Simulating spatial crime patterns:

What do we learn in standard ecological studies of crime?

John R. Hipp*

August 28, 2020

Post-print. Published in Journal of Criminal Justice 70():

Word count (not including references): 7,558

Word count (including references): 8,692

Running Head: "Simulating spatial crime patterns"

* Department of Criminology, Law and Society and Department of Sociology, University of California, Irvine. Address correspondence to John R. Hipp, Department of Criminology, Law and Society, University of California, Irvine, 3311 Social Ecology II, Irvine, CA 92697; email: john.hipp@UCI.edu. A previous version of this manuscript was presented at the People, Places, and Context: Advances in Criminological Theory" Symposium held on April 12-13 2019 at the University of California, Irvine. The symposium participants are thanked for their useful feedback.

Simulating spatial crime patterns:

What do we learn in standard ecological studies of crime?

Abstract

Objectives: Given the spatial nature of offender and target behavior, what do standard ecological studies of crime aggregating measures to different geographic units actually tell us?
Methods: This study used a simple stylized simulation model of crime patterns based on offenders and a distance decay function to capture their typical mobility patterns when committing offenses, and immobile targets.
Results: There were four key results. First, although a measure of targets can explain much of the variance in micro-level models, knowing where offenders live, and their typical distances traveled to offending, greatly improved the model performance. Second, accounting for the typical spatial movement of offenders before aggregating to larger units produces better results based on explanatory power. Third, the explanatory power of targets alone was much weaker when aggregating to larger units despite the fact that the simulated model was entirely based on micro processes, highlighting that variance explained is distinct from causal processes. Fourth, knowing how offenders behave in target-rich versus target-poor environments impacts the results considerably.
Conclusions: The findings demonstrated the consequences of a spatially explicit model of offender and target behavior for ecological studies of crime that aggregate measures to various geographic units.

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*.

Simulating spatial crime patterns:

What do we learn in standard ecological studies of crime?

A common strategy in ecological studies of crime is to aggregate measures to a particular unit of analysis and then estimate models that assess the relationship between these measures and levels of crime in these units. This raises the question from some scholars of what is the "proper" unit of analysis for such analyses (Taylor 2015). This is related to a question of longstanding concern in many fields—the modifiable areal unit problem (MAUP)—in which results can be sensitive to the particular geographic aggregation that is employed (Openshaw and Taylor 1981; Lawson 2006; Hipp 2007a). Some research has proposed estimating models with smaller units nested within larger units with the same general goal (Boessen and Hipp 2015; Deryol et al. 2016; Boessen and Hipp 2018; O'Brien and Winship 2016). The question sometimes posed is at which geographic scale do certain measures operate? One problem is that many of the measures used—such as socio-demographic measures—are proxies for multiple possible processes that would result in crime.

Another fundamental challenge to all of these approaches is that there is an explicit spatial component to crime events. As outlined by Hipp (2016) in his general theory of spatial crime patterns, if one hews to the routine activities perspective that crime is a consequence of the confluence of motivated offenders, suitable targets, and a lack of capable guardians, these persons all move about across the spatial landscape. Indeed, theories such as crime pattern theory (Brantingham and Brantingham 1984; Brantingham and Brantingham 1993) explicitly focus on how offenders and targets move about the landscape, and how their encounters can result in crime opportunities. A large body of studies have studied the spatial patterns of offenders, and found a consistent spatial decay function in which offenders are more likely to commit offenses in nearby locations rather than more distant locations, but nonetheless exhibit a nontrivial amount of spatial movement when committing offenses (Rossmo 2000; Chamberlain and Boggess 2016; Vandeviver, Van Daele, and Vander Beken 2015; Lammers et al. 2015). A consequence is that even if one were to somehow know the location of offenders, this would not provide the proper unit of analysis for measuring their geographic impact on crime given these mobility patterns.

Given the spatial patterning of crime events, a question then is what are the consequences of these spatial patterns for studies that adopt the typical ecological strategy of aggregating measures and crime to particular geographic units of analysis? The goal of this project is to provide some insights on the consequences of these spatial patterns by conducting a relatively simple stylized simulation study to demonstrate some key properties. The spatial simulation will only include offenders, targets, and a distance decay function characterizing typical distances offenders take in travel to crime based on Euclidean distance. By keeping the simulation simple, and yet based on some key features we know about the spatial movement of offenders and the spatial concentration of crime targets, the intention is to provide some insights to researchers about what such existing ecological studies are actually telling us. Next, I describe how the ecological literature has approached aggregating measures in an effort to determine the relationship with crime levels. I then describe the simulation approach that I take. I follow that by presenting the results, and then conclude with implications for ecological models of crime.

Literature review: Spatial Pattern of Crime

A primary theory used to explain the generation of crime incidents is routine activities theory (Felson and Boba 2010; Cohen and Felson 1979). In this perspective, it is the spatial and temporal confluence of offenders, targets, and a lack of guardians that are the posited ingredients for crime events. While a useful perspective, an immediate challenge for researchers exploring this question empirically is defining which persons constitute each of these groups, and/or in which settings or situations do various persons constitute these different categories. Lacking this information, empirical estimation is quite difficult. An additional challenge is to account for the spatial movement of these persons, and a theory explicitly focused on such movement is crime pattern theory (Brantingham and Brantingham 1993, 1995). Crime pattern theory focuses on how the characteristics of the environment (the "urban backcloth") can impact movement, and therefore have consequences for where crime occurs. Residents in their daily lives patronize certain locations (i.e., commercial districts) and therefore such locations can act as "crime generators" given that they congregate a number of suitable targets. The presence of such locations would result in a concentration of crime incidents at certain locations, and a large body of research has explored this question empirically (e.g., Weisburd, Bernasco, and Bruinsma 2009; Weisburd, Groff, and Yang 2012). Similarly, locations that disproportionately attract offenders given that they provide crime opportunities (e.g., bars) are termed crime attractors (Brantingham and Brantingham 2008).

Hipp's (2016) general theory of spatial crime patterns proposed a model of the general pattern of crime locations. This theory combined insights from the daily activities literature (Palmer et al. 2013; Golledge and Stimson 1997; Lentnek, Lieber, and Sheskin 1975) that residents engage in their activities based on a distance decay function—in which they are more likely to patronize closer locations rather than more distant ones—along with the journey to crime literature finding a similar distance decay function for offender behavior (Bernasco and Block 2009; Bernasco 2010; Barker 2000; Rossmo 2000; Rengert, Piquero, and Jones 1999;

Reiss 1967). Thus, residents tend to patronize certain types of establishments as a part of their daily activities, and given the evidence that residents are more likely to travel to closer locations in their daily travels, the theory predicts the general patterns of where residents will go. The combination of this information, along with the insights of routine activities theory on the likelihood of crime incidents given these intersections between offenders and targets, provides an estimate of where and when we would expect crime to occur. A key feature of all these perspectives is that whereas crime may tend to concentrate at certain locations due to crime opportunities, the spatial movement of persons introduces a complication to studies attempting to measure the socio-demographic characteristics of a location, and how that might impact crime.

Meso-level theories of crime

Beyond these micro-level theories of the spatial pattern of crime, there are also meso- and macro-level theories positing that broader structural factors can impact the spatial location of crime. Typically, meso-level theories either posit mechanisms through which more offenders are created—either in general, or for specific scenarios—or posit mechanisms in which more potential guardianship is created. For example, social disorganization theory posits that certain neighborhoods will be able to engage in more informal social control. One consequence is that this would reduce the number of potential offenders in such neighborhoods (Shaw and McKay 1942; Schuerman and Kobrin 1986). Another consequence is that more residents will be willing to engage in guardianship should the need arise (Sampson and Groves 1989; Bursik 1988). As another example, in relative deprivation theory the level of economic inequality creates more offenders by creating a sense of inequity for the more disadvantaged group (Merton 1968; Hipp 2007b). This would lead to higher levels of crime committed by the disadvantaged residents. Likewise, consolidated inequality theory of Peter Blau (Blau and Schwartz 1984) posits that the level of economic inequality *across* racial/ethnic groups also creates offenders by increasing a sense of enmity. And in group threat theory, it is the in-movement of a different racial/ethnic group that creates conflict, and this conflict would also increase the likelihood of residents becoming offenders through violence against the other group (Messner, McHugh, and Felson 2004; Hipp, Tita, and Boggess 2009). It also may spatially locate the violence within the neighborhood in which this transition is occurring, in contrast to the more general spatial patterns of offenders.

Whereas these theories are typically tested by aggregating measures of interest to the meso level of neighborhoods and then assessing their relationship with levels of crime, they typically do not consider mobility by offenders. These meso level theories also typically do not consider the possibility that certain locations can serve as crime generators or crime attractors, and therefore result in concentrated locations of crime. As a consequence, studies testing meso level theories typically do not account for micro locations of crime, nor do they account for the likely spatial mobility of offenders in constructing measures or in their analyses. As Boessen and Hipp (2015) noted, neighborhoods can therefore be seen as both too small and too big: too small to capture broader spatial patterns that cross neighborhood boundaries, but too big to capture crime opportunities that occur on smaller geographic units such as street segments.

In this study I bracket meso and macro theories and do not fully explore them here. I only invoke some of the insights of social disorganization theory in building an estimate of where offenders are located for the simulation; note that these estimates are based on characteristics of the micro street block, which some scholars have argued may be a reasonable geographic setting for considering neighborhoods (Taylor 1997; Weisburd, Groff, and Yang 2012). Whereas future work might consider how these meso-level theories create offenders more exhaustively, or how they might create guardians, I do not explore this here given that the goal is instead to provide ecological insights based on the simulations from a relatively simple crime generating model at the micro geographic level.

Simulation model

The stylized simulation model of crime employed here is relatively simple. I simulate the location of potential offenders across the landscape, and the location of potential targets. For simplification, I will assume targets are immobile in the initial simulations (i.e., business locations), although I will briefly consider mobile targets in some ancillary simulations. In the model, offenders will commit offenses based on an exponential distance decay from their home location.

Even given the limited scope of the current simulation study, there are some decisions to make on which the field of criminology arguably has limited information, or else has competing perspectives. First is the question of whether there is disproportionate likelihood of being an offender. One extreme perspective is that all persons are effectively equally likely to be offenders, or that they can be effectively treated as such given the predominant importance of targets in the spatial landscape (Nawrocki and Carter 2010). A contrasting perspective is that some persons have a disproportionate likelihood of being offenders (Gottfredson and Hirschi 1990). Existing meso-level theories posit that certain neighborhood environments can increase the likelihood of offending by persons, which also implies disproportionate offending. Given these competing perspectives, I simulate data from each of these two conditions to evaluate the varying consequences of each for the spatial distribution of crime.

A second question that has arguably received quite limited attention in the empirical literature is how an offender's offending behavior is impacted by the number of crime opportunities in the local environment? One extreme possibility could be that offenders simply offend proportionately more in richer offending environments. Thus, as the number of targets increases nearby, an offender would engage in more crime incidents. At the other extreme is the possibility that offenders simply offend a certain amount. In this view, offenders in an environment with few crime opportunities will travel further to commit offenses. And an offender in a richer environment would not offend any more, but simply travel to closer locations for crime events (one might expect a shorter distance decay function in this case, but the number of events per offender would remain unchanged). This latter perspective might imply that a time constraint is operating: offenders can only offend so much, given time constraints for committing crimes. It is likely that the true pattern of offender behavior is somewhere in between these two extremes. Nonetheless, I simulate from these two extremes to bound the possible results that would occur.

Levels of aggregation

Given these simulated models of where crime occurs, the question then is what can we learn if we adopt the typical ecological crime strategies? In the primary simulations, a single construct captures targets (and they do not move) and a single construct measures offenders, and we know their typical movement. Given this information, what will the results look like given the typical modeling strategies employed? Note that research commonly includes a number of measures that are imperfect proxies for the presence of offenders, targets, or guardians. Furthermore, existing studies rarely account for offender movement in their measures or modeling strategy.

One strategy is exemplified by micro-level studies. These studies typically aggregate data to small geographic units such as street or census blocks. This research often focuses on measuring targets, or crime generator locations that can attract targets. These studies less often attempt to measure offenders. Only occasional studies have attempted to proxy for where offenders live, and then account for possible spatial movement when offending (Hipp 2016). In this simulation project I demonstrate how accounting for offender movement might be accomplished in a straightforward manner using a distance decay measure.

Another approach is illustrated by meso-level studies, which aggregate data to “neighborhoods” (Sampson and Groves 1989; Krivo and Peterson 1996). These studies are usually more interested in how the social characteristics of the environment might impact the number of offenders in the neighborhood, or the potential for guardianship. These studies typically focus less on specific possible targets, do not consider the micro-concentration of targets, and usually do not explicitly consider spatial movement by targets or offenders. Here I show what we might learn if we aggregate our measures of offenders and targets to neighborhoods, even though the simulated spatial process occurs at a more micro scale.

A third approach is an older macro-level research tradition that aggregates data to larger units such as cities, counties, or metropolitan areas (Rosenfeld, Messner, and Baumer 2001; Golden and Messner 1987). Although crime events occur at a more micro scale, this literature posits that some macro structural characteristics impact the number of offenders, targets, or guardians. The consequence would be higher crime rates in certain macro units, regardless of the mechanisms playing out at the micro scale. Again, the present study shows what we might learn if we aggregate our measures of offenders and targets to macro units, even though the simulated spatial process occurs at a more micro scale.

SIMULATION STUDY

Studies often aggregate data to a particular geographic unit, and then estimate models. But what are the consequences given that offenders move about when committing offenses? To address this question, I conduct a simulation study of crime patterns. I adopt different assumptions on what generates crime, and then simulate data based on those assumptions. I then assess the consequences for typical ecological crime model estimation.

For the simulation, any roughly rectangular area (without peculiar geographic details) would work fine. Rather than generating a simulated environment tabula rasa, I instead use the Orange County, CA area as the environment since it is roughly rectangular. My interest is simply to minimize peculiar boundary effects that can occur if the area has a more unusual shape. I then use actual data for the blocks in the county as the basis for the simulation. I use the actual residential population and the location of residents for various demographic characteristics in blocks based on data from the 2010 U.S. Census and the 2008-12 American Community Survey 5-year estimates that are used to create an estimate of who are "offenders". I include information on the actual location of certain types of business establishments based on Reference USA Historical Business Data for the location of all businesses in 2012 (Infogroup 2015). For simplicity, I do not include guardians in the model.

For the primary simulations, crime is assumed to occur only at certain types of locations. For these simulations, I used retail establishments and restaurants as the only assumed possible targets for crime events (with a small error term of 2.8% to avoid a deterministic relationship in the subsequent models).[1] These crime events can be considered as most similar in spatial pattern to robberies or aggravated assaults. In some of the simulations, I define the entire population as

[1] Note that the results generalize to the use of any types of locations as possible crime locations. By selecting establishments that are relatively geographically clustered, the results are simplified somewhat compared to selecting targets that are more ubiquitous in the environment. Nonetheless, this selection mirrors the existing empirical literature detecting a relative clustering of crime events in the environment (Weisburd, Bernasco, and Bruinsma 2009; Weisburd, Groff, and Yang 2012).

possible offenders. In other simulations, I define only certain types of persons as offenders (disproportionate offending). How offenders are defined is not crucially important; for the purposes of the present simulation analyses the main point is that they are a subset of the total population, and therefore will likely exhibit more spatial clustering than the general population. I constructed a measure of offenders based on the demographic characteristics of residents living in a block that prior research indicates may be associated with greater likelihood of offending: 1) single parent households; 2) households below 125% of the poverty level; 3) new residents in last 5 years; 4) racial/ethnic heterogeneity based on Herfindahl Index[2]; 5) unemployed; 6) persons without at least a bachelor's degree of education; 7) non-immigrants; 8) renters; 9) those aged 15 to 29. Categories 1-5 are based on social disorganization theory, categories 6-8 are based on the general theory of crime (Gottfredson and Hirschi 1990) and the possibility that such persons have a shorter time horizon, and category 9 captures the prime offending ages based on the age/crime curve. Note that the assumption for generating these values is only that persons in each of these groups are more likely to be offenders, and not that particular individuals are offenders, and these values are simply used to compute a plausible estimate of offenders for the simulation model. I then computed the proportion of persons in a block in each of these categories, computed the mean of these proportions, and multiplied this by the block population to get a count of potential offenders (based on the assumption of disproportionate offending).

For simulating the crime data, I then compute the Euclidean distance from the block centroid of each target to the block centroids containing offenders, and compute the probability of the offenders committing a crime at the target(s) in this block based on plugging the distance value into the exponential distance decay function. This value is multiplied by the number of

[2] The Herfindahl ranges from 0 to .8, and it is assumed here that this value represents the proportion of offenders when calculating the number of offenders.

targets in the block, and is therefore the estimate of crime events from these offenders. The same computations are then conducted for all other offenders in all blocks in the simulation area. These estimated crimes at each block are then summed as the estimate of the number of crimes in a block when assuming that offenders engage in unlimited offending. To simulate offending assuming that offenders engage in zero sum behavior, the approach again first calculates the exponential decay based on distance from the offenders' block to every other block with a target(s). These exponential decay values are then summed for the offenders on a block, and then each exponential decay value is divided by this summed value. The result is that the exponential decays now will always sum to 1, and therefore capture the offender's preferred crime locations assuming that there is a set amount of offending. The simulated crime levels in each simulation condition are multiplied by a specific constant to give them all a similar metric.

The impact of altering the relative spatial clustering of crime targets compared to offenders could also be explored in future research. This is outside the scope of the current study whose goal is narrower. Trivially, one can see that the relative spatial concentration of targets versus offenders will impact the degree to which crime is concentrated. It will also impact the conclusions researchers might reach about whether measures of targets or offenders better explain the concentration of crime based on a measure of variance explained. As the simulation demonstrates, such conclusions only provide specific information.

I simulated four different scenarios of how crime is generated, in which I manipulate who are offenders (everybody vs. disproportionate likelihood) and offender behavior (unlimited offending vs. satiation). I assume that offenders target crime locations based on a distance decay function from where they live as an exponential decay with the beta parameter set to a value of -.5 (this assumes that the probability of selecting the location decreases 50 percent for every mile). In ancillary analyses below, I also simulated data based on beta values of .25 and .75. The four simulated scenarios are as follows (and shown in Table 1):

- Scenario 1: certain types of people are more likely to be offenders. I use the offender measure just described. The only possible targets in this model are certain types of business establishments (retail and restaurants). I use an exponential distance decay based on the findings of the journey to crime literature to simulate where offenders will commit crimes. Offenders will increase their number of offenses proportionately (unlimited) if there are more targets nearby.
- Scenario 2: same as scenario 1, except that offenders are assumed to commit a certain number of offenses, and thus will not commit more offenses in a more target rich environment (i.e. zero sum behavior).
- Scenario 3: Similar to scenario 1, except that now everybody in the population is a potential offender (i.e., there is not differential propensity to offend); however, similar to scenario 1, this is not zero sum behavior, as more targets will result in more offenses.
- Scenario 4: Similar to scenario 2, except that now everybody in the population is a potential offender (i.e., there is not differential propensity to offend); but assumes zero sum behavior by offenders.

<<<Table 1 about here>>>

After simulating the data, I then constructed a small set of aggregated variables for the analyses. First, for the dependent variable, I aggregated the simulated crime events to three different units of analysis: 1) blocks (micro units); 2) tracts (meso units that approximate neighborhoods); 3) cities (macro units). Next, for the independent variables I aggregated the summed count of *retail and restaurant establishments* as a measure of crime targets. I constructed two different measures of crime offenders. One measure is simply the *population* in the unit (which is used in the models in which crime is simulated assuming that everyone is equally likely to be an offender). The other offender measure uses the information described earlier to create a measure of those with disproportionate likelihood of being offenders. For the block-level models, these two variables are constructed as an exponential decay surrounding the focal block, to capture the expected mobility of offenders. Thus, the count of offenders in the focal block, and each block surrounding the focal block, are multiplied by the exponential decay function and then summed to compute an estimate of offenders surrounding a particular block. Only occasional studies have adopted such an explicit approach to measuring potential offenders in the surrounding area (Hipp 2016).

For the tract- and city-level models these offender measures are simply aggregated to the tract or city based on their block residence (ignoring potential movement for crime offenses). This mimics the common strategy in ecological analyses. As another strategy, I aggregated the block-level exponential decay offender measures to tracts or cities; although this is not a typical strategy in meso or macro analyses, I demonstrate how the results obtained are improved if one actually uses a measure that includes expected mobility by offenders. Finally, I included an interaction between the targets measure and the offenders measure, to capture how the presence of more offenders near target locations might impact the spatial distribution of crime.

The summary statistics for the variables used in the analyses are presented in Table 2. We are particularly interested in the skewness measure for each variable, as it gives a sense of the degree of clustering across the geographic units for each measure. The count of crime per block is more than twice as skewed when offenders engage in unlimited offending regardless of the opportunities in the nearby environment compared to the scenarios where offenders engage in a satiation process in which they offend the same amount regardless of the opportunities in the nearby environment. As another way to assess the geographic concentration, I adopted the typical approach in crime concentration studies and computed the percentage of crime events occurring in the top 5% of blocks: this value, regardless of whether assuming disproportionate or everybody offending, is 71% when assuming that offenders engage in zero sum offending behavior, and 54% when assuming that offenders engage in unlimited offending. These values are similar to that observed in empirical studies. For comparison, using crime data for 2011-15 from the Southern California Crime Study (Kubrin and Hipp 2016), I find that the top 5% of the blocks across these five years contain 68% of the robberies and 55% of the aggravated assaults, indicating that the simulated crime data exhibits similar spatial clustering (Hipp and Kim 2017). This greater skew for unlimited offending is also present when aggregating crime to tracts (although the gap is narrower), and the difference is nearly gone when aggregating to the largest units of cities. There is greater skew when measuring offenders based on disproportionate offending versus when assuming everyone is equally likely to be an offender (skew values of .23 vs. .12). This difference in concentration is effectively gone when aggregating to larger units. Finally, it is notable that there is much greater skew at the tract level when aggregating offenders based on their expected mobility patterns (buffer) compared to aggregating them based on their residence. This greater skew when accounting for mobility patterns is weaker when aggregating to cities.

<<<Table 2 about here>>>

Results

Aggregating the data to micro-level units

I begin with the models of data aggregated to blocks, presented in Table 3. In the top panel (panel A) the data is based on the simulations using disproportionate offending. Model 1 is the “full” model, as it includes the measures of number of targets in the block, number of offenders in the surrounding buffer with an exponential decay, and the interaction of these two measures. In this model, offenders engage in unlimited offending (they offend more as the target environment becomes richer). As seen by the extremely high R-square (.997) these three variables effectively explain the location of crime. This highlights that if researchers indeed knew where offenders lived, the distance decay function with which they offend, and offenders engaged in unlimited offending, that creating an interaction with the location of targets would effectively explain where crime occurs. The interaction term explains nearly all of the variance (given the very large t-value). In an ancillary model that did not include the interaction term, the R-square was notably lower (.82), indicating that it is *simultaneous* information on offenders and targets that is important for explaining the location of crime in these simulated models.

<<<Table 3 about here>>>

In the second column, I adopt the approach of some micro scholars by only including a measure capturing targets: this model explains 81% of the variance in where crime occurs. This is quite effective, and some might conclude that one therefore need only focus on the location of targets to understand the location of crime. Nonetheless, it is worth noting that the proper model (model 1) explained even more of the variance, and that relying on variance explained in assessing models does not necessarily capture the etiology of crime. Furthermore, this very high R-square in column 2 is much higher than what is typically found in the empirical literature, highlighting that this simulated crime model is much simpler than what actually occurs in a real world environment (not to mention the assumption of no mobility by targets in this simulation).

The third column shows that only accounting for offenders in the surrounding area (and ignoring the presence of targets) does a particularly poor job (explaining just 3% of the variance).

In columns 4-6 are presented the same three models for the simulated data in which it is assumed that offenders engage in zero sum activity (that is, they offend the same amount regardless of how rich the nearby target environment is). In column 4, we see that the “full” model now does not perform nearly as well as in column 1 when offenders engaged in unlimited offending, as it explains 48% of the variance. Thus, how offenders behave in response to the offending opportunities in the environment has very strong consequences for the performance of the model. This is notable given the paucity of studies on how offenders actually behave across such varying circumstances. In column 5 we see that a model including just information on where targets are located performs nearly as well as the “full” model (explaining 47% of the variance), but again does not do nearly as well as in the model in which there is unlimited offending behavior. Once again, the model only including the presence of offenders in the surrounding buffer does quite poorly.

In panel B of Table 3 I present the results for the simulations in which it is assumed that everybody is equally likely to offend. In these models, I include a measure of persons in the surrounding buffer (rather than “offenders”) given that all persons are potential offenders in this model. Once again, the “full” model in column 1 effectively explains the location of crime, with an R-square near 1 when it is assumed that offenders engage in unlimited offending. The variable capturing the interaction of targets and nearby population again effectively explains the location of crime. An ancillary model that did not include the interaction term explained less of the variance (.86), highlighting the importance of simultaneously accounting for *both* offenders and targets. In column 2, we see that only including the presence of targets explains a high percentage of the variance (84%). This is an even higher percentage than in the models with disproportionate offending, as the total population is even less spatially clustered than were the offenders in the panel A models. The model with just offenders again explains effectively none of the variance.

In column 4, the full model is estimated for the scenario in which everyone are potential offenders, but engage in zero sum offending regardless of the environment. We see that the variable for targets is the strongest predictor, and the measures of persons and the interaction variable add little explanatory power. Thus, in column 5 the model with just the targets variable explains effectively the same amount of variance as the full model in column 4.

Aggregating the data to meso-level units

Table 4 presents the results for the models using data aggregated to neighborhoods (tracts). These models capture disproportionate unlimited offending (panel A), disproportionate zero sum offending (panel B), everybody unlimited offending (panel C), and everybody zero sum offending (panel D). There are some key findings to highlight. The "full" models in the simulation with unlimited offending behavior (the first column of panels A and C) consistently have lower variance explained compared to the block-level models. This is not surprising, as these models are not aggregating to the proper unit of analysis at which the true model operates. Thus, the R-square is 79% when assuming that offenders engage in unlimited offending, compared to effectively 100% in the block-level model. However, it is interesting to note that the variance explained of the models with zero sum offending behavior (the first column of panels B and D) is actually higher in these tract-aggregated models than the block models, highlighting that a different strategy would be needed to estimate block-level models in this circumstance.

<<<Table 4 about here>>>

Second, there are sharp differences in the models if we aggregate offenders to the tract level based on their expected mobility behavior, rather than just based on their residence. When we aggregate offenders to the tract level based on their residence, they explain very little variance in the models (the third column in each of the panels), which parallels the findings from the block-level models. When we aggregate offenders to tracts based on expected mobility behavior, we find that the R-squares for the full models are notably higher in column 4 of each panel (especially when offending is assumed to be unlimited) compared to column 1 when aggregating based on residence. As a consequence, the models with just offenders in them (but accounting for expected mobility) explain much more of the variance compared to when aggregating based on residence (column 5 versus column 3 in each panel). The possibility of accounting for potential mobility behavior when aggregating measures to larger units has not been considered in the literature, but seems promising based on these results.[3]

Aggregating the data to macro-level units

Table 5 presents the models in which the data are aggregated to the macro units of cities. There are 42 cities in the simulated environment. One key finding is that the full R-squares are even higher in these models compared to the tract-level models. This is not surprising, as typically when aggregating to larger units one will obtain this result (Hannan 1991). Nonetheless, the variance explained is still less than in the block-level statistical models, which were specified based on the crime generating model. A second very notable finding in these models using highly aggregated data is that a measure of offenders (even one that ignores the mobility of offenders) explains nearly as much of the variance as the "full" model. This is very different from the micro model where offenders alone explained almost no variance in the block-

[3] I also estimated models with the data aggregated to block groups, given that this meso-level geographic unit is occasionally used rather than census tracts. The pattern of results was the same, with the R-squares generally a little bit higher than those for tracts with disproportionate offending, and a little bit lower with everybody as offenders.

level models, and where offenders only explained about 10% of the variance in the tract-level models. This measure of offenders explains fully 90% of the variance in these macro-level models when assuming unlimited offending behavior by offenders, and about 97% when assuming zero sum offending behavior. This latter finding is because offenders do not respond to the presence of more nearby targets by offending more often, and therefore the nearby location of targets is less important for understanding the macro-level crime patterns. These results are notable, as the simulated crime generating process operated entirely at the micro level.

<<<Table 5 about here>>>

A second key finding is that accounting for potential mobility behavior of offenders when aggregating to cities—rather than simply aggregating based on residence—again improves the model fit when assuming unlimited offending behavior. The R-square for the models with just offenders is .98, indicating that simply knowing where offenders live, and where they are likely to travel, effectively explains the level of crime across macro units even when the crime process entirely occurs at the micro level. However, there is no gain when accounting for offender mobility in these macro models when assuming zero sum behavior by offenders. Thus, understanding how offenders are expected to behave depending on the richness of the targets in an area is of notable importance for understanding the behavior of these macro models.

Ancillary simulations

I assessed the robustness of the simulation results in two fashions. First, given that there is uncertainty about the functional form of the distance decay function for offenders, as well as what is the proper value of the beta coefficient if it is indeed an exponential decay, I tested two other possible beta values. I therefore simulated data based on the assumption that the beta value is -.25, -.50 (the earlier results), or -.75. The pattern of results remained very similar in each case, with the R-squares generally falling very slightly as the beta increased (indicating a steeper decay function). So the shape of this function does not impact the results.

Second, I briefly assessed the sensitivity of the results when allowing for mobile targets. There are various ways that mobile targets could be incorporated. One extreme strategy would be a model in which regardless of where targets go, they tend to only be victimized at specific locations; this is closer to what some of the micro crime and place models posit, and would yield very similar results to the earlier simulations with immobile targets. At the other extreme would be a model allowing targets to be victimized nearly everywhere, which would yield simulated data with little relation to crime patterns that are typically observed. I therefore instead simply altered the earlier simulation by using the existing targets and allowing them to be targeted in nearby blocks based on an exponential decay capped at ¼ mile (beta = -.5). This allows comparing a relatively modest change to the existing simulation setup to approximate the impact of incorporating mobile targets. In these results, the R-squares in the block models predictably fell (to about .78 in the full model with unlimited offending and about .70 for zero-sum offending). In the tract models, the R-squares fell somewhat with disproportionate offending, but not with everybody offending. And there were few differences in the city models. Thus, the general pattern of results remained similar. The R-squares for these ancillary models are displayed in Table A1 in the Appendix.

Discussion

This study has simulated crime data from a simple stylized model in which targets are fixed in space, and offenders are distributed across the spatial landscape and exhibit a distance decay pattern in their offending behavior. The results have provided insights into what is learned by ecological studies of crime that aggregate crime and various measures to micro, meso, or macro geographic units. By utilizing a simple model of crime behavior, the study demonstrated some key insights that can be learned. I next highlight some key results.

If we know: 1) who are offenders; 2) how far offenders tend to travel; and 3) where targets are located, we can then build a statistical model that effectively explains the location of crime across micro units. A future challenge would be extending this model to targets that move about: if targets are attracted to certain locations based on a distance decay function, then this information could be used to simulate the number of targets going to a particular location (Hipp 2016). The results of the simulation in the present study highlighted that accounting for the spatial movement of offenders is also important for explaining the location of crime. Whereas existing ecological literature frequently include measures that act as proxies for both offenders and guardians, and possibly even targets (Hipp 2007b; Chamberlain and Hipp 2015; Hipp and Bates 2017), they rarely account for potential mobility behavior. Thus, scholars constructing measures that proxy for offenders typically do not take into account the impact of offenders' spatial movement when offending. This insight may also be useful for incorporating into crime forecasting models.

Although it appeared in these simulations that a measure of targets will typically explain the largest portion of variance in micro models, this is simply because of the relative spatial clustering of targets compared to the spatial clustering of offenders (as well as the tendency of offenders to move about). The ancillary simulations with mobile targets showed similar results, highlighting that if certain locations are particularly likely to attract crime, this will result in target locations explaining a relatively higher amount of variance explained given that they will tend to be more spatially clustered than potential offenders. The simulations nonetheless showed that knowing where offenders live, and their typical distances traveled to offending, greatly improved the model performance. It was the *combination* of targets and nearby offenders that best explained the location of crime. It was interesting to note that the explanatory power of targets alone weakened relatively when aggregating to larger units. Recall that the simulated model of crime events was still entirely based on micro processes in these statistical models aggregated to larger units. Instead, in macro units the measure of offenders alone explained effectively all of the variance across cities. This highlights that variance explained is not the same as capturing causal processes, and therefore the two concepts should not be conflated. However, for city policymakers interested in creating an estimate of how crime levels would be expected to change in the future, this insight could be useful.

Whereas statistical models aggregating data to larger units are certainly feasible, one would still want to consider the underlying spatial process for the aggregation. The results showed that accounting for the typical spatial movement of offenders before aggregating to larger units produces better results based on explanatory power. If one were interested in testing macro-level theories regarding crime, and yet still accounting for micro-processes, the approach demonstrated here of aggregating smaller units which incorporate potential offender movement appears to be a reasonable strategy that has not been considered in the literature. It is worth highlighting that in these models the entire process was theorized to occur at the micro level. So one should not over-interpret these results, as there will be different consequences if the true model also includes meso- or macro- causal processes. The goal here was to illustrate what we can expect to observe if all processes occur only at the micro level.

We also learned that there is a need to better understand offender behavior. When offenders are in a target-rich environment, do they simply offend more often? Or is there a satiation effect? This is a non-trivial issue, as the simulation results shown here highlight that there are very different implications depending on which behavior characterizes offender activity. If a satiation effect characterizes offender behavior, then the spatial co-location of offenders and targets has a weaker impact on the location of crime. But if offenders engage in unlimited offending, then this spatial co-location has very strong effects. The true behavior of offenders likely falls somewhere between these two extremes, but it will be useful for studies to gather empirical evidence of this behavior.

There are limitations to acknowledge for this study. I employed a simple model of crime behavior with the goal of determining what insights it could provide. More complicated simulation models are certainly possible, but the goal here was to provide insights based on a simple model. While the primary models focused on targets that did not move, the simulation with mobile targets implemented a simple model of mobility. More complicated models of target behavior are a useful direction for future research. Another limitation is that the simulation did not include guardians. Again, whereas including guardians would impact where crime occurs—by operating as a damper on crime incidents at locations with higher concentrations of guardians—how much further it would impact the results needs to be explored. We might expect that the presence of guardians would enter such simulated models in a multiplicative function, which highlights the need to consider the crime generating process when specifying statistical models; studies typically estimate additive linear models, but that strategy is arguably not really appropriate given this multiplicative model of the generation of crime. Another limitation is that the simulation model was built on a single environmental backcloth. The goal of the presented results was to show results that are obtained from a plausible model of offender and target behavior based on an environmental backcloth that exists in a typical urban environment in the Sunbelt area of the United States. Future explorations could assess the consequences when using environments with different relative levels of spatial clustering for targets or offenders, and systematically assessing how varying levels of spatial clustering for either offenders or targets impacts their relative contribution to R-square.

In conclusion, this study used a stylized simulation model of crime patterns based on offenders, their typical mobility patterns when committing offenses, and immobile targets, and demonstrated the consequences when ecological studies of crime aggregate measures to micro-, meso-, or macro-level units. Even in this simple stylized simulation model, although the measure of targets is important, knowing where offenders live, and their typical distances traveled to offending, greatly improved the statistical model performance. Furthermore, it was notable that the explanatory power of targets alone was much weaker when aggregating to larger units despite the fact that the simulated model of crime events was entirely based on micro processes. This highlights that variance explained is not the same as capturing causal processes, and therefore the two concepts should not be conflated. A perhaps unexpected insight is that what offender behavior looks like in target-rich versus target-poor environment is crucially important, despite the fact that there is little empirical evidence regarding this point. Finally, an important result is that when aggregating measures to meso- or macro- geographic units, accounting for the typical spatial movement of offenders before aggregating to these larger units produces better results based on explanatory power, highlighting that researchers would be well-served to consider the movement of offenders when estimating ecological models of crime.

References

Barker, Mary. 2000. The criminal range of small-town burglars. In *Profiling Property Crimes*, edited by D. Canter and L. J. Alison. Aldershot: Ashgate.
Bernasco, Wim. 2010. A Sentimental Journey to Crime: Effects of Residential History on Crime Location Choice. *Criminology* 48 (2):389-416.
Bernasco, Wim, and Richard L. Block. 2009. Where Offenders Choose to Attack: A Discrete Choice Model of Robberies in Chicago. *Criminology* 47 (1):93-130.
Blau, Peter M., and Joseph E. Schwartz. 1984. *Crosscutting Social Circles: Testing a Macrostructural Theory of Intergroup Relations*. New York: Academic.
Boessen, Adam, and John R. Hipp. 2015. Close-ups and the scale of ecology: Land uses and the geography of social context and crime. *Criminology* 53 (3):399-426.
———. 2018. Parks as Crime Inhibitors or Generators: Examining Parks and the Role of their Nearby Context. *Social Science Research* 76 (1):186-201.
Brantingham, Patricia L., and Paul J. Brantingham. 1993. Nodes, Paths and Edges: Considerations on the Complexity of Crime and the Physical Environment. *Journal of Environmental Psychology* 13 (1):3-28.
———. 1995. Criminality of Place: Crime Generators and Crime Attractors. *European Journal on Criminal Policy and Research* 3 (3):5-26.
———. 2008. Crime Pattern Theory. In *Environmental Criminology and Crime Analysis*, edited by R. Wortley and L. Mazerolle. Portland, OR: Willan Publishing.
Brantingham, Paul J., and Patricia L. Brantingham. 1984. *Patterns in Crime*. New York: MacMillan.
Bursik, Robert J. 1988. Social Disorganization and Theories of Crime and Delinquency: Problems and Prospects. *Criminology* 26 (4):519-551.
Chamberlain, Alyssa W., and Lyndsay N. Boggess. 2016. Relative Difference and Burglary Location: Can Ecological Characteristics of a Burglar's Home Neighborhood Predict Offense Location? *Journal of Research in Crime and Delinquency* Forthcoming:1-35.
Chamberlain, Alyssa W., and John R. Hipp. 2015. It's All Relative: Concentrated disadvantage within and across neighborhoods and communities, and the consequences for neighborhood crime. *Journal of Criminal Justice* 43 (6):431-443.
Cohen, Lawrence E., and Marcus Felson. 1979. Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review* 44 (4):588-608.
Deryol, Rustu, Pamela Wilcox, Matthew Logan, and John Wooldredge. 2016. Crime Places in Context: An Illustration of the Multilevel Nature of Hot Spot Development. *Journal of Quantitative Criminology* 32 (2):305-325.
Felson, Marcus, and Rachel Boba. 2010. *Crime and Everyday Life*. Fourth Edition ed. Thousand Oaks, CA: Sage.
Golden, Reid M., and Steven F. Messner. 1987. Dimensions of Racial Inequality and Rates of Violent Crime. *Criminology* 25 (3):525-541.
Golledge, Reginald G., and Robert J. Stimson. 1997. *Spatial behavior: A geographic perspective*. New York, NY: The Guilford Press.
Gottfredson, Michael R., and Travis Hirschi. 1990. *A general theory of crime* Stanford, CA: Stanford.

Hannan, Michael T. 1991. *Aggregation and Disaggregation in the Social Sciences*. Lexington, MA: D.C. Heath.
Hipp, John R. 2007a. Block, Tract, and Levels of Aggregation: Neighborhood Structure and Crime and Disorder as a Case in Point. *American Sociological Review* 72 (5):659-680.
———. 2007b. Income Inequality, Race, and Place: Does the Distribution of Race and Class within Neighborhoods affect Crime Rates? *Criminology* 45 (3):665-697.
———. 2016. General theory of spatial crime patterns. *Criminology* 54 (4):653-679.
Hipp, John R., and Christopher J. Bates. 2017. Egohoods: Capturing Change in Spatial Crime Patterns. In *Oxford Handbook of Environmental Criminology*, edited by G. J. N. Bruinsma and S. D. Johnson. New York: Oxford.
Hipp, John R., and Young-an Kim. 2017. Measuring Crime Concentration across Cities of Varying Sizes: Complications Based on the Spatial and Temporal Scale Employed. *Journal of Quantitative Criminology* 33 (3):595-632.
Hipp, John R., George E. Tita, and Lyndsay N. Boggess. 2009. Inter- and Intra-group violence: Is violent crime an expression of group conflict or social disorganization? *Criminology* 47 (2):521-564.
Infogroup. 2015. Reference USA Historical Business Data, edited by Infogroup. Papillion, NE: Reference USA.
Krivo, Lauren J., and Ruth D. Peterson. 1996. Extremely Disadvantaged Neighborhoods and Urban Crime. *Social Forces* 75 (2):619-648.
Kubrin, Charis E., and John R. Hipp. 2016. Do Fringe Banks Create Fringe Neighborhoods? Examining the Spatial Relationship between Fringe Banking and Neighborhood Crime Rates. *Justice Quarterly* 33 (5):755-784.
Lammers, Marre, Barbara Menting, Stijn Ruiter, and W. I. M. Bernasco. 2015. Biting Once, Twice: The Influence of Prior on Subsequent Crime Location Choice. *Criminology* 53 (3):309-329.
Lawson, Andrew B. 2006. *Statistical Methods in Spatial Epidemiology*. Second ed, *Wiley Series in Probability and Statistics*. New York: Wiley.
Lentnek, Barry, Stanley R. Lieber, and Ira Sheskin. 1975. Consumer behavior in different areas. *Annals of the Association of American Geographers* 65 (4):538–545.
Merton, Robert K. 1968. *Social Theory and Social Structure*. New York: The Free Press.
Messner, Steven F., Suzanne McHugh, and Richard B. Felson. 2004. Distinctive Characteristics of Assaults Motivated by Bias. *Criminology* 42 (3):585-618.
Nawrocki, David, and William Carter. 2010. Industry competitiveness using Herfindahl and entropy concentration indices with firm market capitalization data. *Applied Economics* 42 (22):2855-2863.
O'Brien, Daniel Tumminelli, and Christopher Winship. 2016. The Gains of Greater Granularity: The Presence and Persistence of Problem Properties in Urban Neighborhoods. *Journal of Quantitative Criminology*.
Openshaw, Stan, and P.J. Taylor. 1981. The Modifiable Areal Unit Problem. In *Quantitative Geography: A British View*, edited by N. Wrigley and R. J. Bennett. London: Routledge and Kegan Paul.
Palmer, John R.B., Thomas J. Espenshade, Frederic Bartumeus, Chang Y. Chung, Necati Ercan Ozgencil, and Kathleen Li. 2013. New Approaches to Human Mobility: Using Mobile Phones for Demographic Research. *Demography* 50 (3):1105-1128.

Reiss, Albert J. Jr. 1967. Place of residence of arrested persons compared with the place where the offence charged in arrest occurred for Part I and II offences. In *A Report to the President's Commission on Law Enforcement and Administration of Justice*. Washington, D.C.: U.S. Government Printing Office.

Rengert, George F., Alex R. Piquero, and Peter R. Jones. 1999. Distance Decay Reexamined. *Criminology* 37 (2):427-445.

Rosenfeld, Richard, Steven F. Messner, and Eric P. Baumer. 2001. Social Capital and Homicide. *Social Forces* 80 (1):283-309.

Rossmo, D. Kim. 2000. *Geographic Profiling*. Boca Raton: CRC Press.

Sampson, Robert J., and W. Byron Groves. 1989. Community Structure and Crime: Testing Social-Disorganization Theory. *American Journal of Sociology* 94 (4):774-802.

Schuerman, Leo, and Solomon Kobrin. 1986. Community Careers in Crime. *Crime and Justice* 8:67-100.

Shaw, Clifford, and Henry D. McKay. 1942. *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press.

Taylor, Ralph B. 1997. Social Order and Disorder of Street Blocks and Neighborhoods: Ecology, Microecology, and the Systemic Model of Social Disorganization. *Journal of Research in Crime and Delinquency* 34 (1):113-155.

———. 2015. *Community Criminology: Fundamentals of Spatial and Temporal Scaling, Ecological Indicators, and Selectivity Bias*. New York: New York University Press.

Vandeviver, Christophe, Stijn Van Daele, and Tom Vander Beken. 2015. What Makes Long Crime Trips Worth Undertaking? Balancing Costs and Benefits in Burglars' Journey to Crime. *British Journal of Criminology* 55:399-420.

Weisburd, David, Wim Bernasco, and Gerben Bruinsma, eds. 2009. *Putting Crime in Its Place: Units of Analysis in Spatial Crime Research*. New York: Springer Verlaag.

Weisburd, David, Elizabeth Groff, and Sue-Ming Yang. 2012. *The Criminology of Place*. New York: Oxford.

Tables and Figures

Table 1. Four different simulated scenarios

	Who are Offenders?	**Offender behavior**
Scenario 1	Disproportionate	Unlimited
Scenario 2	Disproportionate	Zero sum
Scenario 3	Everybody	Unlimited
Scenario 4	Everybody	Zero sum

Table 2. Summary statistics of simulated measures aggregated to blocks, tracts, or cities

	Blocks				Tracts				Cities		
Crime counts from different simulations	Mean	S.D.	Skew		Mean	S.D.	Skew		Mean	S.D.	Skew
Offenders - satiation	97.2	342.6	6.31		2613	2656	2.43		36268	41286	2.03
Offenders - unlimited	97.0	320.0	15.72		2608	3541	3.95		36207	51131	2.14
Persons - satiation	97.8	347.9	6.44		2629	2665	2.45		36498	39726	1.88
Persons - unlimited	97.0	315.3	15.27		2609	3481	4.01		36217	49573	2.08
Independent variables											
Offenders in buffer (/1000) *	2.5	1.2	0.23		1.3	1.0	2.58		18.4	24.7	2.26
Population in buffer (/1000) *	7.2	3.2	0.12		3.9	2.7	2.74		53.9	69.7	2.18
Offenders - residence (/1,000,000)					1.3	0.6	1.00		18.1	19.8	2.06
Persons - residence (/1,000,000)					3.9	1.7	1.44		54.8	56.2	1.89
Targets	1.6	4.9	12.52		44	54	3.86		615	644	1.38
N	15,676				582				42		

*Note: * are per 1 million for tracts and cities*

Table 3. Models with data aggregated to blocks

Panel A. Disproportionate offending

	Disproportionate, unlimited			Disproportionate, zero sum		
	Full	Just targets	Just offenders	Full	Just targets	Just offenders
R-square	0.997	0.814	0.027	0.483	0.475	0.005
Targets	-0.4	58.8		37.2	48.1	
	-(6.39)	(261.95)		(37.90)	(119.15)	
Offenders	0.8		43.6	8.2		20.4
	(6.83)		(20.69)	(4.74)		(8.93)
Offenders X Targets	22.9			4.2		
	(947.46)			(12.08)		

Panel B. Everybody offending

	Everybody, unlimited			Everybody, zero sum		
	Full	Just targets	Just offenders	Full	Just targets	Just offenders
R-square	0.997	0.843	0.023	0.475	0.473	0.003
Targets	-0.5	59.0		43.0	48.8	
	-(7.39)	(290.46)		(39.15)	(118.65)	
Persons	0.3		15.2	2.7		6.0
	(6.56)		(19.29)	(4.04)		(6.84)
Persons X Targets	7.9			0.8		
	(881.38)			(5.55)		

Note: T-values in parentheses. N = 15,676 blocks

Table 4. Models with data aggregated to tracts

Panel A. Disproportionate offending, unlimited offending

	Aggregated by residence			Aggregated by buffer	
	Full	Just targets	Just offenders	Full	Just offenders
R-square	0.786	0.769	0.089	0.883	0.595
Targets	49.5	57.1		38.1	
	(22.03)	(43.97)		(25.69)	
Offenders	461.0		1800.0	1300.0	2800.0
	(3.40)		(7.51)	(18.37)	(29.17)
Offenders X Targets	3.35			1.37	
	(3.26)			(4.19)	

Panel B. Disproportionate offending, zero sum offending behavior

	Aggregated by residence			Aggregated by buffer	
	Full	Just targets	Just offenders	Full	Just offenders
R-square	0.724	0.693	0.124	0.731	0.398
Targets	38.6	40.6		35.5	
	(20.20)	(36.17)		(21.02)	
Offenders	807.0		1600.0	690.7	1700.0
	(7.00)		(9.07)	(8.38)	(19.57)
Offenders X Targets	0.09			-0.46	
	(0.10)			-(1.24)	

Panel C. Everybody offending, unlimited offending					
	Aggregated by residence			Aggregated by buffer	
	Full	Just targets	Just offenders	Full	Just offenders
R-square	0.810	0.801	0.047	0.892	0.589
Targets	49.7	57.3		39.9	
	(23.18)	(48.39)		(28.23)	
Persons	42.1		436.9	426.6	991.7
	(0.97)		(5.33)	(17.07)	(28.85)
Persons X Targets	1.31			0.41	
	(3.83)			(3.91)	

Panel D. Everybody offending, zero sum behavior					
	Aggregated by residence			Aggregated by buffer	
	Full	Just targets	Just offenders	Full	Just offenders
R-square	0.720	0.698	0.086	0.718	0.366
Targets	39.4	40.9		37.4	
	(19.78)	(36.59)		(21.41)	
Persons	233.8		452.8	189.0	598.4
	(5.80)		(7.37)	(6.12)	(18.32)
Persons X Targets	0.04			-0.17	
	(0.12)			-(1.30)	

Note: T-values in parentheses. N = 582 tracts

Table 5. Models with data aggregated to cities

Panel A. Disproportionate offending, unlimited offending

	Aggregated by residence			Aggregated by buffer	
	Full	Just targets	Just offenders	Full	Just offenders
R-square	0.919	0.869	0.904	0.982	0.977
Targets	26.6	74.0		13.4	
	(2.26)	(16.27)		(3.10)	
Offenders	993.8		2500.0	1700.0	2000.0
	(1.67)		(19.45)	(8.62)	(41.62)
Offenders X Targets	0.28			0.02	
	(1.60)			(0.29)	

Panel B. Disproportionate offending, zero sum offending behavior

	Aggregated by residence			Aggregated by buffer	
	Full	Just targets	Just offenders	Full	Just offenders
R-square	0.971	0.902	0.968	0.968	0.944
Targets	10.9	60.9		24.5	
	(1.93)	(19.21)		(5.26)	
Offenders	1600.0		2100.0	827.7	1600.0
	(5.62)		(34.88)	(3.92)	(25.89)
Offenders X Targets	0.05			0.10	
	(0.54)			(1.30)	

Panel C. Everybody offending, unlimited offending					
	Aggregated by residence			Aggregated by buffer	
	Full	Just targets	Just offenders	Full	Just offenders
R-square	0.917	0.886	0.882	0.981	0.976
Targets	39.9	72.5		14.4	
	(3.36)	(17.66)		(3.12)	
Persons	96.6		827.5	557.3	703.0
	(0.51)		(17.26)	(7.82)	(40.31)
Persons X Targets	0.13			0.01	
	(2.26)			(0.42)	

Panel D. Everybody offending, zero sum behavior					
	Aggregated by residence			Aggregated by buffer	
	Full	Just targets	Just offenders	Full	Just offenders
R-square	0.968	0.914	0.963	0.958	0.930
Targets	14.2	59.0		27.8	
	(2.41)	(20.58)		(5.09)	
Persons	489.4		692.9	249.9	549.9
	(5.15)		(32.09)	(2.97)	(23.02)
Persons X Targets	0.02			0.03	
	(0.75)			(0.98)	

Note: T-values in parentheses. N = 42 cities

Appendix

Table A1. Summary of R-squares from models using different values of Beta for the exponential distance decay of offenders

Models with data aggregated to blocks						
Panel A. Disproportionate offending						
	Disproportionate, unlimited			Disproportionate, zero sum		
	Full	Just targets	Just offenders	Full	Just targets	Just offenders
Beta -.25	0.996	0.816	0.026	0.493	0.484	0.006
Beta -.50	0.997	0.814	0.027	0.483	0.475	0.005
Beta -.75	0.994	0.810	0.027	0.469	0.463	0.005
Mobile targets						
Beta -.25	0.783	0.640	0.021	0.710	0.690	0.004
Beta -.50	0.777	0.633	0.022	0.695	0.675	0.004
Beta -.75	0.768	0.626	0.022	0.677	0.657	0.004
Panel B. Everybody offending						
	Everybody, unlimited			Everybody, zero sum		
	Full	Just targets	Just offenders	Full	Just targets	Just offenders
Beta -.25	0.996	0.844	0.023	0.485	0.482	0.003
Beta -.50	0.997	0.843	0.023	0.475	0.473	0.003
Beta -.75	0.994	0.840	0.023	0.462	0.460	0.003
Mobile targets						
Beta -.25	0.780	0.656	0.019	0.690	0.681	0.002
Beta -.50	0.772	0.649	0.019	0.673	0.663	0.002
Beta -.75	0.762	0.640	0.019	0.653	0.644	0.002
Models with data aggregated to tracts						
Panel A. Disproportionate offending						
	Aggregated by residence			Aggregated by		
	Full	Just targets	Just offenders	Full	Just offenders	
Beta -.25	0.795	0.777	0.083	0.888	0.586	
Beta -.50	0.786	0.769	0.089	0.883	0.595	
Beta -.75	0.772	0.755	0.094	0.872	0.598	
Mobile targets						
Beta -.25	0.624	0.606	0.089	0.728	0.523	
Beta -.50	0.614	0.592	0.096	0.722	0.526	
Beta -.75	0.600	0.573	0.103	0.711	0.523	

Panel B. Everybody offending					
	Aggregated by residence			Aggregated by	
	Full	Just targets	Just offenders	Full	Just offenders
Beta -.25	0.739	0.711	0.117	0.752	0.415
Beta -.50	0.724	0.693	0.124	0.731	0.398
Beta -.75	0.703	0.666	0.133	0.701	0.377
Mobile targets					
Beta -.25	0.756	0.737	0.101	0.767	0.374
Beta -.50	0.741	0.717	0.109	0.750	0.367
Beta -.75	0.722	0.691	0.119	0.727	0.359

Models with data aggregated to cities

Panel A. Disproportionate offending					
	Aggregated by residence			Aggregated by	
	Full	Just targets	Just offenders	Full	Just offenders
Beta -.25	0.919	0.872	0.904	0.982	0.977
Beta -.50	0.919	0.869	0.904	0.982	0.977
Beta -.75	0.917	0.866	0.904	0.980	0.975
Mobile targets					
Beta -.25	0.896	0.854	0.884	0.972	0.968
Beta -.50	0.897	0.852	0.886	0.971	0.967
Beta -.75	0.898	0.851	0.887	0.968	0.965

Panel B. Everybody offending					
	Aggregated by residence			Aggregated by	
	Full	Just targets	Just offenders	Full	Just offenders
Beta -.25	0.963	0.896	0.960	0.967	0.948
Beta -.50	0.971	0.902	0.968	0.968	0.944
Beta -.75	0.978	0.908	0.975	0.968	0.939
Mobile targets					
Beta -.25	0.978	0.933	0.966	0.975	0.933
Beta -.50	0.982	0.933	0.972	0.973	0.931
Beta -.75	0.986	0.932	0.977	0.971	0.928