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***Egohoods as waves washing across the city: a new measure of “neighborhoods”***

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***Egohoods as waves washing across the city: a new measure of “neighborhoods”***

**Abstract**

Defining “neighborhoods” is a bedeviling challenge faced by all studies of neighborhood effects and ecological models of social processes. Although scholars frequently lament the inadequacies of the various existing definitions of “neighborhood”, we argue that previous strategies relying on non-overlapping boundaries such as block groups and tracts are fundamentally flawed. The approach taken here instead builds on insights of the mental mapping literature, the social networks literature, the daily activities pattern literature, and the travel to crime literature to propose a new definition of neighborhoods: egohoods. These egohoods are conceptualized as waves washing across the surface of cities, as opposed to independent units with non-overlapping boundaries. This approach is illustrated using crime data from nine cities: Buffalo, Chicago, Cincinnati, Cleveland, Dallas, Los Angeles, Sacramento, St. Louis, and Tucson. The results show that measures aggregated to our egohoods explain more of the variation in crime across the social environment than do models with measures aggregated to block groups or tracts. Results also suggest that measuring *inequality* in egohoods provides dramatically stronger positive effects on crime rates than when using the non-overlapping boundary approach, highlighting the important new insights that can be obtained by utilizing our egohood approach.

***Keywords:*** neighborhoods, crime, aggregation, spatial effects

**Bio**

**John R. Hipp** is an Associate Professor in the department 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*.

**Adam Boessen** is a doctoral candidate in the department of Criminology, Law and Society at the University of California Irvine. His primary research interests include the community of context of crime, spatial analysis, social networks, and juvenile delinquency. He uses quantitative methodologies to examine networks and neighborhood processes, the relationship between daily activities and crime, and the impact of incarceration on juvenile offenders. His work has been published in *Crime and Delinquency*, *Social Networks*, and *The Annals of the American Academy of Political and Social Science*.

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***Egohoods as waves washing across the city: a new measure of “neighborhoods”***

Neighborhoods have constituted a fundamental unit of interest for sociologists and criminologists for many years. Most prominently, the Chicago school conceptualized an ecological model in which neighborhoods constituted as units existing within this ecology (Park and Burgess 1921; Shaw and McKay 1942). In the latter part of the 20<sup>th</sup> Century, the “neighborhood effects” literature examined the consequences of neighborhood characteristics on outcomes such as delinquent behavior (Sampson 1997), educational achievement (Ainsworth 2002), low birth weight (Morenoff, 2003), and depression (Ross, 2000), to name just a few. Coincident with the advent of multilevel modeling, the neighborhood effects literature has conceptualized neighborhoods using varied ecological units such as blocks, block groups, tracts, zip codes, or neighborhoods as defined by the cities or residents themselves. One commonality of these studies is defining neighborhoods with *non-overlapping* boundaries.

Although defining the boundaries is arguably the most challenging issue for any neighborhood aggregation, there are numerous possible reasons why the non-overlapping boundary approach gained primacy. One reason may be due to the early Chicago researchers who frequently conceptualized neighborhoods in an urban village type model, or because naming certain neighborhoods lent them a degree of “realness”. Another possible reason the non-overlapping boundary approach gained primacy might be because it simplifies certain portions of the analysis (e.g., multilevel analyses). It may also have come about because there is something intuitive about this approach, as each of us believes we know the boundaries of our own neighborhood (thus, assuming that our own personal view of the boundaries is the only existing view).

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Perhaps the most succinct definition of a neighborhood was given by a worker for the Puerto Rican Labor Office, cited in Bursik and Grasmick (1993: 5): “A neighborhood is where, when you go out of it, you get beat up”. This definition emphasizes three key points: first, a neighborhood is a geographic area. This idea contrasts with some theorizing that modern society can be characterized by a general placelessness/boundlessness (Wellman and Leighton 1979). Second, a neighborhood represents a physical area that can have consequences for the amount of crime or other social processes that an individual might experience. The large body of scholarship testing for various neighborhood effects is testament to this possibility. And third, although it can be unclear when a person exactly crosses over a neighborhood boundary, we should not mistake these indistinct boundaries for the lack of something real. This fuzziness should therefore be taken into account.

We argue that explicitly accounting for these blurred boundaries is an appropriate conceptual strategy given that such fuzziness more accurately maps on to the social phenomena under study. This necessitates a move away from the focus on discrete, exclusive, non-overlapping geographic units that characterizes nearly all of the existing literature on neighborhood effects and processes. Our approach assumes that the effect of the structural characteristics on social processes such as crime rates is smoother across the social landscape than is implied by models employing units with non-overlapping boundaries. We therefore propose thinking about neighborhoods as waves washing across the surface of the city, rather than as non-overlapping units.

In this paper, we propose a new strategy for measuring neighborhoods, which we term *egohoods*. Essentially, egohoods are *overlapping* concentric circles that surround each block in the city. Thus, they do not conform to one’s *perception* of the neighborhood, but rather are

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explicitly tied to a particular spatial area. The fact that they are a constant geographic size, rather than constant population, is yet another distinction between egohoods and, say, census tracts.

We illustrate our approach for measuring ecological processes by predicting crime rates from nine cities. After briefly introducing ecological theories positing that structural characteristics affect neighborhood crime rates, we discuss the theoretical underpinnings of our egohoods approach and then explicitly describe how egohoods are constructed. After describing the data and methods for the study, we present the results. In the conclusion, we emphasize that this is a general approach that can be employed to gauge neighborhood processes regardless of the social phenomena under study.

## **Crime in neighborhoods**

### *The relationship between neighborhood structural characteristics and crime*

One of the most consistently employed ecological theories of crime is social disorganization theory (Bursik 1988; Sampson and Groves 1989; Shaw and McKay 1942). This theory posits that certain socio-structural characteristics of the geographic area affect the amount of crime and disorder. These structural characteristics include the level of concentrated disadvantage, residential instability, the presence of broken households, the degree of racial/ethnic heterogeneity, and economic inequality (Hannon 2002; Hipp 2007b; Lynch and Addington 2007; Sampson and Groves 1989). In social disorganization theory, these structural characteristics are hypothesized to reduce the number of social relations within the geographic area, which then reduces residents' willingness to provide informal social control against possible offenders, impacting the amount of crime and disorder (Sampson and Groves 1989). These social relations can be informal through social network ties, or formal through participation in voluntary associations. Given the importance of social ties (Bellair 1997;

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Browning, Feinberg, and Dietz 2004; Sampson 2004; Sampson and Groves 1989), the ecological unit should be appropriately defined to accurately capture the salient ties. This issue we argue is rarely addressed in prior research and is the focus of the present study.

*Motivation for egohoods – Moving beyond non-overlapping boundaries*

We argue for a reorientation away from the common approach in nearly all prior research of defining neighborhood units with non-overlapping boundaries and towards an approach utilizing overlapping neighborhoods. For many research questions—especially studies of ecological processes leading to the geographic distribution of crime—we argue that the non-overlapping boundary approach does not map onto social reality as well as does our egohood approach using overlapping boundaries. An implication of our approach is that residents are not part of a single neighborhood, but *many* neighborhoods. Ours is not the first multiple neighborhood conceptualization, as one well-known approach is the community of limited liability perspective that conceptualized neighborhoods as nested units (Boyd and Richerson 1985; Hunter 1974; Janowitz 1952; Lynch and Addington 2007) in which a household might be part of a school catchment area, a specific housing development, a political congressional district, or even the broader community or city. Each of these areas (that may be only somewhat overlapping) vie for a person's loyalty and commitment, spawning a community of limited liability (Janowitz 1952; Suttles 1972). Nonetheless, these various units within a particular dimension themselves are conceptualized as non-overlapping. Another recent example of an approach that placed individuals into more than one, though non-overlapping, neighborhood used a network clustering approach (Hipp, Faris, and Boessen 2012).

Our strategy takes a different tack by building overlapping neighborhoods, and is motivated by the insights of four research traditions: 1) the network literature on the spatial



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distribution of social ties, 2) the daily activities pattern literature, 3) the mental mapping

literature, and 4) the travel to crime literature. We argue that a key insight emanating from each of these traditions is that residents effectively exist at the center of their social world. Our approach explicitly builds on this insight.

One important insight comes from the network literature and the question of the spatial distribution of social ties. Research has shown that a physical distance decay function tends to characterize the likelihood of social ties among residents (Caplow and Forman 1950; Festinger, Schachter, and Back 1950; Hipp and Perrin 2009). For those living towards the center of a non-overlapping boundary neighborhood, such evidence is not problematic. However, for those living near the boundary, such evidence is inconsistent with the hypothesis of the non-overlapping boundary approach. That is, the non-overlapping boundary approach assumes that residents will interact with people further away from them spatially (but in the same non-overlapping neighborhood), rather than interacting with households closer to them but across a neighborhood boundary.

A second insight comes from the daily activities pattern literature (Lee and Kwan 2010; Ren and Kwan 2009) and routine activities theory (Felson 2002; Lynch and Addington 2007; Miethe and Meier 1994), which focus on where residents spend their time during daily activities. If non-overlapping neighborhood boundaries were appropriate, residents would spend the bulk of their work time and free time shopping and running errands within their own non-overlapping neighborhood. This becomes questionable when we consider residents living on the edge of a neighborhood: would they really spend all of their time within that particular neighborhood rather than spending time in the neighborhood across the street from them? Whether strolling about their geographic proximity, or engaging in shopping and other activities, there is evidence

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that persons tend to travel in the area around their homes in a concentric circle (Moudon, Lee, Cheadle, Garvin, Johnson, Schmid, Weathers, and Lin 2006; Sastry, Pebley, and Zonta 2002).

For example, the British Crime Survey proxied neighborhoods by asking residents about the area within a 15 minute walk of their home, suggesting something akin to an egohood (Sampson and Groves 1989). Indeed, 87% of the respondents to a survey in Los Angeles felt their “neighborhood” was this size or smaller (Sastry, Pebley, and Zonta 2002). As further evidence of the importance of geographic proximity, this same study in Los Angeles found that whereas 15.6% of respondents patronized a grocery store in the same tract, 33.8% patronized one within a 15 minute walk; similarly, they were twice as likely to attend a church within a 15 minute walk (27.6%) than a church in the same tract (11.8%), suggesting that the concentric circle approach is a more appropriate measure of neighborhood (Sastry, Pebley, and Zonta 2002).

The mental mapping literature comes from the field of geography, and arguably appears intuitive from the belief that all residents are able to identify their own “neighborhood” (for a classic example, see Lynch 1964). This approach focuses on residents’ *perception* of the neighborhood. Three recurring features of this literature are notable: 1) a focus on the degree of agreement among residents regarding the specific boundaries of their neighborhood; 2) a focus on the relative size of these neighborhoods (and whether they differ by the characteristics of the person or the geographic location of the residents in the larger community); and 3) remarkably little progress in attaining consensus around conclusions regarding points 1 and 2. Although studies frequently attempt to find agreement among residents on the identified boundaries for their neighborhoods, little agreement is generally found (Chaskin 1997; Coulton, Korbin, Chan, and Su 2001; Grannis 2009; Guest and Lee 1984; Haney and Knowles 1978; Lee and Campbell 1997).

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Interestingly, what is noted almost in passing in these studies (when it is mentioned at all) is that most respondents tend to place themselves in the *center* of their neighborhood. This can be seen in the maps drawn by residents in Grannis (2009: pages 99-101), as well as another study noting that “most residents’ homes also were near the centroids of their maps” (Coulton, Korbin, Chan, and Su 2001: 375). The implications of this relatively consistent finding have not been drawn out previously. We argue that this general centering tendency is important for understanding ecological processes.

A fourth insight that is specific to the question of crime in neighborhoods comes from the distance to crime literature (Capone and Nichols 1976; Rengert, Piquero, and Jones 1999). This literature consistently shows that offenders tend to exhibit a distance decay function when it comes to their travel to crime events (Bernasco and Block 2009; Capone and Nichols 1976; Rengert, Piquero, and Jones 1999). Offenders are more likely to commit crimes at locations closest to them, and this likelihood declines as they travel further from where they live, implying a concentric circle type of effect. One wrinkle to this pattern is some research suggesting that offenders will not offend in their immediate environment (Brantingham and Brantingham 1984; Rengert, Piquero, and Jones 1999), but then exhibit a distance decay function beyond this immediate area. In either case, this pattern is not consistent with a non-overlapping boundary approach to neighborhoods. Were a non-overlapping boundary process at work, such a smooth distance decay function would not be observed, given such a posited preference for committing crimes within one’s own neighborhood.

### *Conceptualizing Egohoods*

The aforementioned considerations suggest the need for a conceptualization in which persons are in the center of their geographic space. Given this, we suggest that there are then

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two possible analytic directions to take. The first approach conceptually follows in the tradition of the multilevel literature and considers the effect of an environment *on* a person or group. This burgeoning literature conceptualizes each individual as the center of a particular area and then draws a buffer of some radius around each person as the “context” of interest. We refer to this as the individual social environment (ISE) perspective, and the focus is usually on the context of a particular individual. In an early example of this approach outside of social science, Silander and Pacala (1985) created a buffer of a particular radius around members of a particular plant species (*Arabidopsis thaliana*) to create what they termed their “neighborhood”, and estimated the effect of various characteristics of these buffers on the fecundity of these plants. More recent scholarship in the public health literature has adopted a similar approach of creating a buffer around persons (often children or adolescents) and then estimating the effect of various physical and social characteristics of this buffer on physical activity (for a nice overview of this literature, see Brownson, Hoehner, Day, Forsyth, and Sallis 2009). For example, one study measured the effect of violent crime rates in a ½ mile buffer on the physical activity of youth (Gómez, Johnson, Selva, and Sallis 2004). This idea was extended by Reardon and colleagues (Lee, Reardon, Firebaugh, Farrell, Matthews, and O'Sullivan 2008; Reardon, Matthews, O'Sullivan, Lee, Firebaugh, Farrell, and Bischoff 2008) to construct measures of segregation by using a nearby buffer area as a measure of the racial context experienced by a household, and then aggregating these buffers to the metropolitan area as a measure of segregation. Given that the ISE approach conceptualizes the buffer as the social environment of a person, it often employs a distance decay function to account for the fact the nearby areas will be more important than farther away areas.

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Although the ISE approach has typically focused on the effect of an environment on a *person*, it is straightforward to generalize it to the effect of an environment on a *streetblock*. In this case, the conceptual question becomes how the characteristics of some area including and surrounding a block *impacts* the level of crime in the block. In the language of routine activities theory, this strategy conceptualizes the effect of possible motivated offenders in the surrounding area on the amount of crime in a particular block based on the possible presence of suitable targets and willing guardians in the block. Although we believe this ISE approach can be analytically useful for certain research questions, it is not the one we adopt here.

The second approach, and the one we employ here, builds on the ecological neighborhoods and crime literature and considers how the environment might impact the general level of crime. Instead of an interest in how the social environment *affects* a particular individual (or block), we are interested in the social context of some collectivity. Just as the common approach using non-overlapping boundaries measures the socio-demographic context of some unit and assesses how it is related to the general level of crime within the unit, our egohoods approach measures the social environment as a proxy for various social processes that are occurring within an area. Thus, our egohoods approach does not posit a causal effect of an environment *on* some individual or small area. Our conceptual innovation is to relax the non-overlapping boundary assumption of the ecological approach and allow for overlapping neighborhoods.

We follow Taylor and colleagues (Taylor 1997; Taylor, Gottfredson, and Brower 1984) and Grannis (2009) in arguing that street blocks are fundamental units that should not be split into separate neighborhoods. The local street block as the primary unit is reasonable given the evidence that residents are much more likely to have social interactions with those living on the

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same local block (Caplow and Forman 1950; Festinger, Schachter, and Back 1950; Grannis 2009; Hipp and Perrin 2009). Therefore to construct egohoods, we draw a circle around every block with some particular radius to create overlapping buffers of all blocks in a city. We consider each of these buffers to be ecological units of interest, similar to the non-overlapping boundary approach that considers neighborhoods to be an ecological unit of interest. Whereas the ISE approach focuses on the buffer around a particular person (or street block) to be the context of interest only for the person (or street block) in the center of the buffer, our approach conceptualizes this entire concentric circle as the unit of interest. This is an important conceptual distinction: whereas the ISE approach treats each buffer as the “neighborhood” and therefore frequently employs a distance decay function given that it is attempting to capture the environment of a particular person, our approach defines the circle around a block, as well as the circles around all of the blocks *within* that circle as relevant to the central block.

To understand this idea, consider Figure 1. The dots show the block centroids for one part of Chicago, and the thicker outlines show the non-overlapping boundaries of census tracts. In the first panel of Figure 1, we have denoted the block of interest with a star, and have drawn a buffer around it of some particular radius. In this example, we have drawn a circle buffer with a ½ mile radius. In the second panel we display the adjacent block to the left as a cross symbol, which is also at a block centroid. We can draw a buffer with a 1/2 mile radius around this block as well, which we have indicated with the cross-hatched area. Note that there is considerable overlap between the blocks contained within the cross block’s buffer (cross-hatch area) and those in the star block’s buffer, but there are slight differences. We then repeat this pattern of drawing buffers for *all* of the blocks in the city to create egohoods. An important implication of our approach is that whereas every block has its own buffer containing a number of other blocks, it is

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also the case that *each block is contained in the buffers of many other blocks*. Specifically, a block will be part of the buffers of all the blocks in its *own* buffer.

<<<Figure 1 about here>>>

When egohoods are constructed for all blocks in the city, a particular block is tied not only to the blocks in its own buffer, but to the buffers of these blocks as well. As such, the egohood of the focal block will contain portions of the buffers of all of the blocks within its own buffer. Thus, the closer two blocks are geographically, the more buffers they will share with each other. For example, in the third panel of Figure 1, consider the triangle that we have now added near the left edge of the cross block's cross-hatched area: the buffer of this triangle block contains less than half the blocks in the cross's buffer (the ones falling within the intersection of the triangle's buffer and the cross's buffer). The remaining blocks within the triangle's buffer are further away from the cross's focal block and yet share a buffer with the cross block. As a consequence, our approach implies a social process with an inherent spatial decay function and accounts for the relational nature of spatially proximate social areas. In fact, if one were to draw all of the buffers around the blocks within the cross block's buffer, one would find that blocks physically closest to the cross block would most frequently "share" a buffer with the cross block, whereas blocks further away from the cross block would share fewer buffers. Note that a distinction between egohoods and the ISE approach is that the latter would only consider the effect of the cross-hatched buffer (along with a distance decay) on the block denoted with a cross at the center, whereas egohoods consider the entire area.

If we were to sequentially replicate this exercise of drawing overlapping buffers for each of the blocks in the city, the egohoods would appear as something akin to a wave passing through the city. Thus, any given block will be more or less part of various egohoods that can be

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defined throughout the city. Rather than saying that a block *belongs* to a particular discrete neighborhood, we talk about its *degree* of belonging to these buffers.

The “waves” of egohoods that we have described as cascading across the city imply a certain degree of smoothness to the overall process. Contrary to the non-overlapping boundary approach, egohoods do not pose constraints in the physical and social landscape of the city but in fact have the ability to explicitly incorporate discontinuities directly into their construction.

Whereas the non-overlapping boundary approach typically creates boundaries based on observed physical boundaries (e.g., rivers, freeways) or social boundaries (e.g., the location at which the economic, or racial/ethnic, character of the residents sharply changes), egohoods simply continue to wash over the surface of the city, effectively incorporating the information from such social boundaries. The implication is that we will obtain numerous egohoods with a considerable degree of heterogeneity within them (given that they sometimes span social boundaries).

Note that a social boundary is hypothesized to affect the formation of social ties due to preferences for within group interactions (Feld 1982; Hipp and Perrin 2009; McPherson, Smith-Lovin, and Cook 2001): indeed, if no such in-group preference were present, such social “boundaries” would not exist. Given that the ecological crime literature posits that the presence of social ties has an important inhibiting effect on the presence of crime, measuring this heterogeneity is *precisely* what we wish to capture. We are therefore capturing the heterogeneity that exists across the social landscape, in contrast to the non-overlapping boundaries approach that divides the city into geographic units defined by maximizing homogeneity within them (given that nearly all “neighborhood” clustering algorithms attempt to maximize homogeneity within units, and heterogeneity across units) (for a nice overview, see Duque, Ramos, and Suriñach 2007). For example, census tracts were initially constructed by the Census Bureau to



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be relatively homogeneous neighborhoods (Green and Truesdell 1937; Lander 1954), the “natural community areas” of Chicago were designed to be relatively socially homogeneous (Wirth and Bernert 1949), as were the “neighborhood clusters” Sampson et al. created (Sampson, Raudenbush, and Earls 1997). Our approach allows us to detect this heterogeneity in the social landscape that may well have important implications for the level of crime in these areas. In contrast, the non-overlapping boundary approach attempts to create a social surface that minimizes the true level of heterogeneity that exists. Given recent evidence that offenders might actually target locations with higher levels of racial/heterogeneity, a method that minimizes the true amount of heterogeneity that exists may not be wise (Bernasco and Block 2009).

Given that the non-overlapping boundary approach utilizes physical and social boundaries to demarcate neighborhoods, this maximizes heterogeneity *across* neighborhoods and therefore requires an explicit spatial model to account for this. However, virtually all existing studies fail to do this. Although studies commonly model a spatial process in which the amount of crime in one neighborhood affects the crime in nearby neighborhoods (Browning, Feinberg, and Dietz 2004; Hipp 2007b; Nielsen and Martinez 2003; Walsh and Taylor 2007), this does not account for social boundaries. What is needed is to make a distinction between boundaries that are somewhat *soft* (when nearby neighborhoods are relatively similar based on social characteristics), and cases in which a *hard* social boundary exists (when nearby neighborhoods are very different based on some social characteristic such as race/ethnicity). Failing to differentiate between hard and soft boundaries in the spatial process implicitly assumes that the presence of hard social boundaries have no implication for adjacent neighborhoods. The same issues arise for *physical boundaries*, as they imply a need to specifically model this spatial process in the non-overlapping boundary approach.

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In principle it is straightforward to account for boundaries in our egohood approach.

Whereas our default approach uses a weight of one for all blocks within the radius, we can assign a different weight for blocks on opposite sides of a physical boundary (some value between 0 and 1). For a discussion of this idea, see Reardon and O’Sullivan (2004: 130). We do not incorporate such weights in the present study, in part because there is too little existing empirical evidence to provide guidance on the appropriate values for these weights. As a consequence, we are therefore “stacking the deck” against our approach since we are ignoring physical boundaries: we feel this is reasonable given that our goal is to test how much is gained from the simple “smooth” egohoods approach that ignores physical boundaries. Including information on physical boundaries should only improve our estimates, and will be pursued in future work.

## Data and Methods

### *Data*

We compare our egohood approach with two common non-overlapping boundary definitions of neighborhoods--census block groups and tracts—as well as the individual social environment (ISE) approach. We utilize crime event data from nine cities around the year 2000: 1) Buffalo; 2) Chicago; 3) Cincinnati; 4) Cleveland; 5) Dallas; 6) Los Angeles; 7) Sacramento; 8) St. Louis; 9) Tucson. These cities were not selected randomly, but rather are a convenience sample of cities with available crime data at point locations. Therefore, this study does not generalize to the population of cities, but rather simply focuses on these cities separately as independent tests of our approach. These data were obtained directly from the police departments, and therefore suffer from the same limitations of all sources of official crime data given that not all crimes are reported, and not all are recorded (Lynch and Addington 2007;

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Mosher, Miethe, and Philips 2002). Nonetheless, we have no reason to suspect that these data are any less valid than other official crime data sources, and Baumer (2002) found that underreporting of Part 1 crimes is not systematically related to structural characteristics of neighborhoods. There are 93,638 blocks, 9,839 block groups, and 3,146 tracts in these cities.

### *Dependent Variables*

The dependent variables are from the crime reports officially coded and reported by the police departments in each of the nine cities. Given that we have point data, we geocoded these events to latitude-longitude point locations, allowing us to flexibly aggregate crimes to various definitions of “neighborhood”. We classified crime events into six Uniform Crime Report (UCR) crime types: aggravated assault, robbery, homicide, burglary, motor vehicle theft, and larceny. We averaged these measures over three years (2000-02) to minimize yearly fluctuations (except Cincinnati, for which we averaged the data from 2002-04 given that 2002 was the earliest year for which we had crime data.).

### *Independent variables*

Our neighborhood structural characteristics are from 2000 U.S. Census data. For the non-overlapping boundary approach using block groups or tracts, it is straightforward to create the various measures. For the egohoods, some of the measures we use are available from the U.S. Census block aggregations. To construct our measures for egohoods, first, we determine the blocks that are within a particular egohood using ArcGIS 9.3 by drawing a radius of a particular distance around every set of block centroids. Any block that is within, or intersects with, the radius is considered part of the egohood. Given that we have little prior reason to specify a particular radius for our egohoods, we adopt an exploratory approach of defining egohoods based on three different radii: 1) ¼ mile radius (about the population size and area of

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block groups in these cities); 2) ½ mile radius (about the population size of tracts in these cities); and 3) ¾ mile radius (about the population size of two tracts in these cities).<sup>1</sup> We are therefore able to assess the performance of the models at these various aggregations and the relative effectiveness of the various structural characteristics.<sup>2</sup>

For blocks that are near the boundary of a city, we only include crime and census information from the blocks in the same city that lie within their buffer given that we only have crime information for those blocks.<sup>3</sup> To assess whether this affects our results, we estimated ancillary models that excluded buffers that did not contain information for all blocks within the buffer: these results were essentially the same as those presented in our main analyses.

We created the structural measures by summing the information from the blocks within the buffer. For example, to compute the percent African American in a buffer we summed up the number of African Americans in all blocks in the buffer, and divided this by the sum of the population in all blocks in the buffer.<sup>4</sup> The measures using the block information include the following: percent vacant units, percent owners, percent African American percent Latino, percent of residents aged 16 to 29 (as these are the prime ages of offenders), and population density for block groups and tracts (and population size for egohoods given that their constant

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<sup>1</sup> Note that these population sizes will differ based on the density of the city. Thus, in a very dense city such as New York, a half mile radius will include a much larger population than would a typical tract. On the other hand, in a small town a half mile radius will include a smaller population than that of a typical tract. Thus, the correspondence between a ½ mile radius and the population of a tract only occurs in certain settings.

<sup>2</sup> Note that just 2.0% of the blocks with population and crime data were isolates in the ¼ mile radius egohoods. All other blocks with population and crime had blocks nearby (the mean number of nearby blocks was 13.6 with a standard deviation of 6.5).

<sup>3</sup> Another approach would include the demographic information for all blocks within an egohood but still only focus on blocks with available crime information. Given that we only have crime information available for blocks within the city, this would require assuming that the blocks with crime data are not systematically different from the blocks not within the city for a particular buffer, which may not be a tenable assumption. This is an instance of the well-known boundary problem (Anselin 1988; Bennett, Haining, and Griffith 1984), and the non-overlapping boundary approach also makes the same assumption of no effect from these neighborhoods in nearby cities.

<sup>4</sup> Note that in this approach larger blocks (based on population) will have a larger impact on the unit. This is precisely as desired, as such larger blocks constitute a larger proportion of the unit. This is also the case when computing variables aggregated to non-overlapping units, such as tracts.

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area size by design results in population effectively measuring population density). We also constructed a distributional measure of racial/ethnic heterogeneity as a Herfindahl index (Gibbs and Martin 1962: 670) of five racial/ethnic groupings (the groups are white, African-American, Latino, Asian, and other races), which takes the following form:

$$(1) \quad H = 1 - \sum_{j=1}^J G_j^2$$

where  $G$  represents the proportion of the population of racial/ethnic group  $j$  out of  $J$  groups.

Certain measures available from the U.S. Census, such as income, are not aggregated to blocks (for disclosure reasons given that few respondents in any given block receive the long-form questionnaire). Instead the smallest geographic units to which they are aggregated are block groups. For these variables, it is more challenging to construct our egohood measures. We adopt the following approach: 1) determine the blocks within a particular egohood; 2) apportion each block's share of the block group count variable (proportionate to the population of the block) assuming homogeneity across the block group; 3) aggregate these values over the blocks in the egohood; and 4) compute the measures of interest.

We capture the economic environment of the neighborhood with the average household income and a measure of inequality. The average income measure is constructed by first assigning household incomes to the midpoint of their reported range (given that the Census only reports household incomes in particular ranges), and then computing the average income for residents in the block group from this information. We measure economic inequality by including the standard deviation of the logged household income. For this measure, we again compute the midpoints of the income bins, log these values, multiply them by the number of observations in each bin to get the incomes of these households, compute the mean logged

Measuring egohoods

income, and then compute the standard deviation of the incomes in a buffer based on these values.<sup>5</sup> Given that crowding may increase crime, we computed the percentage of households that are classified as being crowded (greater than one resident per room).

To compare our egohoods approach with the ISE approach, we also constructed measures based on buffers with a distance decay function. Although there are many different distance decay functions that could be employed as noted by Reardon and O'Sullivan (2004), for greater comparability, we used the biweight kernel, as employed in Reardon et al's (2008) study of segregation. This can be represented as  $(1 - (\text{dist}(p,q)/r)^2)^2$  where  $r$  is the radius of the buffer and  $\text{dist}(p,q)$  is the distance in miles between the two blocks. When aggregating ISE measures from block or block group data, we multiply them by the distance decay value.

The summary statistics for the variables used in the analyses are presented in Table 1.

<<<Table 1 about here>>>

## Methods

We estimated two sets of models. In the first set, we estimated Poisson models given that the outcome measures are counts. Models with evidence of overdispersion were estimated as negative binomial regression models. We included the population within the unit as an offset measure (log transformed, with a coefficient constrained to one), which effectively estimates the outcome measure as a crime rate.<sup>6</sup> We estimated these models for each crime type for each city with eight different aggregations: egohoods with ¼ mile buffers, egohoods with ½ mile buffers,

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<sup>5</sup> Although some use the Gini coefficient for capturing inequality, our approach yielded a very similar measure. Testing our approach using tract aggregated data, we found the logged standard deviation to yield values correlated .88 with the Gini coefficient in 2000. Given that software to create such Gini values (Nielsen and Alderson 1997) is not automated for such large scale computations as necessitated by our egohood approach, we adopted this simplification given that it yielded relatively similar results.

<sup>6</sup> We also estimated ancillary models that dropped observations with small populations (defined as those with the smallest 5% of population values for each city). These results were generally quite similar to those presented in the main analyses, increasing confidence in the robustness of the findings.

### Measuring egohoods

egohoods with  $\frac{3}{4}$  mile buffers, ISE's with  $\frac{1}{4}$  mile buffers, ISE's with  $\frac{1}{2}$  mile buffers, ISE's with  $\frac{3}{4}$  mile buffers; block groups, and tracts. Given the abundance of models, the results for each city are presented in an online appendix (GIVE WEBSITE LOCATION). In the Appendix (Tables A1 to A6), we present the averaged results over the nine cities for these various aggregations for each crime type. In the manuscript tables, we only present the results for  $\frac{1}{4}$  mile and  $\frac{1}{2}$  mile egohoods (but not  $\frac{3}{4}$  mile egohoods given that results are typically similar, but weaker), tracts (but not block groups, given that the results are similar and tracts are the most common convention in the field), and  $\frac{1}{2}$  mile ISE's (given that the  $\frac{1}{4}$  mile and  $\frac{3}{4}$  mile results are relatively similar).

The second set of models was estimated as spatial error models. On the one hand, the construction of egohoods by definition creates a high degree of spatial error, which affects the standard errors. On the other hand, ignoring correlated spatial errors will still yield consistent coefficient estimates (Anselin 1988: 59) and our large sample sizes suggest that our estimates should be relatively accurate.<sup>7</sup> Given that there is not currently an off the shelf spatial error estimator for a Poisson outcome, we estimated spatial error models in which the outcome is the logged crime *rate*. We constructed out spatial weights and estimated the spatial error models using R (R Development Core Team 2012) and the *spdep* package (Bivand 2012). Given that we expected a relatively strong spatial effect, we constructed the spatial weights matrix using a relatively flat distance decay (inverse root distance), with a cutoff at 2.5 miles and is row standardized.

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<sup>7</sup> We did not include spatial lags in the block group or tract models, given that this would only be taking away from the effects of the covariates. Nonetheless, we estimated ancillary models that followed prior literature in accounting for spatial effects by including spatial lags of the predictor variables (Anselin 2003; Elffers 2003; Hipp 2010; Morenoff 2003; Sampson, Morenoff, and Earls 1999). These models only explained a very small additional amount of the variance in the location of crime compared to the models without these spatial lags.

## Measuring egohoods

Thus, the models in the first set correctly account for the count nature of the outcome variable but obtain inefficient and biased parameter estimates given that they ignore the spatial correlation in the error terms. The models in the second set correctly account for the spatial correlation of the residuals but must assume a normal distribution to the outcome measure; however, if the counts are not too small the relative coefficient estimates will approximate those of a count model (indeed, this is the case for five of our six outcome measures). By estimating the two sets of models, we are able to assess whether our results are robust in both instances. We estimated spatial error models for each crime type for each city aggregated to: egohoods with  $\frac{1}{4}$  mile buffers, egohoods with  $\frac{1}{2}$  mile buffers, block groups, and tracts. These averaged results over the nine cities for these various aggregations for each crime type are presented in the Appendix (Tables A7 and A8).

There was no evidence of influential observations in the models. There was also no evidence of collinearity problems in the models we estimated. The largest variance inflation factor values were observed in the  $\frac{3}{4}$  mile egohood models, and even these were not problematic. For example, whereas the largest value observed was 10.55 for percent Latino in the Los Angeles model, if we use the techniques of O'Brien (2007) and adjust for the model R-square (.65) and sample size (28,879), the standard error for this coefficient was just 8% as large as one from a model with a single predictor variable, a sample size of 500, and an R-square of .2 (a model that would not normally be considered unproblematic).

One goal of this study is to compare how well each neighborhood aggregation predicts the amount of crime. We cannot simply compute the variance explained for each of these aggregation methods and compare them, as a well-known issue is that correlations and variance explained among larger aggregated units are always going to be larger (Hannan 1991). We



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address this issue by instead disaggregating our results to common units—blocks—and then assessing the degree of fit within blocks. Therefore, we adopted the following steps (this example is for a block group model): 1) estimate the model; 2) generate the predicted mean of crime events for each geographic unit in the estimated model (each block group); 3) apportion this mean of crime events to each of the blocks within the geographic unit (the block group) proportionate to the population in the block (given that the model assumes a homogeneous crime rate across the blocks within a block group); 4) compute the partial correlation (controlling for population) between this mean crime count in each block and the actual number of crime events in the block. Note that the non-overlapping boundary approaches assume a constant level of crime across the blocks within each unit, which is exactly how we compute this partial correlation.

For our egohoods, this process is a bit more involved because each block is in fact contained within many buffers. In each of the buffers, the amount of crime predicted by the model is uniform across the blocks within the buffer. Thus, a particular block will have a predicted value of crime for each buffer to which it belongs. We average these predicted values of crime for each block, and then correlate this average value to the actual number of crime events in the block as an assessment of the model fit. Note that each block is averaged many times in the egohood approach, given that this is a fundamental assumption of the strategy.<sup>8</sup>

## **Results**

### *Predicting crime with different neighborhood aggregations*

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<sup>8</sup> Of course, if the non-overlapping boundary model is correct, then this additional averaging will provide little extra information given that we would expect a constant rate of crime over the blocks in the unit. In fact, as information is “incorrectly” incorporated from nearby areas, the mean would be pulled further from the true value. It is only to the extent that the non-overlapping approach is not correct that averaging will provide additional unique information that will improve the predictions of crime.

### Measuring egohoods

We begin by focusing on the relative quality of the prediction of crime for our egohood models compared to models using more traditional aggregations of block groups or tracts. Given that the results demonstrate considerable robustness across cities, and for a more parsimonious presentation, we average across cities the partial correlation (controlling for population size) between the predicted count from the model and the actual number of crime events. These averaged results are presented in Figure 2.

>>>Figure 2 about here<<<

Beginning with the aggravated assault models on the far left side of Figure 2, the five bars show the average partial correlation in the predicted count of aggravated assaults in the blocks of the cities with the actual count of aggravated assaults: the first three bars are egohoods of varying radii (0.25 miles, 0.5 miles, and 0.75 miles), the fourth bar uses block groups as the units of analysis and the fifth bar uses tracts. A striking pattern is that egohoods as the unit of analysis—particularly those with  $\frac{1}{4}$  mile and  $\frac{1}{2}$  mile radius—are much better at explaining the amount of crime across the social environment than either block groups or tracts as the unit of analysis. Whereas the average partial correlation between the predicted count and the actual count of aggravated assaults in blocks is just .30 using block groups as the unit of analysis, and .31 when using tracts, the partial correlation is .32 for  $\frac{3}{4}$  mile egohoods, .36 for  $\frac{1}{4}$  mile egohoods, and .37 for  $\frac{1}{2}$  mile egohoods. Thus,  $\frac{1}{2}$  mile egohoods produce an 18% improvement in the prediction of the amount of aggravated assaults in each of the blocks across these cities compared to tracts.

The pattern of results is similar when looking at robbery rates, as seen in the second clump of five bars from the left in Figure 2. Once again, the partial correlation between the predicted count of crime events in blocks and the actual count is higher in our egohoods than

### Measuring egohoods

when aggregating to block groups or tracts, and once again the highest correlations are achieved for the two egohoods using the smallest radius. Thus, the partial correlation is 25% larger for egohoods with a ½ mile radius compared to tracts.

For homicides, the models do the weakest job of predicting this type of crime, regardless of the aggregation used. Whereas the partial correlation between the predicted count of homicides and the actual count is .18 when aggregating to block groups, the partial correlation is .21 when aggregating to ¼ mile egohoods. Thus, the model does 14% better in explaining the geographic distribution of homicides in blocks across these cities when aggregating to ¼ mile egohoods instead of block groups.

Turning to the property crimes, the models in general are better at predicting the location of both burglaries and motor vehicle thefts. In these models, the difference between the performance of our egohoods with the more traditional block groups and tracts is even greater. For example, the partial correlation between the predicted crime counts in blocks and the actual counts for ½ mile egohoods compared to tracts is 25% larger for larcenies and about 50% larger for motor vehicle thefts and burglaries.

### *Comparing the effects of covariates*

We next ask whether there are different effects for our ecological covariates when using egohoods compared to the more traditional aggregations of block groups or tracts. We present the average of the results over these nine cities for the violent crime types in Table 2, and the property crime types in Table 3. These Tables display the results for the ¼ mile egohoods, ½ mile egohoods, and tracts.

>>>Table 2 about here<<<<

### Measuring egohoods

We begin by pointing out that the measure of percent vacant units generally has stronger effects when using our egohoods as the aggregating unit than when aggregating to the block group or tract. In row 2 of Table 2 we see that a one percentage point increase in vacancies in the ¼ mile egohood increases aggravated assaults .035 units and a similar increase in a ½ mile egohood increases aggravated assaults .039 units, whereas a similar increase in tracts increases assaults .028 units. Thus, this effect is 39% larger in ½ mile egohoods compared to tracts. The effects of vacancies when aggregating to egohoods compared to discrete units are also 22% larger for robberies, 61% larger for homicides, and 55% larger for burglaries. For motor vehicle thefts and larcenies, the effects of vacant units are particularly strong for the smaller ¼ mile egohoods.

<<<Table 3 about here>>>

We next turn to the effects of our two *distribution* measures: racial/ethnic heterogeneity and inequality. For racial/ethnic heterogeneity, we see that aggregating to egohoods produces considerably larger effects than when aggregating to discrete units. For example, the size of the effect for ½ mile egohoods is more than twice as large as tracts for the outcomes of aggravated assaults or homicides, three times as large for burglaries, 30 to 40% larger for robberies and motor vehicle thefts, and 70% larger for larcenies.

The pattern for inequality is even stronger, and demonstrates that our egohoods are a particularly good unit of analysis for detecting this effect. For all crimes except homicides, when aggregating inequality to discrete units, higher levels of inequality appear to result in *lower* crime rates. However, aggregating to egohoods exhibits very strong *positive* effects of inequality on all of these types of crime. A one standard deviation increase in inequality increases the property crime types 7 to 10%, and the violent crime types 14 to 15%. These are very large

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differences, and suggest that our egohoods are most useful for measuring inequality. Given that prior work often does not test for inequality in neighborhoods, or finds weak effects, these results suggest that the egohood approach more accurately captures the distribution of inequality. In general, the effects are strongest for the ½ mile radius egohoods, although in some instances the effects are equally strong with the larger (¾ mile) radius.

We briefly discuss the results for other variables in the model. Although the effect of crowded households was essentially nonexistent in the models aggregated to tracts, crowding showed a relatively strong effect when aggregated to egohoods for aggravated assault, homicide, burglary and motor vehicle theft. The effect of the population density measure was consistently negative for all crime types, and always exhibited the strongest effect for the smallest egohoods. The effects for the percent of African Americans and Latinos were not consistent over cities, with some positive effects and some negative effects. Average household income exhibited consistently negative effects on the various types of crime, consistent with expectations, and there were few differences regardless of the aggregation. The effect of the percent aged 16 to 29 generally showed a negative effect regardless of the aggregation used, which is contrary to expectations, but mimics the findings from prior research (Hannon and Knapp 2003; Hipp and Yates 2011; Krivo and Peterson 1996; Villarreal 2002).

### *Spatial error models*

To assess whether accounting for the spatial correlation in the residuals alters our conclusions, we estimated spatial error models in which the outcome was the logged crime rate (see Tables A7 and A8 in the Appendix).<sup>9</sup> The substantive conclusions from these models are

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<sup>9</sup> Whereas the spatial error model is typically used when non-overlapping spatial units are hypothesized to have measurement error across them, our egohoods approach *explicitly* creates measurement error across units by construction. Although our approach explicitly creates this measurement error, we argue that the spatial error model nonetheless corrects for this interdependence. Furthermore, as we show in the results below, the inefficiency of the

### Measuring egohoods

very similar to those from the models just discussed. Here we focus only on the few differences that were observed. For the egohoods models, only two differences were observed: first, whereas vacancies appeared to have a stronger effect on certain crime types when aggregated to ¼ mile egohoods in the non-spatial models, the effect of vacancies was always stronger in the ½ mile egohoods in the spatial error models. Second, whereas racial/ethnic heterogeneity sometimes showed a stronger effect in larger egohoods in the non-spatial models, it always showed a stronger effect in the ¼ mile egohoods in the spatial error models; furthermore, the gap in the size of the effect for racial/ethnic heterogeneity between the egohoods and tract models was narrower in these spatial error models compared to the earlier models. The remaining pattern of effects remained generally unchanged. The one exception were the spatial error homicide results which showed counterintuitive negative effects for heterogeneity and inequality; nonetheless, the fact that the normality of the outcome is so strongly violated by the large number of zeroes for the homicide models suggests that the Poisson estimator is preferred (Osgood 2000). As further evidence, we estimated these as OLS models (ignoring spatial autocorrelation), and the results were very similar to the spatial error models; thus, the spatial results differ from our main results because they ignore the count nature of the data, and not due to the spatial effects. For the tract models, other than the fact that the effect of homeowners was weaker in the spatial error models, the results were relatively unchanged. Again, the relative similarity of the spatial error models results to those ignoring the spatial error is unsurprising (Anselin 1988: 59).

### *Measuring individual social environments (ISE)*

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models not accounting for the correlated spatial errors is not problematic given our large sample size; with a smaller sample, ignoring the spatial error could be more problematic.

## Measuring egohoods

Although we have argued why we conceptually prefer our egohoods approach, we also earlier described the ISE approach. In this strategy, the outcome of interest is the amount of crime in the block, and the context of interest is the buffer surrounding and including the block. We estimated these models and compare the results to the egohoods models. On the one hand, we find that these models do a better job of explaining the location of crime events compared to the models aggregating to block groups or tracts, similar to the findings for the egohoods models. As seen in Figure A1 in the Appendix, compared to the block group models the ½ mile ISE models have a partial correlation that is 16% larger for aggravated assault, 50% larger for motor vehicle theft, about 80 to 90% larger for robbery and burglary, and 140% larger for larceny. In fact, the partial correlations for the ½ mile ISE models are similar to the ½ mile egohoods models: whereas the partial correlations are slightly higher for egohoods for burglaries and motor vehicle thefts, the partial correlations are slightly higher for the ISE models for aggravated assaults and homicides, and much higher for homicides and larcenies. Thus, either of these overlapping boundary approaches improve on the non-overlapping boundary approach.

On the other hand, the results show that despite the similarities between the egohoods and ISE approaches, the conceptual differences also manifest as empirical differences. For example, we see that the effect of vacancies in the ½ mile ISE models is consistently weaker than in the egohoods models (see table 4). We also see that the negative effect of average household income is typically not as large in the ISE models compared to the egohoods models.

<<<Table 4 about here>>>

The most striking result is that whereas we saw dramatically strong positive effects of inequality on crime rates in the egohoods models, they are essentially nonexistent in the ISE models (this mirrors the results in the discrete neighborhoods models). Thus, whereas there

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appears to be a strong positive effect of general inequality on the level of crime in an ecological area (an egohood), there is no evidence that the level of inequality in a surrounding area will increase the level of crime in the block in the center of that area (the ISE approach). Thus, inequality is better captured as a process in an ecological unit, rather than as a construct that *acts upon* a block.

Finally, there is evidence that the effects of the population density and household crowding measures are stronger in the ISE models compared to the egohoods models. A block with higher levels of household crowding in a ½ mile buffer surrounding it will have considerably higher rates of all of these crime types. On the other hand, as the level of population increases in the surrounding ¼ mile buffer, the amount of crime on a block actually decreases.

## **Conclusion**

Over the last few decades social scientists have argued for the importance of the neighborhood context for various individual and community outcomes (Sampson, Morenoff, Gannon-Rowley 2002). Yet there is still little agreement on how to measure community processes and conceptualize neighborhoods (Bursik 1988; Leventhal and Brooks-Gunn 2000; Wooldredge 2002). This study has introduced an *egohood* to conceptualize and measure neighborhoods. Egohoods center a radius around each census block to create neighborhoods that are analytically and socially dependent across the city landscape. Rather than relying on non-overlapping boundary units such as census tracts or block groups, we suggest that egohoods more appropriately capture the social context of most cities by conceptualizing overlapping boundaries between neighborhoods. This study illustrated the use of egohoods for crime rates



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and found that egohoods show an improvement in model fit for explaining the location of crime in cities over the more traditional non-overlapping boundary approach of aggregating to block groups or census tracts. Thus, if one wants to know where crime is located, predictions using our egohoods approach appear to do better than predictions based on the more traditional block groups or tracts aggregations.

Most existing studies conceptualize neighborhoods as having non-overlapping boundaries to capture social homogeneity, essentially treating each neighborhood as a unique urban village that is socially and geographically independent from the rest of city and other neighborhoods. In other words, the non-overlapping boundary approach for defining neighborhoods creates fissures between neighborhoods that are spatially proximate. By bracketing neighborhoods with non-overlapping boundaries, this approach assumes that the social context of importance is the same for all residents, even those living near the edge of a boundary. Researchers using spatial regression analysis attempt to model the extra-local environment by incorporating the effects of nearby neighborhoods; however, this approach still assumes that non-overlapping boundaries are reasonable, and almost certainly requires a more sophisticated model of the spatial process than is generally employed. We suggest that egohoods are a less restrictive approach for bounding neighborhoods and overcome many of the flaws in the non-overlapping boundary framework because they explicitly capture heterogeneity across the city by allowing for the interdependence of neighborhoods.

Egohoods allow for directly testing how covariates operate depending on the scale of the unit of analysis. Given that egohoods are a new concept, there is no a priori guidance on the size of radius to draw around the focal block. We therefore adopted an exploratory approach of drawing various sized radii ranging from  $\frac{1}{4}$  mile to  $\frac{3}{4}$  miles and our results indicated relative

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similarity over these various radii.<sup>10</sup> Nonetheless, the strongest effects were generally detected for the ¼ mile and ½ mile radii. Interestingly, in these cities, these are approximately the size of block groups and tracts, respectively, two Census boundary definitions commonly used to proxy neighborhoods. However, they would not match tracts or block groups in cities containing appreciably more or less density. Furthermore, the proper scale can differ for various measures, and appeared to do so in this study, suggesting that a single “unit” is not appropriate. Thus, more work will need to explore the most salient size of buffers across cities with different spatial regimes.

Whereas some variables showed stronger effects when using the larger sized radius for egohoods, others showed stronger effects using the smaller sized radius. The fact that social processes unfold over varying scales is not surprising, and prior work has suggested this very possibility (Hipp 2007a). For example, the structural measure of population density suggests particularly micro processes as the strongest effects were detected when using the ¼ mile radius. This is consistent with routine activities theory, as the presence of greater population nearby may provide more potential guardians. Such effects may well be washed out when using larger units of analysis with possibly arbitrary boundaries. It could also be that even smaller units—such as streetblocks—would capture these particular processes even better than these smaller egohoods (Weisburd, Bernasco, and Bruinsma 2009; Weisburd, Bushway, Lum, and Yang 2004). Future research may wish to test the extent to which the effects of streetblocks co-exist with those of varying sized egohoods.

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<sup>10</sup> Our approach of constructing egohoods based on a circular buffer around the block is based on the principle of physical distance as a constraining feature of neighborhoods and assumes symmetry in all directions. Although other shapes are possible, such as rectangles or squares around the central block, we believe such an approach is unprincipled other than mimicking the most common shape used in constructing non-overlapping neighborhoods. The square or rectangular shape requires an asymmetric assumption of distance, which seems implausible. Nonetheless, future work may wish to test other possible shapes.

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In contrast, the distribution measures of racial/ethnic heterogeneity and economic inequality tended to show stronger effects when aggregated to ½ mile egohoods (approximately the size of a tract). These effects were sometimes as strong for the larger ¾ mile radius egohoods. Of particular note was that the egohood approach strongly improved the performance of economic inequality as a predictor of the location of crime. Whereas prior work has rarely considered the possible importance of inequality in neighborhoods on crime rates (for exceptions, see Crutchfield 1989; Hipp 2007b; Messner and Tardiff 1986), we showed that this positive effect is present and dramatically stronger when using egohoods. This result suggests that the effects of distribution measures such as inequality might be masked when specified within non-overlapping boundary areas because their effect is crucially dependent on how their boundaries are defined (Wong 1997). It therefore may be premature to conclude that inequality does not have important effects on local crime rates (Pridemore 2011). It is worth emphasizing that the strategy of constructing neighborhoods explicitly based on a homogeneity assumption (as is common in the non-overlapping boundary approach) artificially reduces the level of racial heterogeneity or inequality measured across the social landscape, making it particularly difficult to detect the effects of these structural measures on various outcomes such as crime events. Egohoods appear more effective at gauging distributional measures because egohoods by definition are spatially dependent. These findings also emphasize the point that for certain structural measures—such as distributional measures—focusing on extremely micro areas, if followed exclusively, will miss these effects (Weisburd, Bernasco, and Bruinsma 2009).

Notably, even the ISE approach did not detect such a strong positive effect for inequality. This highlights the conceptual difference between our egohoods strategy and the ISE approach: the ISE strategy posits that some particular context *acts upon* a person or street block, and

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therefore posits that a higher level of inequality in the surrounding area increases crime in a focal block. Our egohoods approach posits that the level of inequality in some ecological unit increases the level of crime within that same ecological unit, and therefore is agnostic about where this crime takes place. Although this still leaves unexplained exactly how this inequality effect plays out, it is nonetheless the case that our approach is able to detect a very strong effect that the ISE approach fails to detect. It also highlights that the ISE approach may still be useful if the model is carefully parameterized. For example, one might wish to construct a measure of the *difference* in the income level of the surrounding buffer and the income level of the block as one way to capture inequality in the ISE approach. Whether this would capture inequality as well as our egohoods strategy would need to be determined with future analyses.

Given that the egohoods approach has an implicit distance decay feature to it (as a result of the overlapping buffers), and the ISE approach has an explicit distance decay function, one might presume that with an appropriate distance decay function the ISE approach could provide mathematically identical results. Despite the apparent similarities in the two approaches, we are skeptical that they would be mathematically identical in all cases given that they have fundamentally different outcome measures. Our findings for the effects of inequality on crime rates are consistent with this notion. Whereas both approaches may construct a similar environment with a similar distance decay, the ISE approach assumes that the environment is *acting upon* a single block or person at the center of the environment. In contrast, the egohoods approach posits that the entire environment is capturing the social process (and therefore the outcome measure is constructed at the geographic unit of the entire egohood). This difference suggests that there will not be mathematical equivalence between the two approaches.

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Nonetheless, it will be useful to assess whether this is always the case. Furthermore, researchers will want to keep in mind the differing conceptual perspectives of each of these approaches.

Although we have argued that our overlapping approach best approximates the social world in general, there may be instances in which residents of a geographic location are able to come together as a collectivity. If residents banded together with regularity, the city social landscape would appear as a collection of such non-overlapping groups forming for social action. We argue that this is empirically not the case and that a more appropriate approach would consider such collectivities as a *potentiality*: various areas across the social landscape have a *latent* potential for such collective action. Thus, rather than starting with an assumption of existing non-overlapping areas/groups—which we argue is empirically and conceptually inaccurate—we suggest that a better approach treats this as a collective action problem in response to challenges to the neighborhood. Given that collective action in this case is fundamentally geographically based (as neighborhoods are contiguous), we might consider these as *latent* neighborhoods with more or less potential to cohere when challenges arise. Combining such a latent neighborhood concept with our egohood approach is a useful direction for future research.<sup>11</sup>

This study was an initial exposition of the concept of egohoods, and a large amount of work is necessary in the future to flesh out the various possibilities and limitations of this approach. Accordingly, we acknowledge some limitations of this study. First, one challenge we encountered in creating structural characteristics for egohoods is that some variables from the U.S. Census are not aggregated to units smaller than block groups. We adopted an approach

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<sup>11</sup> A recent study modeled the possibility that boundaries of neighborhoods might be endogenous (Rey, Anselin, Folch, Arribas-Bel, Gutiérrez, and Interlante 2011). This is an interesting direction, and it will be useful to assess how much traction it can provide compared to our egohood approach that does not start from an assumption of non-overlapping boundaries. It also highlights that this collective action problem implies that the boundaries of the collectivity are possibly endogenous.

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common in the geospatial literature of using a uniform distribution assumption when assigning these measures to the blocks within an egohood, although more sophisticated imputations should be explored in future research. We suspect that more sophisticated imputations may not make a large difference when constructing egohood measures, nonetheless, this should be tested.

Second, our results showed somewhat inconsistent effects across cities for certain covariates; however, given that such inconsistencies were also observed when aggregating to block groups or tracts, this may speak more to the appropriateness of the covariates rather than the aggregation technique. Indeed, to the extent that virtually any model is mis-specified, correcting the scale or boundaries of the units will not address this problem. Model specification remains a crucial issue. Third, although the spatial error model is meant to account for measurement error across non-overlapping units, our egohoods approach *explicitly* creates measurement error across units. Although we have suggested that the spatial error model corrects for this constructed interdependence, future work will need to assess that this is indeed the case.

Fourth, future research should explore the impact of different weights for physical boundaries to more effectively account for these boundaries in the city landscape. As we described, it is straightforward in principle to incorporate physical boundaries into the egohood approach. However, there is very little information available about the precise weights that should be used when incorporating such physical boundaries into egohoods. What is needed is much more information on how physical boundaries actually impact the formation of social ties. For example, if large physical boundaries such as freeways and rivers truly impact neighborhood social tie formation in a non-trivial manner (Grannis 2009), this would have strong consequences for residents in blocks closest to such boundaries. The egohood approach predicts that residents in such blocks would have fewer social ties, and a lower sense of collective efficacy, than other

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blocks. Research would need to explore these hypotheses directly. Relatedly, the boundary problem is well known in spatial analysis, and may be an issue for egohoods in cities with irregularly shaped boundaries (e.g., Los Angeles). Future research will need to assess the extent to which this is indeed the case. Nonetheless, the considerable benefits of the egohood approach shown here suggest this would be a fruitful area of future research.

In conclusion, we have proposed a novel approach to conceptualizing and measuring neighborhoods—what we have termed *egohoods*. A crucial insight of our approach is the decision to move away from the dominant paradigm of constructing neighborhoods as non-overlapping units across the social landscape. As Suttles (1972) pointed out, such non-overlapping units do not necessarily match up to the social reality experienced within the city. Although other scholars have also noted this limitation of the non-overlapping boundary approach (Grannis 2009; Massey and Denton 1993; Porter, Kirtland, Neet, Williams, and Ainsworth 2005), prior work has nonetheless generally failed to rigorously measure neighborhoods with fuzzy or overlapping boundaries. We suggest that conceptualizing egohoods as waves washing across the surface of the city is a more accurate representation of the social landscape. Importantly, we demonstrated that the egohood approach resulted in an improvement in explaining the location of crime in cities, and better captured the positive effect of inequality on crime rates. Future research can use egohoods to explore a host of spatially dynamic social phenomena (e.g. mobility, employment locations, neighborhood councils, gangs), and therefore will hopefully be useful to scholars for understanding numerous social phenomena.

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**Tables and Figures**

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Table 1. Summary statistics of variables used in analyses, all nine cities combined

	Block groups		Tracts		0.25 mile egohoods		0.5 mile egohoods		0.75 mile egohoods	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
<b>Outcome variables</b>										
Aggravated assault rate	208.8	245.2	211.7	200.1	220.4	287.6	212.9	206.7	210.1	184.8
Robbery rate	138.8	199.1	134.4	148.3	150.0	247.3	143.8	168.6	141.0	142.0
Homicide rate	4.6	9.8	4.6	6.8	4.5	10.2	4.4	6.2	4.3	4.9
Burglary rate	346.8	336.9	324.0	267.8	384.2	378.0	366.1	276.9	358.0	241.2
Motor vehicle theft rate	290.7	326.7	282.1	232.8	307.0	374.9	302.0	272.5	297.2	219.2
Larceny rate	823.9	1,325.5	786.1	884.1	1,007.6	1,982.9	977.1	1,327.9	943.8	1,041.3
<b>Independent variables</b>										
Percent vacant units	6.80	7.82	7.21	7.17	8.10	8.04	8.21	6.98	8.21	6.67
Percent owners	52.79	28.73	47.63	26.28	50.80	27.59	48.10	24.56	47.05	23.05
Average household income	55,361	37,910	53,652	36,122	53,707	36,006	52,544	32,252	51,835	29,827
Percent black	26.67	35.99	27.56	35.59	26.61	35.04	26.87	33.87	26.99	33.39
Percent Latino	23.95	28.37	25.51	28.61	26.15	28.06	26.73	27.25	27.13	26.81
Racial/ethnic heterogeneity	0.35	0.21	0.38	0.21	0.38	0.21	0.41	0.20	0.42	0.20
Inequality	0.86	0.15	0.89	0.12	0.90	0.11	0.92	0.10	0.92	0.09
Percent aged 16 to 29	22.00	9.30	23.13	8.98	22.32	8.55	23.02	7.65	23.34	7.20
Percent crowded households	12.85	16.04	14.12	16.14	13.69	14.93	13.91	14.34	14.08	14.03
Population	1,275	869	3,989	2,122	1,578	1,292	5,972	4,500	10,241	7,886
Population density (square mile)	12,102	10,745	12,078	11,152						

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Table 2. Types of violent crimes rates for various neighborhood definitions, parameter estimates averaged over models from nine cities

	Aggravated assaults				Robberies				Homicides			
	1/4 mile egohoods	1/2 mile egohoods	Tracts	Ratio (a)	1/4 mile egohoods	1/2 mile egohoods	Tracts	Ratio (a)	1/4 mile egohoods	1/2 mile egohoods	Tracts	Ratio (a)
Vacancies	0.035 ** (23.901)	0.039 ** (29.433)	0.028 ** (3.897)	1.39	0.032 ** (14.566)	0.027 ** (14.871)	0.022 * (2.320)	1.22	0.036 ** (13.400)	0.039 ** (18.873)	0.024 * (2.490)	1.61
Owners	-0.008 ** (-16.657)	-0.004 ** (-9.094)	-0.010 ** (-3.415)	0.39	-0.016 ** (-24.911)	-0.013 ** (-21.136)	-0.016 ** (-4.913)	0.78	-0.003 ** (-3.187)	-0.002 ** (-3.241)	-0.004 (-1.146)	0.52
Average household income	-0.015 ** (-16.999)	-0.017 ** (-24.161)	-0.015 ** (-3.146)	1.15	-0.009 ** (-5.538)	-0.011 ** (-10.286)	-0.012 (-1.533)	0.92	-0.015 ** (-5.509)	-0.015 ** (-8.703)	-0.019 * (-1.964)	0.81
Percent black	0.011 ** (30.841)	0.009 ** (36.433)	0.018 ** (6.559)	0.52	0.010 ** (22.014)	0.008 ** (28.559)	0.015 ** (4.761)	0.53	0.014 ** (21.024)	0.011 ** (31.652)	0.024 ** (6.501)	0.44
Percent Latino	0.011 ** (12.534)	0.008 ** (14.444)	0.011 ** (2.701)	0.70	0.007 ** (6.258)	0.012 ** (10.510)	0.007 † (1.666)	1.58	0.016 ** (9.750)	0.015 ** (14.833)	0.006 ** (2.949)	2.52
Racial/ethnic heterogeneity	0.252 ** (7.194)	0.335 ** (11.284)	0.159 (0.941)	2.11	0.793 ** (12.752)	0.823 ** (17.538)	0.632 † (1.888)	1.30	0.563 ** (4.378)	0.536 ** (6.886)	0.226 (0.612)	2.37
Income inequality	0.826 ** (6.944)	1.303 ** (14.722)	-0.240 (-1.552)	OPP	0.869 ** (6.454)	1.370 ** (12.174)	0.246 (-0.499)	5.57	0.997 ** (3.929)	1.388 ** (8.533)	1.354 (1.619)	1.03
Percent aged 16-29	-0.003 (-0.814)	-0.006 ** (-5.400)	-0.007 (-1.362)	0.87	-0.005 (-1.101)	-0.012 ** (-6.594)	-0.006 (-0.699)	1.88	-0.002 (0.586)	-0.005 (-0.845)	-0.015 (-1.001)	0.35
Percent crowding	0.011 ** (3.788)	0.019 ** (3.649)	0.002 (0.089)	7.56	0.001 (1.641)	-0.001 (-1.451)	-0.014 (-0.659)	0.09	0.008 ** (2.603)	0.012 ** (3.313)	0.001 (0.208)	13.62
Population density	-0.260 ** (-23.527)	-0.053 ** (-16.408)	-0.033 ** (-3.447)		-0.350 ** (-23.333)	-0.042 ** (-9.448)	-0.030 ** (-2.945)		-0.146 ** (-6.006)	-0.024 ** (-5.072)	-0.023 (-1.115)	
Intercept	2.493 ** (26.764)	1.864 ** (22.845)	3.532 ** (7.545)		2.423 ** (17.849)	1.773 ** (14.249)	2.986 ** (5.385)		-2.516 ** (-11.429)	-2.804 ** (-18.942)	-2.098 ** (-3.044)	

Note: \*\*  $p < .01$ ; \*  $p < .05$ ; †  $p < .10$ . T-values in parentheses.  $N = 93,638$  for egohoods and 3,146 for tracts. Cities are Buffalo, Chicago, Cincinnati, Cleveland, Dallas, Los Angeles, Sacramento, St. Louis, Tucson

Note: (a): Ratio of 1/2 mile egohood parameter estimate to tract estimate. OPP indicates an opposite signed coefficient.

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Table 3. Types of property crimes rates for various neighborhood definitions, parameter estimates averaged over models from nine cities

	Burglaries				Motor vehicle thefts				Larcenies			
	1/4 mile egohoods	1/2 mile egohoods	Tracts	Ratio (a)	1/4 mile egohoods	1/2 mile egohoods	Tracts	Ratio (a)	1/4 mile egohoods	1/2 mile egohoods	Tracts	Ratio (a)
Vacancies	0.025 ** (20.267)	0.026 ** (21.724)	0.016 ** (2.698)	1.55	0.019 ** (12.197)	0.015 ** (9.458)	0.017 * (2.341)	0.89	0.025 ** (15.609)	0.013 ** (9.512)	0.018 * (2.069)	0.71
Owners	-0.005 ** (-14.896)	-0.003 ** (-8.115)	-0.006 * (-2.026)	0.50	-0.008 ** (-20.053)	-0.006 ** (-14.696)	-0.009 ** (-3.375)	0.62	-0.017 ** (-34.511)	-0.015 ** (-28.682)	-0.019 ** (-5.816)	0.81
Average household income	-0.007 ** (-8.773)	-0.009 ** (-15.282)	-0.011 ** (-2.783)	0.88	-0.011 ** (-13.811)	-0.015 ** (-21.824)	-0.013 ** (-3.214)	1.13	-0.002 * (-2.525)	-0.005 ** (-5.172)	-0.004 (-0.839)	1.35
Percent black	0.002 ** (11.077)	0.001 ** (12.467)	0.005 * (2.262)	0.19	0.002 ** (16.905)	0.001 ** (20.466)	0.005 ** (2.863)	0.12	-0.001 (-0.906)	-0.004 (1.030)	0.004 (0.215)	OPP
Percent Latino	0.003 ** (2.842)	-0.001 ** (5.377)	0.003 (0.348)	-0.23	0.000 ** (5.598)	0.002 ** (9.825)	0.005 (1.103)	0.32	-0.014 ** (-5.059)	-0.009 (-0.416)	0.000 (0.060)	OPP
Racial/ethnic heterogeneity	0.357 ** (11.012)	0.353 ** (12.917)	0.114 (0.811)	3.10	0.516 ** (13.228)	0.582 ** (17.190)	0.406 † (1.813)	1.43	0.267 ** (6.270)	0.287 ** (8.375)	0.168 (0.601)	1.70
Income inequality	0.503 ** (5.711)	0.838 ** (12.159)	-0.094 (-0.904)	OPP	0.500 ** (3.906)	0.989 ** (10.557)	-0.225 † (-1.743)	OPP	0.064 (0.162)	0.634 ** (7.167)	-0.707 * (-2.478)	OPP
Percent aged 16-29	-0.002 (-0.043)	-0.006 ** (-5.669)	0.002 (0.365)	OPP	0.001 (1.438)	-0.004 ** (-3.725)	-0.002 (-0.267)	1.97	0.003 ** (3.042)	-0.007 ** (-4.139)	0.002 (0.632)	OPP
Percent crowding	0.002 (-0.393)	0.008 * (-2.090)	-0.005 (-0.643)	OPP	0.003 ** (2.622)	0.001 (0.054)	-0.014 (-0.833)	OPP	-0.014 ** (-4.287)	-0.007 ** (-5.161)	-0.030 * (-2.192)	0.23
Population density	-0.285 ** (-34.212)	-0.052 ** (-22.220)	-0.032 ** (-4.847)		-0.405 ** (-39.680)	-0.096 ** (-31.480)	-0.052 ** (-6.119)		-0.536 ** (-49.081)	-0.113 ** (-32.882)	-0.056 ** (-6.444)	
Intercept	3.759 ** (47.537)	3.315 ** (45.926)	4.342 ** (10.119)		3.745 ** (40.843)	3.317 ** (37.719)	4.495 ** (10.327)		5.988 ** (57.260)	5.483 ** (51.396)	6.605 ** (13.050)	

Note: \*\*  $p < .01$ ; \*  $p < .05$ ; †  $p < .10$ . T-values in parentheses.  $N = 93,638$  for egohoods and  $3,146$  for tracts. Cities are Buffalo, Chicago, Cincinnati, Cleveland, Dallas, Los Angeles, Sacramento, St. Louis, Tucson

Note: (a): Ratio of 1/2 mile egohood parameter estimate to tract estimate. OPP indicates an opposite signed coefficient.



Measuring egohoods

Table 4. Types of crime rates for neighborhoods based on the individual social environment (ISE) approach, a 1/2 mile distance decay function in which the block is the center of interest, parameter estimates averaged over models from nine cities

	Aggravated assault	Robbery	Homicide	Burglary	Motor vehicle theft	Larceny
Vacancies	0.018 ** (4.700)	0.006 (1.058)	0.016 (1.634)	0.005 † (1.884)	-0.004 † (-1.671)	-0.004 (0.040)
Owners	-0.011 ** (-6.982)	-0.021 ** (-11.002)	-0.009 (-1.622)	-0.009 ** (-7.453)	-0.012 ** (-10.069)	-0.021 ** (-17.055)
Average household income	-0.012 ** (-4.451)	-0.005 (-0.849)	-0.008 (-0.624)	-0.003 (-0.314)	-0.009 ** (-3.564)	0.000 (1.150)
Percent black	0.012 ** (10.828)	0.011 ** (9.483)	0.010 ** (5.400)	0.002 ** (4.411)	0.001 ** (7.469)	-0.001 (0.107)
Percent Latino	0.000 * (2.262)	0.002 (1.174)	0.015 † (1.734)	-0.005 (-1.505)	-0.009 (0.812)	-0.019 ** (-4.861)
Racial/ethnic heterogeneity	0.409 ** (3.265)	0.888 ** (5.398)	0.446 (1.173)	0.506 ** (5.473)	0.596 ** (6.213)	0.317 ** (4.966)
Income inequality	-0.128 (-1.282)	-0.057 (-0.189)	0.209 (0.289)	-0.268 † (-1.850)	-0.428 ** (-2.750)	-0.465 * (-2.345)
Percent aged 16-29	-0.002 (-0.663)	-0.007 (-1.100)	0.005 (0.440)	-0.001 (-0.253)	0.005 (1.127)	0.002 (0.466)
Percent crowding	0.031 ** (3.765)	0.018 * (2.513)	0.034 † (1.791)	0.022 ** (3.241)	0.021 ** (3.605)	0.007 † (1.763)
Population density	-0.314 ** (-10.657)	-0.364 ** (-9.616)	-0.152 † (-1.747)	-0.372 ** (-17.817)	-0.493 ** (-20.368)	-0.566 ** (-27.476)
Intercept	-6.170 **	-6.226 **	-11.554 **	-4.928 **	-4.776 **	-2.781 **

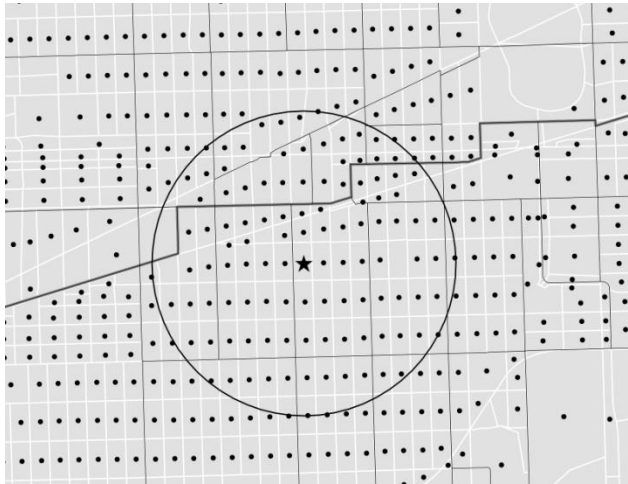
Measuring egohoods

-(22.755)      -(20.384)      -(11.943)      -(24.290)      -(21.167)      -(15.120)

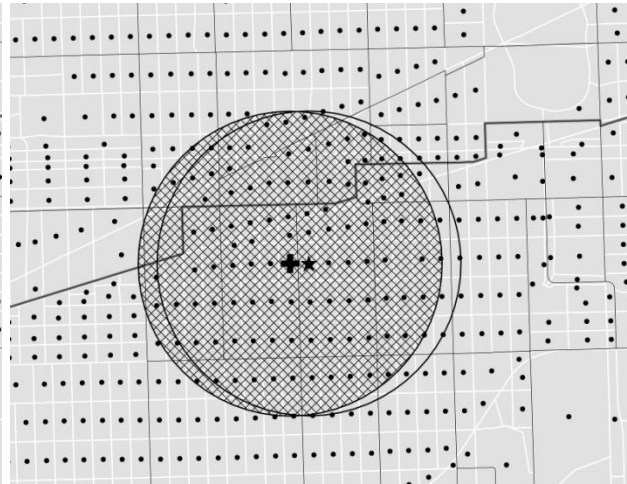
*Note: \*\* p < .01; \* p < .05; † p < .10. T-values in parentheses. N = 93,638. Cities are Buffalo, Chicago, Cincinnati, Cleveland, Dallas, Los Angeles, Sacramento, St. Louis, Tucson*

Measuring egohoods  
Figure 1

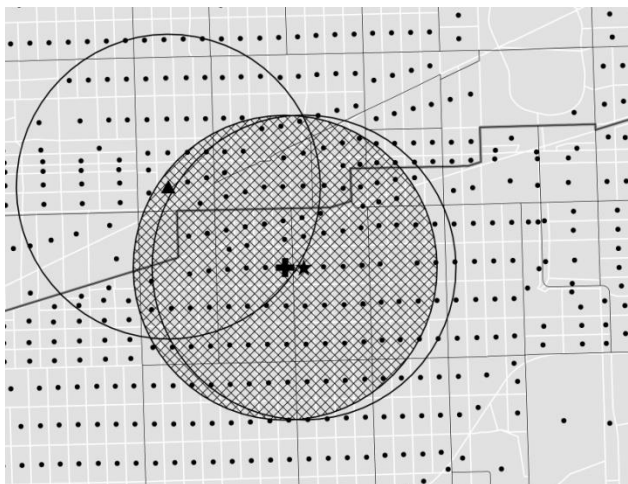
A



B



C



**Figure 2: Partial correlation of crime count with predicted crime count**

