIT captures situational characteristics that might either enhance or inhibit the likelihood of a crime event during this time period. The parametric functional form is left unspecified in this equation given the generality of the theory. We do know that if there are either no potential offenders or no potential targets, then there will be no crime event. Thus, this is likely a multiplicative relationship, although beyond that the appropriate functional form is an empirical question.

The notion of situational characteristics builds on the insights of Wikström (2006) and the notion of a background tapestry, as developed in crime pattern theory (Brantingham and Brantingham 1984; Brantingham and Brantingham 2008). These ideas come from the crime prevention through environmental design literature, which focuses on how features of the physical environment affect visibility, for instance, or characteristics that affect the notion of territoriality, which can impact the sense of the location as an attractive target (Newman 1972).

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[1] The actual length of the time segment for analytical purposes is unclear, and might differ based on the substantive crime being studied. Given that offender and target must coincide in space and time implies a short segment; however, motivated offenders may remain fixed at prime locations and therefore the target would be at risk as soon as he/she moved into the location, implying a longer time segment could work. The model is focused on general patterns in crime events and not specific events, and therefore longer time segments may be satisfactory.

It should be emphasized that the situational characteristics in this equation are capturing the effect of these characteristics *independent* of their effect on changing the number of targets or guardians at the location. However, these characteristics *can* increase the probability of offenders coming to the location given that these characteristics presumably lower the probability of detection of the crime event. Thus, whereas a retail environment might attract persons who come to shop, therefore changing the number of offenders, targets, and guardians at the location, the situational characteristics are those that have an additional impact on the possibility of crime. Thus, the crime generators that the Brantinghams (Brantingham and Brantingham 1995) referred to are reflected in O, T, and G in this equation. In the language of Wikström (2006), they are a cause of a cause. The crime attractors of the Brantinghams are part of the situational characteristics (SIT) of a location that make it more attractive to offenders, and therefore offenders are more likely to visit the location. Additionally, these situational characteristics may increase the probability of persons *acting as* offenders through an interactionist perspective: as one example, locations serving alcohol such as bars or nightclubs provide a situation in which persons may be more likely to behave as offenders *in that situation*. Of course, if these situational characteristics increase the probability of crime events, they might decrease the willingness of targets or guardians to come to the location, as will be discussed shortly.

We can also specify an analogous equation that captures the pattern of property crimes. The main difference compared to equation 1 for violent crimes is that many property crime targets do not spatially move. Whereas the targets for violent crimes are persons, and the theory must take into account their spatial patterns, property crime targets are structures, items, or vehicles rather than persons. For motor vehicle thefts, equation 1 captures this process given that the number of automobiles in a location can vary over different time periods. The equation for burglaries or larcenies, however, would be altered as:

(2) $$\text{Prob}(C_{qbt}) = f(O_{bt}, T_{b}, G_{bt}, SIT_{bt})$$

where all terms are defined as before with the one change being that the targets (T) do not have a *t* subscript. This is because the number of targets in a location (homes or other structures) does not vary over time periods of the day. The number of guardians or offenders can change over time periods, but not the targets.

Given equation 1 or 2, ideally we would have direct measures of O_{bt}, T_{bt}, G_{bt}, and SIT_{bt}. This would capture the fundamental insights of routine activities theory. In principle, with this information we could estimate the functional form. Arguably, at this historical point in time, the collective field of criminology provides minimal evidence informing the functional form of this equation and does not provide reasonable estimates of plausible parameter values. Empirical studies have explored pieces of this equation: for example, studies have tested whether crime events are more frequent near crime attractors, which are posited to increase the number of crimes present at a location (Bernasco and Block 2011; Groff and McCord 2011; Roncek and Maier 1991; Sherman, Gartin, and Buerger 1989), whether crime occurs more frequently in areas with a larger ambient population (Andresen 2011; Andresen and Jenion 2008), and whether the presence of certain types of businesses influences the amount of crime nearby (Kubrin and Hipp 2014; Lipton and Gruenewald 2002). This collective body of research provides suggestive evidence that the presence of persons nearby is likely important, but it does not try to actually measure the presence of offenders, targets, or guardians. Furthermore, this literature provides no guidance on plausible parameter values for equations 1 or 2.

General theory of spatial crime patterns

Wheraes equations 1 and 2 represent routine activities theory, here I will substitute estimates for O, T, and G based on where offenders, targets, and guardians are *likely* located, and their *likely* spatial patterns. The general spatial theory of crime patterns developed here proposes constructing estimates of these *spatial potentials* based on prior evidence regarding these three types of persons and key insights from existing empirical evidence of spatial patterns. What we need are two broad sets of information: 1) an estimate of the number of offenders, targets, or guardians and where they live across the spatial landscape; 2) an estimate of where these persons are most likely to travel during a 24 hour period. I undertake this task next.

Motivated offenders and their spatial patterning

Persons vary in the degree to which they are motivated offenders: I term this offender intensity, denoted O_I. At one extreme, some persons would almost never consider committing an offense and thus have values very close to 0 for being a motivated offender. At the other extreme, some persons may be extremely willing to commit a crime and therefore be looking continuously for criminal opportunities (and therefore have a value close to 1 for being a motivated offender) (Gottfredson and Hirschi 1990). Yet many individuals may lie somewhere on this continuum in that they would consider committing an offense only in some instances. Thus, individuals may react through a threshold process where each person has a particular likelihood of becoming an offender in a particular situation.

Ideally, we would know all individuals' propensities to be offenders in certain environments and where they are located at all times. We generally do not know this information, so we instead need to estimate individuals' likelihoods of being offenders and their spatial patterns of behavior. One approach, and the simplest assumption, is that everyone has an equal tendency to be an offender; in this case, we would use the spatial distribution of persons as an estimate of offenders. A second approach utilizes insights from existing research on how different demographic characteristics influence propensities to be an offender to compute estimates of the locations of motivated offenders. A challenge for computing such estimates is that we cannot simply view the characteristics (demographic or otherwise) from a sample of known offenders: this strategy would fail to account for the fact that certain types of persons might have differential *opportunities* to commit crimes given their spatial location. We must account for context near a person to accurately compute estimates for the predictive model developed here.

<u>Locating offenders: social demography strategy</u>

I next describe one possible approach to measure the spatial location of where potential offenders live. This *social demography strategy* builds a model in which the outcome measure is the latent variable of individuals' offender intensity (O_I). This equation would be:

(3) $$O\_I_{iq} = f(TRAIT_i, NGH_h, OPP_{qbt} * dist\_O_{hb})$$

where O_I_q is the intensity level for someone to be an offender for crime type q, *TRAIT* is a matrix of trait characteristics for individual i that capture a latent proclivity for committing this type of crime (e.g., low self-control Gottfredson and Hirschi 1990), *NGH* is a matrix of neighborhood characteristics for the home block (h) of the offender or some area around the block corresponding to a "neighborhood" that might either increase or decrease the likelihood of someone becoming an offender, and OPP_{qbt} captures the opportunities for crime type q in block b and time t that are within the context of the person, which is measured based on a distance decay function between the home block h and the target block b (*dist_O*). Opportunities would be measured based on the information from equations 1 and 2: essentially, locations with more targets and fewer guardians. For neighborhood effects, early work in the social disorganization theory framework posited that certain structural characteristics increased the number of offenders in a neighborhood (Shaw and McKay 1942; Schuerman and Kobrin 1986). Thus, the outcome measure is the number of offenses committed by a person, and the offender intensity is computed by conditioning out the number of opportunities nearby.

If we had an estimate of a person's likelihood of being an offender based on their demographic characteristics and/or the structural characteristics of their neighborhood, then we could construct an aggregated measure of potential offenders at location *h* (the home block):

(4) $$O\_I_{qh} = f(B_1 TRAIT_i, B_2 NGH_h)$$

where O_I is the aggregated offender intensity for crime type *q* in home block *h*, TRAIT captures the demographic characteristics of the residents in block *h*, B_1 is a vector of parameters capturing the likelihood of such persons being offenders (this vector of parameters comes from estimating equation 3), *NGH* is a matrix of neighborhood characteristics, B_2 is a vector of parameters capturing their effect (also estimated in equation 3). Equation 4 yields the sum of O_I_i of persons in the block (a weighted average) for crime type *q*, controlling for the local context. If we desire an estimate of the number of crimes *committed* by these residents we would include $OPP_{qbt}*dist\_O_{hb}$ in this estimate; however, here we desire offender intensity and thus this is conditioned out.

Where offenders travel

Once we have an estimate of where offenders live across the broader area, we next need a model of where offenders might move about in the spatial landscape. Most commonly we consider them at their home location, which certainly captures their location for a large period of the day. However, we can also consider where offenders go throughout the day and the journey to crime research explores this idea explicitly (Bernasco and Block 2009; Bernasco 2010; Barker 2000; Rossmo 2000; Rengert, Piquero, and Jones 1999; Reiss 1967).

For any particular person who is a potential offender, we can express their crime activity based on a combination of nearby opportunities and an assumed preference for committing crimes nearby (therefore warranting a distance decay function). A challenge for understanding the spatial pattern of offenders is accounting for the presence of opportunities across the spatial area, and a large body of journey to crime research demonstrates a distance decay effect in which offenders prefer to travel shorter distances to commit crimes (as discussed in Rossmo 2000). One strategy for estimating this latent distance decay uses discrete choice models (McFadden 1978) to directly incorporate into the model the spatial distribution of opportunities in relation to offender residence (Clare, Fernandez, and Morgan 2009; Bernasco and Block 2009; Bernasco 2010). This implies the model:

(5) $$\mathrm{Prob}(C_{qbt}) = f(O\_I_i, \mathit{dist\_O}_{ibt}, T_{bt}, G_{bt}, SIT_{bt}, SOCDIST_{ibt})$$

where C is a crime incident of type *q* at location *b* at time *t*, O_I is a latent measure of offender intensity of individual *i* (the frequency and willingness to commit an offense),[2] *dist_O* is the distance from offender *i* to a particular location *b*, T is the number of targets at location *b* at time *t*, G is the number of guardians at location *b* at time *t* that may affect the probability of being caught if committing the offense, SIT are a set of situational characteristics that characterize the environment at a particular point in time, and SOCDIST measures social distance, or a set of neighborhood characteristics that characterize the similarity of persons in the environment (*b*) to a particular offender (*i*) at a particular point in time (*t*). "Social distance" measures difference based on various social categories that are salient in a society at a point in time, such as race or

[2] If this is estimated on a sample of known offenders, then this would either be constrained to a value of 1 (given that everyone in the sample was an offender) or else could be weighted by the number of known offenses.

age (Merton 1968). Thus, there is evidence that offenders are more likely to select a location if the persons there are of a similar racial/ethnic background as themselves (Bernasco and Block 2009). Note that some research has suggested that there is a tendency for repeat crime events over short-term temporal and spatial distance (Gorr and Lee 2014; Lammers et al. 2015; Short et al. 2009) as offenders learn of more desirable targets based on recent crime events; this would be represented in the equation by a relative increase in O_I at the location and nearby over some period of time based on prior crime incidents. The work of Wikström is also relevant here, particularly for understanding the composition of SIT_{bt}, as it focuses on the characteristics of micro-locations in which offenders might be more likely to commit crimes; his approach focusing on the time at which offenses happen is particularly useful for the time subscript of SIT.

The functional form of this equation is general, and allows for the distance decay function to differ over various times of day and days of week.[3] The research on journey to crime typically does not take into account the time of day or day of week that the trip occurred and therefore based on existing research it is necessary to compute an average distance decay function over time periods. Equation 5 allows for temporal variability based on evidence from future research.[4] One challenge is that it is difficult to know what values to use for T and G in this equation; I turn to this issue next.

Suitable targets and their spatial patterning

Targets will differ depending on the type of crime being considered. For property crimes, the targets will not be persons, but instead are houses, businesses, automobiles, etc. The relative attractiveness of a target typically depends on the extent to which it is CRAVED: concealable,

[3] Typically, studies using this approach do not include measures of T or G subscripted by *t*, but only assumed fixed over time. It would be useful to relax this assumption in future empirical work.

[4] Equation 5 assumes that the probability of an incident does not depend on the number of suitable targets within a reasonable distance of an offender. If there are very few opportunities nearby, offenders may target specific locations more often (although this would increase the probability of being detected).

removable, available, valuable, enjoyable, and disposable (Clarke 1999). Thus, for the particular property crime of interest, a better estimate of the presence of the most desirable targets across the spatial landscape will improve the precision of the estimates.

For violent crimes, persons may vary in the degree to which they are suitable targets. Furthermore, a person can vary in the degree to which he/she is a suitable target across different types of violent crime and certain situations. Again, the challenge is determining the extent to which any person is a suitable target for a particular type of crime given that "suitable target" is a latent measure. Whereas using victimization surveys allows determining the extent to which certain types of persons are victims, this assumes equal exposure to high crime potential environments which may not be an appropriate assumption. In fact, this observed victimization is a complicated expression of the extent to which a person is actually in environments in which there are motivated offenders nearby and a lack of guardians. Certain types of people will experience victimization more frequently because they self-select into *high crime potential* locations (independent of the extent to which they are a suitable target). This can be represented as:

(6) $$V_{qi} = f(T\_I_{qi}, HCP_{qbt})$$

where V is victimization for person *i* of crime type *q*, T_I_{qi} is target intensity, or the extent to which the person is likely to be a victim of crime type *q*, and HCP is a high crime potential area for crime type *q* at location *b* in time period *t*. More specifically, HCP is a probabilistic, relative term rather than a discrete 0/1 measure, which captures locations with higher values for equation 1 *per target* in the location. Recall that equation 1 predicted the number of crimes that would occur at a location at a particular time; dividing this by the number of targets in the location at the time would yield the relative risk to any particular target in the location. Equation 6 shows that a person's victimization rate will be a multiplicative function of the extent to which a person is a suitable target and the amount of time spent in relatively high crime potential locations.

We wish to assess the characteristics that explain which types of persons are more likely to be targets, thus their target intensity (*T_I*) for a particular type of crime (*q*):

(7) $$T\_I_{iq} = f(TRAIT_i, NGH_h)$$

where *TRAIT* is a matrix of traits that alter the desirability of a person or place as a target (e.g., age, gender, income, education, race, etc) and *NGH* is a matrix of characteristics of the neighborhood that might make a person more likely to be a target (e.g., persons from neighborhoods with gangs may be more likely to be targeted by opposing gangs). It is also the case that certain types of persons are more likely to select into more risky environments, thus:

(8) $$HCP_{iqbt} = f(TRAIT_i, NGH_h, dist\_HCP_{bh})$$

where the terms are similar to those in equation 7, except that now we also include a measure of the relative proportion of high crime potential areas near a home block based on a distance decay function ($dist\_HCP_{bh}$), as these will impact the likelihood of entering such locations. Thus, in equation 6 it could be that persons who are more likely to be victims are more attractive targets (T_I_q), or because they are more likely to spend time in high crime potential (HCP) locations, or both.

Where targets go

Given an estimate of where suitable targets live, we next need a model of where they are likely to go during the day. This model will be the same for guardians, as there is little reason to suspect that guardians have a distinct spatial pattern from targets as both cases represent persons simply going about their normal routines of the day. We need to consider various general locations persons will visit. This list can vary across societies, but in current U.S. society the following arguably constitute the primary spatial patterning of persons (Kutter 1973): 1) jobs (these trips most frequently occur in the day, although sometimes in the evening); 2) school; 3) retail (e.g., grocery stores, shopping districts, etc); 4) entertainment (e.g., restaurants, movie theatres, bars, parks, recreation); 5) churches (typically only once per week). For these various types of trips, there is a choice set based on the spatial distribution of alternative choices. For example, a resident who wishes to go to a grocery store chooses among the grocery stores available in an area; nonetheless, the resident will be more likely to choose a grocery store that is closer to them rather than one farther away. If we knew the distance decay function that defined residents' choice of a grocery store, then we could use this information to estimate *potentials* for which grocery stores residents are likely to patronize. Thus:

(9) $$LU_{zbt} = f(SIT_{b}, P_{bt}, SOCDIST_{ibt}, dist\_T_{h}, C_{bt},)$$

where LU is land use type *z* in block *b* at time *t* that the person might choose to patronize, SIT_{b} captures the physical characteristics of the location that may make it more or less desirable as a destination at different times, P_{bt} captures the number of people at the place at a particular time[5], $SOCDIST_{ibt}$ is the social distance of the individual to the persons at the location at a particular time, dist_T is the distance between the location and the home block of the person (the potential target), and C_{bt} is the amount (or threat) of crime at location *b* at time *t*, which would have an expected negative effect. Again, the functional form of this equation is left general. For example, the functional form for the effect of social distance is uncertain, as it might be a negative linear relationship or a nonlinear relationship in which persons prefer a small amount of heterogeneity, as found in a study of perceived crime and disorder (Hipp 2010).

[5] How many people are desired may vary for different types of locations, and across different people. For some locations, such as parks, certain persons may prefer few people nearby. For other locations, such as retail locations, some persons may prefer that many people are there, others may prefer few persons, and yet others may prefer some, but not too many, implying a nonlinear function.

Note that this choice implies a competition effect in which choosing one location means not choosing another, but this is not necessarily always the case. Thus, we can consider the *probability* of going to a particular location. Note as well that the choice set may have consequences: persons don't necessarily always choose one option. Instead, the probability of choosing a location may increase with the number of options. For example, if there are several retail locations nearby, one might spend more time at retail locations; if there are instead few retail locations nearby a person may rarely go to a retail location. On the other hand, a person may only go to a single grocery store even if many are nearby; however, one may be less likely to go to a grocery store, or go more rarely, if there are fewer nearby. There is some empirical uncertainty regarding expected behavior on this point, suggesting a need for more empirical evidence on this issue.

There is a body of research focusing on where residents typically travel during the day. For example, Boessen (2014) computed distance decay estimates for patronizing grocery stores based on a sample of residents in Los Angeles. A study of Brisbane likewise computed distance decay estimates for various types of trips (Shobeirinejad et al. 2013). Based on parameter estimates from such studies, we can use this information in the following manner: for each home block in a city (*h*), we can compute the distance to the K closest grocery stores (say, five). For each of those K grocery stores we can compute the probability of residents in that home block patronizing the store. By multiplying each of these predicted probabilities by the number of persons in the home block, we would obtain an estimate of the number of persons from the home block that would patronize each of those K grocery stores based on the distance decay function:

(10) $$T_{hbk(\mathrm{LUz})} = \mathrm{Pop}_h\left(\frac{\left(LU_z, distT_{hbk}\right)}{\sum_{k=1}^{K}\left(LU_z, distT_{hbk}\right)} \right)$$

where LU_z is the land use of interest (z) and $distT_{hbk}$ is the distance decay function that captures how far persons typically travel to this land use type, K captures the number of such land use options near the residents, and Pop_h is the number of persons living on the home block. For grocery stores, this equation normalizes these results such that the proportions sum to 1 for each person. Thus, we obtain the probability of going to any particular grocery store. By performing similar computations for each home block in the city (block *h* of *H* blocks) we would have estimates of the number of persons that would patronize the grocery stores in the blocks (*b*) across the city. Thus, we can sum these up for each block (*b*):

(11)
$$T_{b(LUz)} = \sum_{k=1}^{K} \sum_{h=1}^{H} T_{hbk(LUz)}$$

With this overall number of patrons, we would then need to distribute them by the time of day and day of week they likely patronize the stores. Based on information about general patterns of business for grocery stores, such estimates could be constructed.

Similar computations could be performed for other types of trips, including types of retail, types of entertainment, churches, etc. For general retail locations, we may not wish to normalize this to 1 as it may be that persons will more frequently patronize retail establishments if there are more such establishments nearby. For jobs, estimates exist from other data sources for where individuals actually commute (i.e., the Longitudinal Employer-Household Dynamics survey). Note that these equations can also take into account heterogeneity of persons. With more specific information about the clientele that certain types of establishments cater to, and taking into account the socio-demographic characteristics of residents in various home blocks, the model could be made even more specific to the city under study.[6] For example, persons may prefer certain types of grocery stores rather than other types. This would be

$$T_{hbk(\mathrm{LUz})(\mathrm{g})} = \mathrm{Pop}_{h(g)}\left(\frac{\left(LU_z, distT_{hbk(g)}\right)}{\sum_{k=1}^{K}\left(LU_z, distT_{hbk(g)}\right)} \right) \quad (12)$$

where now the number of targets is subscripted by group g of G groups and the right hand side of the equation now accounts for group-specific processes with the g-subscript. We could also account for different temporal patterns by specific groups if we expect these patterns to differ appreciably by modifying the distribution of persons from equation 11. However, it is worth emphasizing that to be of interest here, such variability must be substantial enough to impact the estimates from these equations; it is an empirical question whether such variability is important or if it simply averages out to very small differences.

Finally, given that persons typically spend a considerable amount of time in their home location, we need to compute the number of persons in a location because they live there. These persons are either inside the house, on their street, or walking on nearby streets. The distinction between whether persons are inside their residences or out on the street has important consequences: a person on the street would enter our model just as persons who have traveled to a particular land use in that they can be offenders, targets, or guardians. However, persons inside their home are somewhat different. Except for very specific crime types, persons inside their home would not be offenders at this location and time point, although they can be guardians to the extent that they can, or do, look outside their windows or can hear what is occurring on the

[6] These heterogeneity considerations may be most important when areas are transforming in various manners. For example, when gentrification is occurring, the types of locations that match to certain types of persons may be particularly important to account for when making estimates of the spatial location of persons. This may also be important when racial/ethnic transformation is occurring in the area, as certain group members may be more likely to go to specific locations.

street or at nearby locations (Reynald 2010, 2011). Persons inside their homes can be targets for certain types of crimes but not others.

To know the number of residents at a location, we would need to compute the population that lives at the location and subtract out those who are likely not there during a certain period of time (these people are outside the neighborhood). For example, Boessen (2014) subtracted from the day-time population school-aged children and those who commute to work. In addition, one might construct probability estimates of the number of persons likely outside the block based on general patterns observed for persons of particular demographics (for example, young adults aged 21-29 might be more likely to be away from the home compared to adults aged 65 and up, etc). Of those who have not left the neighborhood, we also need to distinguish between persons inside their own home or outside on local streets (*o*). Thus:

(13) $$POP_{ht(o)} = f(P_{ht}, SIT_{ht},)$$

where P is a vector of the number of persons in various demographic categories who live in home block *h* -- and these various characteristics could be weighted by their likelihood of being outside the neighborhood or their likelihood of being outdoors in the neighborhood and SIT captures characteristics of the block that increase or decrease the likelihood of persons being outside the neighborhood, or outdoors in the neighborhood.

Capable guardians and their spatial patterning

There is a need to distinguish between: 1) active guardians, and 2) passive guardians. *Active guardians* are someone who is in a location and would intentionally do something to prevent a crime such behavior is observed (Reynald 2010, 2011). *Passive guardians* are persons who are simply present at a location and may prevent a crime event from occurring by acting as a potential witness. An offender typically cannot distinguish between active and passive guardians, so seeing someone present may be enough to act as a deterrent. For nearly all crime types, an offender will prefer to commit a crime when there is no one other than the target nearby. The lack of others nearby minimizes the possibility of potential witnesses and capable guardians who might otherwise intervene to prevent the crime from occurring.

Nonetheless, the communities and crime literature has particularly focused on potential active guardians, and the notion that persons vary in the degree to which they are willing to act as a capable guardian (Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997). However, less considered is that a person may vary in the degree to which he/she is willing to act as a guardian depending on the location: whereas a person may be very willing to act as a guardian near their own home, or in their own neighborhood, an individual may be less willing to do so at other locations (e.g., near their work, at a shopping center, while on vacation, etc). Given that theories such as collective efficacy theory also posit a contextual effect in which persons' willingness to act as guardians will differ depending on their sense of the attitudes of others in the location, willingness to act as a guardian will not simply depend on one's own personal characteristics but also characteristics of the surrounding environment (Sampson, Raudenbush, and Earls 1997). Thus, the question is whether for any location and time will a person act as a guardian?

Regarding active guardians and where they are more likely to take on this role, we can, for simplicity, imagine three classes of persons: 1) those who will never be an active guardian; 2) those who will be an active guardian in some locations but not others (i.e., act as an active guardian in their own home, streetblock, or neighborhood, but not elsewhere); 3) those will be active guardians anywhere they go. This implies:

(14) $$AG\_I_{qbt} = f(TRAIT_i, SIT_{bt}, \text{dist\_G}_{bh}, O_{bt}, G_{bt})$$

where *AG_I* is the probability of a person being an active guardian (their AG intensity) for crime type *q* in location *b* at time *t*, TRAIT is the set of characteristics of a person that is stable over time, SIT is a set of physical characteristics in location *b* at time *t*, *dist_G* measures the distance from the guardian's home location (*h*) to this location (*b*), O is the number of offenders at this location at this time (a greater number of potential offenders present may inspire fear and thus reduce the likelihood of guardianship occurring), and G is the number of other guardians at this location at this time, as guardianship may be conceived as a collective action problem in which willingness may depend on the presence of other potential guardians (Steenbeek and Hipp 2011). It is likely that a threshold effect captures the likelihood of a person switching to acting as an active guardian (and this likelihood would decay with distance from their home location). Another possibility is that persons act as guardians at locations where they work, or what is referred to as place managers (Brantingham and Brantingham 1993). Note that most existing neighborhoods and crime literature focuses exclusively on guardianship in the home neighborhood (Sampson and Groves 1989; Hipp 2007; Bellair 2000). This literature typically posits that the demographic characteristics of the neighborhood affects the relative proportion of guardians, and this is captured in equation 14 through the TRAIT, G and SIT measures.

For assessing guardianship outside the home neighborhood, I argue that it is useful as a starting point to simply measure the presence of passive guardians. That is, the number of people present in an environment is a reasonable proxy of passive guardianship. This implies using the same spatial movement equations as for potential targets (equations 9-13). It is worth emphasizing that a potential offender typically cannot distinguish between active and passive guardians. Therefore, in many instances the presence of passive guardians may have a similar inhibitory effect on crime as would the presence of active guardians, although this is a useful area for future research.

Building a spatial model of the location of crime

The goal of the general theory of spatial crime patterns is to predict the location of offenders, targets, and guardians at points in time. This information could be used to predict the spatial occurrence of crime events. Thus, we would like to estimate the presence of crime in a location based on equation 1, which we repeat here:

$$\text{Prob}(C_{qbt}) = f(O_{bt}, T_{bt}, G_{bt}, SIT_{bt}) \qquad (15)$$

If we had the actual elements of this equation, we could focus on determining the proper functional form while estimating the probability of a crime event of crime type q in street block *b* during 10-minute block *t*. For example, if we knew the presence of grocery stores, retail establishments, restaurants, etc, and if we knew how many people patronized these locations at particular times of day we could insert this information into the model. The likely nonlinearity of this equation implies that actually estimating the number of offenders, targets, and guardians at a location at a point in time would be quite informative for computing crime rates at both the micro and macro geographic levels.

Given that we do not have the actual information on how many persons are at locations at all time periods, the proposed theory builds estimates.[7] We can compute estimates of the number of each of these types of people across the spatial landscape and where they go, and then compute the probability of crime at various locations across the spatial landscape. This implies these modifications to equation 15:

[7] Note that an alternative theoretical strategy would be to actually try to measure the presence of persons in locations. With the advent of digital cameras, this task is not as far-fetched as it once may have seemed. Such a strategy would also want to assess the relative proportion of offenders within the mix of persons present, a task that poses its own set of challenges.

(16) $$Prob(C_{qbt}) = f(O\_I_{bt}, T\_I_{bt}, G\_I_{bt}, SIT_{bt})$$

in which O_I, T_I, and G_I are the offender, target, and guardian intensity of the location. For example, information on offender intensity comes from equation 4 and the distance decay function for offenders comes from equation 5. Information on targets and guardians comes from equation 7, and where they travel comes from equation 9, and their activity near their home comes from equation 13.

EMPIRICAL EXAMPLE AS PROOF OF CONCEPT

Although there are numerous components of the theory that allow for testing (as I discuss more in the conclusion), here I present a brief empirical demonstration as a proof of concept. For this example I use data from a single city: Santa Ana, CA with a population of about 330,000. This demonstrates using the theory to predict micro locations of crime. I will make several simplifying assumptions for the purpose of this demonstration. One such simplification is that I aggregated robberies to one hour time periods (rather than 10 minute ones) simply due to data sparseness. For this example, the crime data comes directly from the Santa Ana police department for three years (2009-11), and has been geocoded and placed into Census blocks. I focus here on robbery, given that it is a challenging crime for spatial reasons given that both offenders and targets exhibit mobility. The average number of robberies per year in a block during a particular one hour period is shown in Figure 1.

<<<Figure 1 about here>>>

As a first step, I need an estimate of where offenders live in the city. I use a simplified version of the *social demography strategy* described earlier. I use two sources of data from other locations for information on offender demographic characteristics: 1) 2013 National Incident-Based Reporting System (NIBRS) data that provides information on the age structure of typical robbers; 2) 2013 arrest data from St. Petersburg, FL, which provides information on the socio-demographic characteristics of neighborhoods in which robbery arrestees live. Recall that I would ideally account for the opportunity context surrounding these offenders and arrestees, but I avoid this complexity here in this simple demonstration. I instead simply compute the tendency to be offenders based on the characteristics of these offenders and arrestees. Table 1 shows the age structure of robbery offenders in the NIBRS data in the top panel, and the average socio-demographic characteristics of the neighborhoods of arrestees in St. Petersburg in the bottom panel. This table shows the relative rate of offenders compared to the general population. I then multiply this information by the demographic composition of blocks in Santa Ana and blocks within 5 miles of the city (to capture boundary effects) to compute the estimated potential offenders in each block.[8]

For potential targets, I use the population of the blocks in the city and blocks within 5 miles of the city to account for boundary effects. In this demonstration I simply use the population as potential targets, rather than weighting based on the typical demographic characteristics of victims.

To assess where potential targets go, I used data from Reference USA on the location of several amenities in 2010. These data provide addresses of all businesses in the region, and I geocoded them and placed them in Census blocks. Then I computed the number of amenities in each block based on the following categories: 1) retail; 2) entertainment; 3) bars; 4) grocery

[8] To do this: 1) for the St. Petersburg data, I estimated a negative binomial regression model of the number of offenders regressed on the neighborhood socio-demographic characteristics; 2) I multiplied the coefficients from that model by the neighborhood composition in my sample, and exponentiated the value to gen an estimated count of offenders; 3) I multiplied the age demographics variables in my sample by the ratios from the NIBRS data and a constant such that the mean count across neighborhoods for this approach after exponentiating equaled that of step #2 (to weight them equally); 4) I computed the average of the values from #2 and #3 as an estimate of the number of offenders in a block.

stores; 5) convenience stores; 6) liquor stores; 7) fruit and vegetable stands; 8) sporting establishments; 9) restaurants.

For each block in the city (and within 5 miles) I used equations 9-11 described earlier in the paper to: 1) compute the distance to every other block in the region; 2) compute the number of each type of amenity in the every other block in the region divided by distance to capture an inverse distance decay effect from the focal block to the amenity block; 3) sum up the total number of options for a particular amenity for the residents of a block; 4) divide the value in #2 by the value in #3 to normalize the options for a block (note that this assumes a zero sum willingness to patronize an amenity type, regardless of how many are nearby; this could, of course, be relaxed); 5) multiply the value in #4 by the population of the block to capture the number of persons expected to go to a location. As a final step, I need to allocate these potential patrons to various times of day. I do this by: 1) assuming that the number of employees in the county for each amenity capture the relative number of people who patronize each amenity type; 2) assuming that residents will patronize a grocery store once per week (to get a baseline frequency estimate for comparison); 3) computing the ratio of county employees for an amenity to county grocery store employees and multiplying this by 52 times per year to get an estimate of the number of times persons patronize an amenity; 4) dividing this value by days in the year and 24 hours in the day to get an estimate of the number of persons going to a location during a particular hour. Note that the population that is out varies during different times of day, as well as for different types of amenities; again, I ignore this complexity here for this demonstration, but it can be incorporated in more detailed explorations of the theory. I include the total local population in the models, rather than attempting to assess individuals’ probability of being outside as described earlier as this is an additional complexity that could be explored in future tests of the theory.

In all models I included sociodemographic control variables that are standard in the crime and place literature. I constructed from the U.S. Census the following variables at the block level: *population*; *concentrated disadvantage* (a factor score of percent single parent households, percent at 125% of poverty, average household income, and percent with at least a bachelor's degree); *residential stability* (standardized and combined percent owners and average length of residence); *percent black*; *percent Latino*; *percent Asian*; *racial/ethnic heterogeneity* (a Herfindahl index of percent white, black, Asian, Latino, and other race).

The models are estimated as logistic regression given that slicing the crime events into 24 one hour periods in the day results in almost no blocks experiencing more than one robbery. I first estimate a model in which all 24 one hour periods are not distinguished. I then estimate 24 separate models in which the outcome variable is the number of robbery events during that one hour period in the day. In all models I included the measures of offenders, targets, and an interaction of these two variables. Also, robust standard errors are used to correct for clustering by block given the repeated observations for each block. In addition, in the first model I tested nonlinearities and included the quadratic form of targets and its interaction with the number of offenders. These nonlinearities were never significant in the hourly models.

Results

The model predicting all robbery events for the three years is shown in Table 2. The estimates of targets and offenders present are all statistically significant, as well as the interactions. I plot the results to visually represent them in Figure 2. As seen there, the number of robberies in a block monotonically increases as the number of targets increases (the x-axis).

And the number of robberies also increase as the number of offenders increase (the lines in the graph, which represent 1) no offenders, 2) low offenders, 3) high offenders, and 4) very high offenders), up to a point of relatively high number of targets in which the lines essentially lie on each other. These lines are only plotted at values in the data: thus, neighborhoods with no offenders (the bottom line) typically will not have very many persons in them (targets). At the lower end of targets, a block with a high number of offenders is at risk of about 7.5-8% more robberies than a block with a low number of offenders. And a block with a very high number of offenders is about 6-7% more at risk of a robbery than a block with a high number of offenders.

<<<Table 2 about here>>>

<<<Figure 2 about here>>>

I compared the results of this demonstration to an alternate strategy that is common in the crime and place literature of focusing primarily on the number of targets. In this alternative approach, I computed a measure of the number of employees of these amenities, as employees are a reasonable proxy for the number of patrons, which provide targets. I find that my approach explains 18% more of the variance (based on the pseudo r-square) than does this alternative approach that is common in the literature.

I next estimated models in which the outcome variable of robberies was aggregated to each of the 24 one-hour periods in a day. The results of these models are shown in Table 3. The interaction term of the number of offenders and targets in a block is nearly always negative, which is consistent with the idea that the presence of more targets also implies the presence of more potential guardians, which will have a depressant effect on robberies. We also see that the coefficients for offenders and targets are almost always positive, and oftentimes statistically significant (by slicing the data as thin as I am here, statistical power is weaker than is usually the case).

<<<Table 3 about here>>>

All interactions were plotted, and can be characterized by just two patterns. Figure 3a plots the results for the 1-2am time period, and demonstrates that as the number of targets in a location increase the number of robberies increase (given the upward sloping lines). However, the number of robberies is higher if there are potentially more offenders in the area (based on the separate lines). The pattern for the other very early time periods in the day (2-8am) was the same (not shown). Furthermore, the pattern in the early evening hours (from 5-11pm) was also similar to this. The pattern is different in the middle of the day, as the presence of targets typically is capturing the presence of many people implying the presence of potential guardians. As seen in Figure 3b, the number of robberies during 10-11am is largely driven by the potential presence of offenders (the separate lines). An increase in the number of targets has no effect, or a negative effect, for locations with potentially many offenders (given the flat or downward sloping lines). The plot for the 11am-noon period was similar (not shown).

<<<Figures 3a and 3b about here>>>

As another way to assess the utility of this approach, in this same table the bottom row for each time period displays the percentage increase in the pseudo r-square for the presented models compared to a model that instead adopted the more common approach of including the total number of employees for these various crime attractors/generators (which is typically considered a proxy for the presence of offenders). The pseudo r-square is almost always higher in these primary models. During certain time periods this model shows a notable improvement in variance explained: between 1 and 4am this model does considerably better (improving the pseudo r-square between 58% and 109%). The fact that the model does so much better late at night may be because it is attempting to capture the presence of offenders, whose presence is particularly important when there are few potential guardians nearby. The model does much better from 6-7am and from 10am-noon, in each case because it is capturing the possible presence of offenders. The model also does somewhat better in the evening (7-8pm and 10pm-midnight).

Although this is a very simple demonstration of the theory in which I only crudely constructed some of the measures, as a proof of concept it works to demonstrate the utility of this theory for micro studies of crime location. More refined measures would likely improve the predictions of the theory, which I leave to future research. Furthermore, as I discuss in the conclusion, there are also *macro* implications of this general theory of spatial crime patterns that can be explored empirically.

IMPLICATIONS OF THIS FORMAL THEORY

Needed empirical tests

There are several implications from formalizing this general theory of spatial crime patterns, which can provide guidance for future research. First, it makes clear that although we have some knowledge regarding the parameters and functional form of some of these equations presented here, we have quite limited knowledge regarding many of the equations. Whereas some of these equations come directly from existing literature, the advantage of formalizing these equations is that it makes clear points at which our empirical knowledge is quite limited and therefore suggests areas in which more research is needed. The following equations need considerably more empirical evidence regarding the parameter values.

First, although equations 1 and 2 are fundamental to routine activities theory, we do not even have plausible estimates of the parameter values. What is needed is information on the presence of persons at various locations at different times of day and estimates of the proportion of those persons who are offenders, targets, and guardians to estimate the relationship with various types of crime at such locations at those time periods. Second, from equation 3, we need estimates of which individual and neighborhood characteristics impact the offender intensity of persons, while also accounting for the crime opportunities in an area to get an estimate of the latent offender intensity of persons. Third, from equation 7, we need estimates of which individual and neighborhood characteristics impact the target intensity of persons. These models would take into account the tendency of such persons to be in high crime opportunity locations to get an estimate of the latent target intensity of persons. Likewise, we need better estimates of the extent to which certain types of property constitute the most attractive targets. The burgeoning literature focusing on crime at place is making progress in this regard (e.g., Bowers 2014; Groff and McCord 2011; Wikström et al. 2010).

Fourth, we need distance decay estimates on how far residents are likely to travel to access various types of land use for equation 9. Some of this information may be available in existing research on studies exploring this question using discrete choice analysis, along with careful estimation of the distance decay function (McFadden 1978). Relatedly, we need information on the extent to which persons will more frequently patronize certain types of land use if it is more prevalent in their nearby environment. Fifth, based on estimates of these distance decay functions, research needs to assess the extent to which such information, combined with the spatial distribution of persons, is actually able to predict where persons are likely to go. This would require computing estimates of the number of persons patronizing land uses in the area and then assessing whether this estimate matched actual counts of patronage in the area. We also need better information on the likelihood of various types of persons to spend time at their home, and in the neighborhood around their home, to have better estimates for equation 13. We would also need the probability that individuals are aware of the local environment if they are inside their home and their probability of being outside on the neighborhood streets. Finally, equation 14 highlights that we need information on which types of persons are likely to engage in active guardianship when they are at various physical distances from their own home.

A priori predictions of the theory

An advantage of this general theory of spatial crime patterns is that it can generate a priori predictions. First, by using these equations, along with the spatial distribution of persons and land use characteristics, the theory can generate predictions regarding the level of crime in small micro units of analysis at various times of day. Using very crude measures, I provided a simple demonstration here how the theory can make predictions regarding the spatial distribution of crime across the street segments or blocks within a particular city at certain times of day. This simple proof of concept demonstration implies that more sophisticated implementations of the theory might have great promise.

Second, the theory could make testable predictions regarding the level of crime across macro units such as cities or counties, etc. Based on the spatial distribution of persons and land use, along with the predicted spatial patterns of persons, the theory would make predictions about the level of crime at various times across the street segments of a city, which could then be summed to the city level. By constructing such estimates for a large number of cities, the theory would have testable implications for the level of crime across these various cities. This may have important implications for the law of crime concentration (Weisburd 2014) that proposes that the concentration of crime will be similar across different macro units.

Third, by utilizing a simulation approach along with the equations described here, predictions could be made about the change in crime at various spatial scales based on proposed changes to the built environment. These simulations would provide predicted changes in crime in micro locations, as well as predictions about the expected change in the overall level of crime in the larger macro unit. For example, if a new business district were proposed for construction, this theory would provide an estimate of the number of persons expected to patronize this district and the other business locations that individuals would no longer be expected to patronize as a result. This new business district would result in changes in the spatial pattern of where persons go and the theory would have testable implications for how the levels of crime would change at these various locations at various time points as a consequence of this change.

In conclusion, this general theory of spatial crime patterns provides four main contributions. First, these equations make the ideas involved in the theory explicit, and clarify points at which our current state of empirical evidence is lacking and therefore highlight areas of needed research. Second, by creating measures of spatial “potentials” of offenders, targets, and guardians, this theory provides an explicit grounding for operationalizing spatial effects in studies of place and crime. Third, the equations provide an explicit consideration of offenders and where they might travel, and allow for empirical predictions of levels of crime at micro and macro scale while incorporating potential offenders. Fourth, these equations suggest ways that researchers could use simulations to predict stable patterns, as well as changes, in the levels of crime at both micro and macro scales. By leveraging the simple insight that humans prefer to travel shorter rather than longer distances (Zipf 1949), this theory provides considerable potential insights for the location of crime events.

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Tables and Figures

Table 1. Demographic characteristics of potential offenders (not accounting for local context)

Panel 1. Percent of population, and robbery offenders, constituted by different age categories based on NIBRS data in 2013

Age categories	Total population	Robbery offenders	Ratio
0-9	13.4	0.0	0.00
10-14	6.7	2.2	0.33
14-19	7.3	22.5	3.08
20-24	6.7	27.7	4.11
25-29	6.5	19.1	2.93
30-34	6.3	10.6	1.69
35-39	6.3	6.8	1.08
40-49	14.7	7.4	0.50
50-59	16.8	3.2	0.19
60 and up	15.5	0.6	0.04

Note: N = 46,032 offenders; total population of 51,098,195 in these cities

Panel 2. Neighborhoods of arestees in St. Petersburg, FL, and all neighborhoods

	Total city	Blocks with robbery arestees	Ratio
Percent single parent households	17.7	26.1	1.47
Percent at or below 125% of poverty level	21.6	29.7	1.37
Average household income	62,244	47,111	0.76
Percent with at least a bachelor's degree	26.9	21.6	0.80
Average home value	221,354	184,802	0.83
Average length of residence	10.1	8.4	0.83
Percent in same house 1 years ago	84.3	77.9	0.92
Percent immigrants	12.6	12.1	0.97
Percent single family housing units	69.9	57.6	0.82
Percent in crowding	3.1	3.4	1.09
Concentrated disadvantage	-0.04	4.60	

Note: N = 4,830 blocks in city; 3,360 blocks with robbery arestees

Table 2. Outcome variable is all robberies in Santa Ana from 2009-11, regardless of time of day

Targets	1.605	**
	(6.47)	
Targets squared	-0.480	**
	-(4.73)	
Offenders	0.184	*
	(1.99)	
Targets X Offenders	-0.303	**
	-(2.75)	
Targets squared X Offenders	0.112	**
	(3.17)	
Population	0.205	**
	(5.31)	
Population squared	-0.008	**
	-(2.80)	
Concentrated disadvantage	0.067	
	(1.34)	
Residential stability	-0.239	**
	-(4.71)	
Percent black	0.063	*
	(2.04)	
Percent Latino	0.009	*
	(2.22)	
Percent Asian	0.006	
	(1.45)	
Racial/ethnic heterogeneity	-1.077	**
	-(2.75)	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values below coefficient estimates. Negative binomial regression model. N = 2,875 blocks*

Table 3. Hourly models including variables capturing targets and offenders in blocks in Santa Ana

	Midnight	1:00 AM	2:00 AM	3:00 AM	4:00 AM	5:00 AM	6:00 AM	7:00 AM	8:00 AM	9:00 AM	10:00 AM	11:00 AM
Targets	0.333	1.320 **	1.662 **	1.009 †	0.818 †	1.138 †	0.800 *	1.677 *	1.895 †	0.811	0.716	1.031
	(0.92)	(3.03)	(4.23)	(1.65)	(1.67)	(1.95)	(1.99)	(2.42)	(1.66)	(1.14)	(0.69)	(1.26)
Offenders	0.216	0.477 *	0.735 **	0.464 †	0.232	0.295	0.665 **	0.702 *	0.529	0.028	1.133 *	1.029 *
	(1.19)	(2.16)	(3.36)	(1.75)	(0.69)	(1.57)	(3.32)	(2.12)	(0.85)	(0.07)	(2.33)	(2.49)
Targets X offenders	0.001	-0.406 **	-0.699 **	-0.393	-0.276	-0.251	-0.307 *	-0.316 †	-0.778	-0.225	-0.757 *	-0.978 †
	(0.01)	-(2.85)	-(3.64)	-(1.62)	-(1.33)	-(1.37)	-(2.40)	-(1.73)	-(1.36)	-(1.30)	-(1.99)	-(1.79)
Percent increase in r-square	7.5%	61.8%	109.4%	58.3%	11.1%	9.8%	50.0%	11.9%	2.8%	-9.0%	47.3%	47.1%

	Noon	1:00 PM	2:00 PM	3:00 PM	4:00 PM	5:00 PM	6:00 PM	7:00 PM	8:00 PM	9:00 PM	10:00 PM	11:00 PM
Targets	-1.435	1.367 *	0.426	0.802	-0.009	0.842 *	1.437 **	1.795 **	0.588 †	1.078 *	1.170 **	1.198 *
	-(1.44)	(2.29)	(0.68)	(1.39)	-(0.02)	(2.17)	(3.15)	(4.11)	(1.68)	(2.47)	(3.18)	(2.53)
Offenders	0.254	0.206	0.443 *	-0.035	0.472 **	0.221	0.342	0.362	0.356 *	0.136	0.374 *	0.108
	(0.68)	(0.71)	(2.13)	-(0.14)	(3.24)	(1.40)	(1.38)	(0.91)	(2.11)	(0.63)	(2.01)	(0.36)
Targets X offenders	0.349	-0.466 *	-0.107	-0.071	0.054	-0.114	-0.452 **	-0.693 *	-0.139	-0.286 *	-0.360 **	-0.437 *
	(1.52)	-(2.33)	-(0.52)	-(0.46)	(0.38)	-(1.10)	-(3.06)	-(2.47)	-(1.49)	-(2.06)	-(3.10)	-(2.16)
Percent increase in r-square	10.4%	15.0%	5.0%	11.0%	8.5%	5.9%	13.5%	41.5%	17.6%	12.1%	23.5%	21.4%

Note: N = 2,875 blocks. All models include block-level control variables: logged population, concentrated disadvantage, residential stability, percent black, percent Latino, percent Asian, and racial/ethnic heterogeneity

Note: "percent increase in r-square" is compared to a model that instead includes the total employees in: retail, accomodations/food, bars, groceries, convenience stores, liquor store, fruit/vegetable stands, sporting goods, restaurants

Figure 1. Average number of robberies per year in blocks by hour in Santa Ana (averaged over 2009-11)

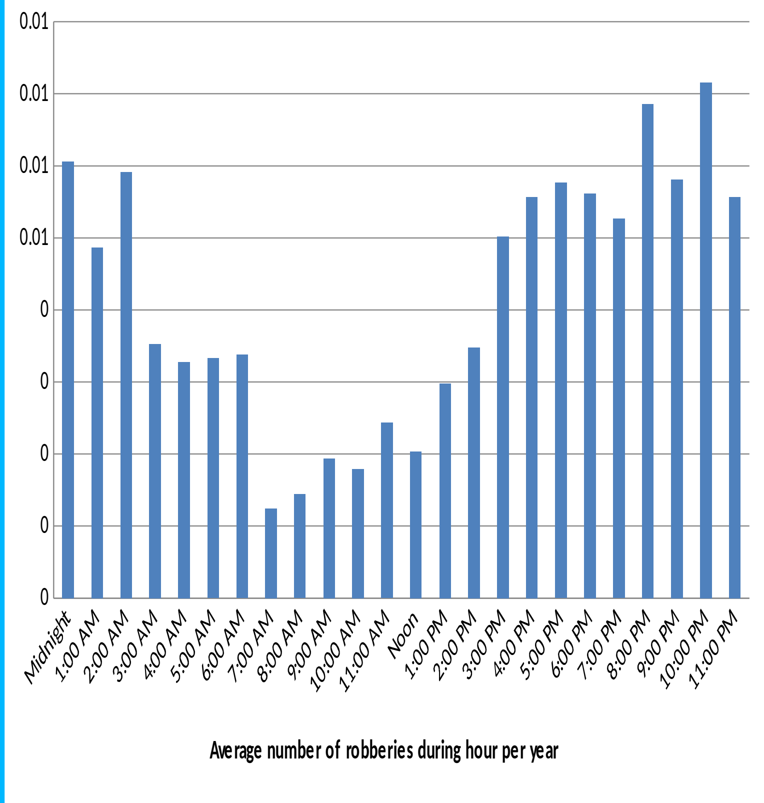

Figure 2. Effect of targets and offenders on robbery rates in Santa Ana (all times of day)

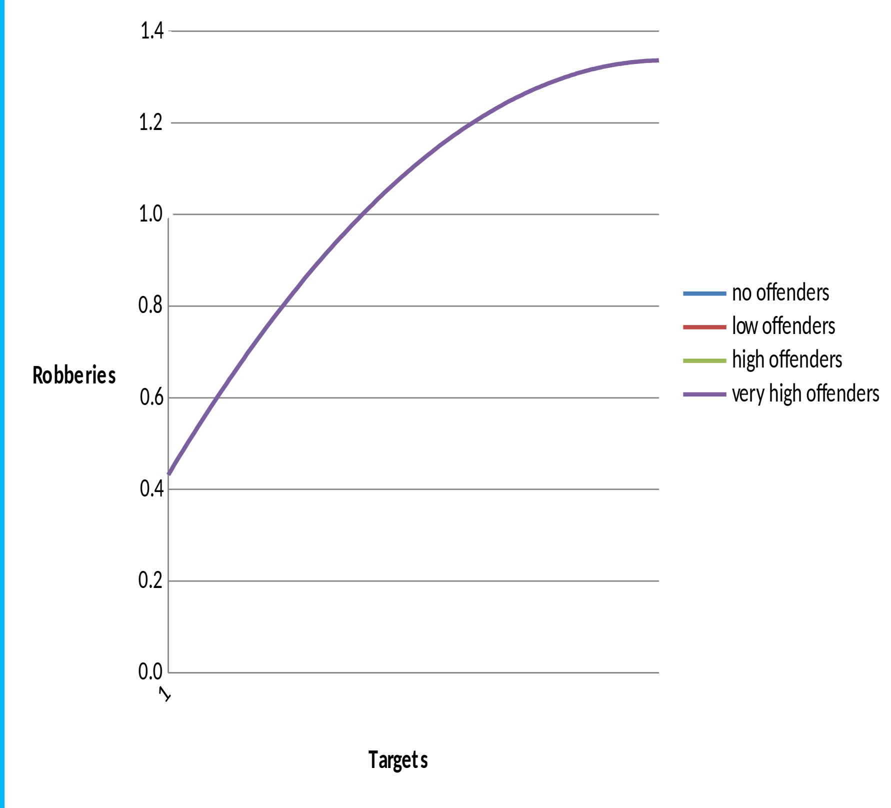

Figure 3a. Model prediction of robberies based on potential presence of offenders and targets from 1-2am

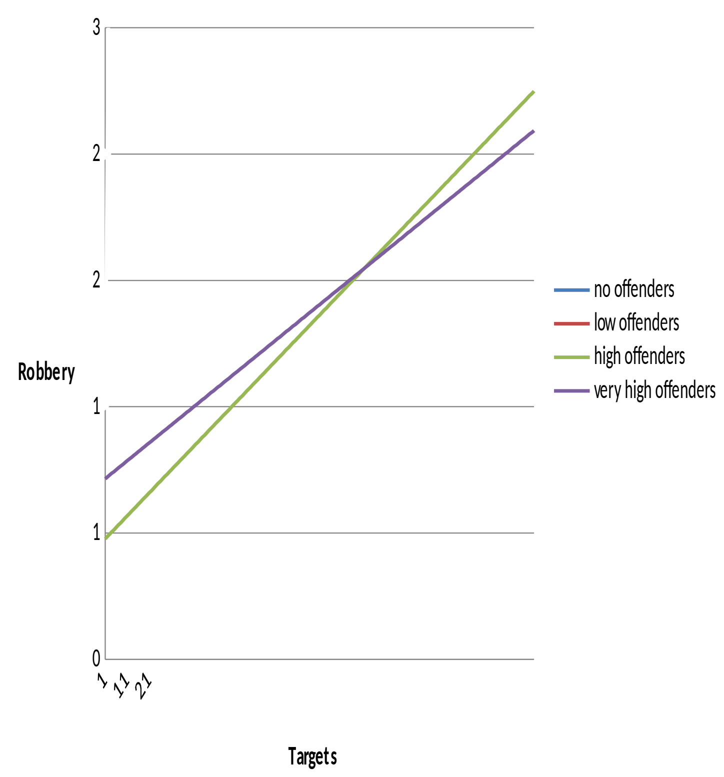

Figure 3b. Model prediction of robberies based on potential presence of offenders and targets from 10-11am