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

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December 20, 2012

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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*.

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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 20th 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).

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

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;

Measuring egohoods
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

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).

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

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.

Measuring egohoods

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

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

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

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.

Measuring egohoods

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;

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

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).[1] We are therefore able to assess the performance of the models at these various aggregations and the relative effectiveness of the various structural characteristics.[2]

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.[3] 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.[4] 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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[1] 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.

[2] 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).

[3] 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.

[4] 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.

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

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

income, and then compute the standard deviation of the incomes in a buffer based on these

values.[5] 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 $(1-(dist(p,q)/r)^2)^2$ where r is the radius of the buffer and

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.[6] 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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[5] 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 (Nielson 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.

[6] 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.

egohoods with ¾ mile buffers, ISE's with ¼ mile buffers, ISE's with ½ mile buffers, ISE's with

¾ 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 ¼

mile and ½ mile egohoods (but not ¾ 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 ½ mile ISE's (given that the ¼ mile and ¾ 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.[7] 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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[7] 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.

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 ¼ mile buffers, egohoods with ½ 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 ¾ 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.[8]

Results

Predicting crime with different neighborhood aggregations

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[8] 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.

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 ¼ mile and ½ 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 ¾ mile egohoods, .36 for ¼ mile egohoods, and .37 for ½ mile egohoods. Thus, ½ 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

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 (3/4 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).[9] The substantive conclusions from these models are

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[9] 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

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

Measuring egohoods

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 ¼ mile to ¾ miles and our results indicated relative

Measuring egohoods
similarity over these various radii.[10] 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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[10] 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.

Measuring egohoods

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.

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.[11]

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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[11] 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.

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

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.

References

Ainsworth, James W. 2002. "Why Does It Take a Village? The Mediation of Neighborhood Effects on Educational Achievement." *Social Forces* 81:117-152.

Anselin, Luc. 1988. *Spatial Econometrics: Methods and Models*. Boston: Springer.

—. 2003. "Spatial Externalities, Spatial Multipliers, And Spatial Econometrics." *International Regional Science Review* 26:153-166.

Baumer, Eric P. 2002. "Neighborhood Disadvantage and Police Notification by Victims of Violence." *Criminology* 40:579-616.

Bellair, Paul E. 1997. "Social Interaction and Community Crime: Examining the Importance of Neighbor Networks." *Criminology* 35:677-703.

Bennett, R.J., R.P. Haining, and D.A. Griffith. 1984. "Review Article: The Problem of Missing Data on Spatial Surfaces." *Annals of the Association of American Geographers* 74:138-156.

Bernasco, Wim and Richard L. Block. 2009. "Where Offenders Choose to Attack: A Discrete Choice Model of Robberies in Chicago." *Criminology* 47:93-130.

Bivand, Roger and Luc Anselin with contributions by Micah Altman, Renato Assunção, Olaf Berke, Andrew Bernat, Guillaume Blanchet, Eric Blankmeyer, Marilia Carvalho, Bjarke Christensen, Yongwan Chun, Carsten Dormann, Stéphane Dray, Rein Halbersma, Elias Krainski, Pierre Legendre, Nicholas Lewin-Koh, Hongfei Li, Jielai Ma, Giovanni Millo, Werner Mueller, Hisaji Ono, Pedro Peres-Neto, Gianfranco Piras, Markus Reder, Michael Tiefelsdorf, and Danlin Yu. 2012. *spdep: Spatial dependence: weighting schemes, statistics and models. R package version 0.5-51*. Vienna, Austria: R Foundation for Statistical Computing.

Boyd, Robert and Peter J. Richerson. 1985. *Culture and the Evolutionary Process*. Chicago: University of Chicago.

Brantingham, Paul J. and Patricia L. Brantingham. 1984. *Patterns in Crime*. New York: MacMillan.

Browning, Christopher R., Seth L. Feinberg, and Robert D. Dietz. 2004. "The Paradox of Social Organization: Networks, Collective Efficacy, and Violent Crime in Urban Neighborhoods." *Social Forces* 83:503-534.

Brownson, Ross C., Christine M. Hoehner, Kristen Day, Ann Forsyth, and James F. Sallis. 2009. "Measuring the Built Environment for Physical Activity: State of the Science." *American Journal of Preventive Medicine* 36:S99-S123.

Bursik, Robert J. 1988. "Social Disorganization and Theories of Crime and Delinquency: Problems and Prospects." *Criminology* 26:519-551.

Bursik, Robert J. and Harold G. Grasmick. 1993. *Neighborhoods and Crime*. New York: Lexington.

Caplow, Theodore and Robert Forman. 1950. "Neighborhood Interaction in a Homogeneous Community." *American Sociological Review* 15:357-366.

Capone, Donald L. and Woodrow W. Nichols. 1976. "Urban Structure and Criminal Mobility." *American Behavioral Scientist* 20:199-213.

Chaskin, Robert J. 1997. "Perspectives on Neighborhood and Community: A Review of the Literature." *The Social Service Review* 71:521-547.

Coulton, Claudia J., Jill Korbin, Tsui Chan, and Marilyn Su. 2001. "Mapping Residents' Perceptions of Neighborhood Boundaries: A Methodological Note." *American Journal of Community Psychology* 29:371-383.

Crutchfield, Robert D. 1989. "Labor Stratification and Violent Crime." *Social Forces* 68:489-512.

Duque, Juan Carlos, Raúl Ramos, and Jordi Suriñach. 2007. "Supervised Regionalization Methods: A Survey." *International Regional Science Review* 30:195-220.

Elffers, Henk. 2003. "Analysing Neighbourhood Influence in Criminology " *Statistica Neerlandica* 57:347-367.

Feld, Scott L. 1982. "Social Structural Determinants of Similarity among Associates." *American Sociological Review* 47:797-801.

Felson, Marcus. 2002. *Crime and Everyday Life*. Thousand Oaks, CA: Sage.

Festinger, Leon, Stanley Schachter, and Kurt Back. 1950. *Social Pressures in Informal Groups*. Stanford, CA: Stanford University Press.

Gómez, Jorge E., Beth Ann Johnson, Martha Selva, and James F. Sallis. 2004. "Violent crime and outdoor physical activity among inner-city youth." *Preventive Medicine* 39:876-881.

Grannis, Rick. 2009. *From the Ground Up: Translating Geography into Community through Neighbor Networks*. Princeton: Princeton.

Green, Howard Whipple and Leon E. Truesdell. 1937. *Census Tracts in American Cities*. Washington, D.C.: U.S. Department of Commerce, Bureau of the Census.

Guest, Avery M. and Barrett A. Lee. 1984. "How urbanites define their neighborhoods." *Population & Environment* 7:201-214.

Haney, Wava G. and Eric S. Knowles. 1978. "Perception of neighborhoods by city and suburban residents." *Human Ecology* 6:201-214.

Hannan, Michael T. 1991. *Aggregation and Disaggregation in the Social Sciences*. Lexington, MA: D.C. Heath.

Hannon, Lance. 2002. "Criminal Opportunity Theory and the Relationship between Poverty and Property Crime." *Sociological Spectrum* 22:363-381.

Hannon, Lance and Peter Knapp. 2003. "Reassessing Nonlinearity in the Urban Disadvantage/Violent Crime Relationship: An Example of Methodological Bias from Log Transformation." *Criminology* 41:1427-1448.

Hipp, John R. 2007a. "Block, Tract, and Levels of Aggregation: Neighborhood Structure and Crime and Disorder as a Case in Point." *American Sociological Review* 72:659-680.

—. 2007b. "Income Inequality, Race, and Place: Does the Distribution of Race and Class within Neighborhoods affect Crime Rates?" *Criminology* 45:665-697.

—. 2010. "A Dynamic View of Neighborhoods: The Reciprocal Relationship between Crime and Neighborhood Structural Characteristics." *Social Problems* 57:205-230.

Hipp, John R., Robert W. Faris, and Adam Boessen. 2012. "Measuring 'neighborhood': Constructing network neighborhoods." *Social Networks* 34:128-140.

Hipp, John R. and Andrew J. Perrin. 2009. "The Simultaneous Effect of Social Distance and Physical Distance on the Formation of Neighborhood Ties." *City & Community* 8:5-25.

Hipp, John R. and Daniel K. Yates. 2011. "Ghettos, thresholds, and crime: Does concentrated poverty really have an accelerating increasing effect on crime?" *Criminology* 49:955-990.

Hunter, Albert. 1974. *Symbolic Communities*. Chicago: University of Chicago.

Janowitz, Morris. 1952. *The community press in an urban setting*. Glencoe, IL: Free Press.

Krivo, Lauren J. and Ruth D. Peterson. 1996. "Extremely Disadvantaged Neighborhoods and Urban Crime." *Social Forces* 75:619-648.

Lander, Bernard. 1954. *Towards an Understanding of Juvenile Delinquency*. New York: Columbia.

Measuring egohoods

Lee, Barrett A. and Karen E. Campbell. 1997. "Common Ground? Urban Neighborhoods as Survey Respondents See Them." *Social Science Quarterly* 78:922-936.

Lee, Barrett A., Sean F. Reardon, Glenn Firebaugh, Chad R. Farrell, Stephen A. Matthews, and David O'Sullivan. 2008. "Beyond the Census Tract: Patterns and Determinants of Racial Segregation at Multiple Geographic Scales." *American Sociological Review* 73:766-791.

Lee, Jae Yong and Mei-Po Kwan. 2010. "Visualisation of Socio-Spatial Isolation Based on Human Activity Patterns and Social Networks in Space-Time." *Tijdschrift voor Economische en Sociale Geografie* 102:468-485.

Lynch, James P. and Lynn A. Addington. 2007. "Understanding Crime Statistics: Revisiting the Divergence of the NCVS and UCR." Pp. 340. Cambridge: Cambridge University Press.

Lynch, Kevin. 1964. *The Image of the City*. Cambridge, MA: MIT.

Massey, Douglas S. and Nancy A. Denton. 1993. *American Apartheid: Segregation and the Making of the Underclass*. Cambridge, MA: Harvard.

McPherson, Miller, Lynn Smith-Lovin, and James M Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27:415-444.

Messner, Steven F. and Kenneth Tardiff. 1986. "Economic Inequality and Levels of Homicide: An Analysis of Urban Neighborhoods." *Criminology* 24:297-317.

Miethe, Terance D. and Robert F. Meier. 1994. *Crime and its Social Context: Toward an Integrated Theory of Offenders, Victims, and Situations*. Albany: State University of New York Press.

Morenoff, Jeffrey D. 2003. "Neighborhood Mechanisms and the Spatial Dynamics of Birth Weight." *American Journal of Sociology* 108:976-1017.

Mosher, Clayton J., Terance D. Miethe, and Dretha M. Philips. 2002. *The mismeasure of crime*. Thousand Oaks, CA: Sage.

Moudon, Anne Vernez, Chanam Lee, Allen D. Cheadle, Cheza Garvin, Donna Johnson, Thomas L. Schmid, Robert D. Weathers, and Lin Lin. 2006. "Operational Definitions of Walkable Neighborhood: Theoretical and Empirical Insights." *Journal of Physical Activity and Health* 3:S99-S117.

Nielsen, Amie L. and Ramiro Martinez. 2003. "Reassessing the Alcohol-Violence Linkage: Results from a Multiethnic City." *Justice Quarterly* 20:445-469.

Nielsen, Francois and Arthur S. Alderson. 1997. "The Kuznets Curve and the Great U-Turn: Income Inequality in U.S. Counties, 1970 to 1990." *American Sociological Review* 62:12-33.

O'Brien, Robert M. 2007. "A Caution Regarding Rules of Thumb for Variance Inflation Factors." *Quality & Quantity* 41:673-690.

Osgood, D. Wayne. 2000. "Poisson-Based Regression Analysis of Aggregate Crime Rates." *Journal of Quantitative Criminology* 16:21-43.

Park, Robert E. and Ernest W. Burgess. 1921. *Introduction to the science of sociology*. Chicago: University of Chicago.

Porter, D.E., K.A. Kirtland, M.J. Neet, J.E. Williams, and B.E. Ainsworth. 2005. "Considerations for using a geographic information system to assess environmental supports for physical activity." *Prevention Chronic Disease* 1:A20.

Pridemore, William Alex. 2011. "Poverty Matters: A Reassessment of the Inequality–Homicide Relationship in Cross-National Studies." *The British Journal of Criminology* 51:739-772.

R Development Core Team. 2012. *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Reardon, Sean F., Stephen A. Matthews, David O'Sullivan, Barrett A. Lee, Glenn Firebaugh, Chad R. Farrell, and K. Bischoff. 2008. "The Geographical Scale of Metropolitan Racial Segregation." *Demography* 45:489-514.

Reardon, Sean F. and David O'Sullivan. 2004. "Measures of Spatial Segregation." *Sociological Methodology* 34:121-162.

Ren, Fang and Mei-Po Kwan. 2009. "The impact of the Internet on human activity–travel patterns: analysis of gender differences using multi-group structural equation models." *Journal of Transport Geography* 17:440-450.

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

Rey, Sergio J., Luc Anselin, David C. Folch, Daniel Arribas-Bel, Myrna L. Sastré Gutiérrez, and Lindsey Interlante. 2011. "Measuring Spatial Dynamics in Metropolitan Areas." *Economic Development Quarterly* 25:54-64.

Sampson, Robert J. 1997. "Collective Regulation of Adolescent Misbehavior." *Journal of Adolescent Research* 12:227-244.

—. 2004. "Networks and Neighbourhoods: The Implications of Connectivity for Thinking About Crime in the Modern City." Pp. 157-166 in *Network Logic: Who Governs in an Interconnected World?*, edited by H. McCarthy, P. Miller, and P. Skidmore. London: Demos.

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

Sampson, Robert J., Jeffrey D. Morenoff, and Felton Earls. 1999. "Beyond Social Capital: Spatial Dynamics of Collective Efficacy for Children." *American Sociological Review* 64:633-660.

Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. "Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy." *Science* 277:918-924.

Sastry, Narayan, Anne R. Pebley, and Michela Zonta. 2002. "Neighborhood Definitions and the Spatial Dimension of Daily Life in Los Angeles." Santa Monica, CA.

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

Silander, John A. Jr. and Stephen W. Pacala. 1985. "Neighborhood Predictors of Plant Performance." *Oecologia* 66:256-263.

Suttles, Gerald D. 1972. *The Social Construction of Communities*. Chicago: University of Chicago.

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* 34:113-155.

Taylor, Ralph B., Stephen D. Gottfredson, and Sidney Brower. 1984. "Block Crime and Fear: Defensible Space, Local Social Ties, and Territorial Functioning." *Journal of Research in Crime and Delinquency* 21:303-331.

Villarreal, Andres. 2002. "Political Competition and Violence in Mexico: Hierarchical Social Control in Local Patronage Structures." *American Sociological Review* 67:477-498.

Walsh, Jeffrey A. and Ralph B. Taylor. 2007. "Predicting Decade-Long Changes in Community Motor Vehicle Theft Rates: Impacts of Structure and Surround." *Journal Of Research In Crime And Delinquency* 44:64-90.

Measuring egohoods

Weisburd, David, Wim Bernasco, and Gerben Bruinsma. 2009. "Putting Crime in Its Place: Units of Analysis in Spatial Crime Research." Pp. 256. New York: Springer Verlaag.

Weisburd, David, Shawn Bushway, Cynthia Lum, and Sue-Ming Yang. 2004. "Trajectories of Crime at Places: A Longitudinal Study of Street Segments in the City of Seattle." *Criminology* 42:283-321.

Wellman, Barry and Barry Leighton. 1979. "Networks, Neighborhoods, and Communities: Approaches to the Study of the Community Question." *Urban Affairs Quarterly* 14:363-390.

Wirth, Louis and Eleanor H. Bernert. 1949. "Local Community Face Book of Chicago." in *The Chicago Community Inventory*. Chicago, IL: University of Chicago.

Wong, David W. S. 1997. "Spatial Dependency of Segregation Indices." *Canadian Geographer* 41:128-136.

Tables and Figures

Measuring egohoods

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
Outcome variables										
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
Independent variables										
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						

Measuring egohoods

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

Measuring egohoods

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

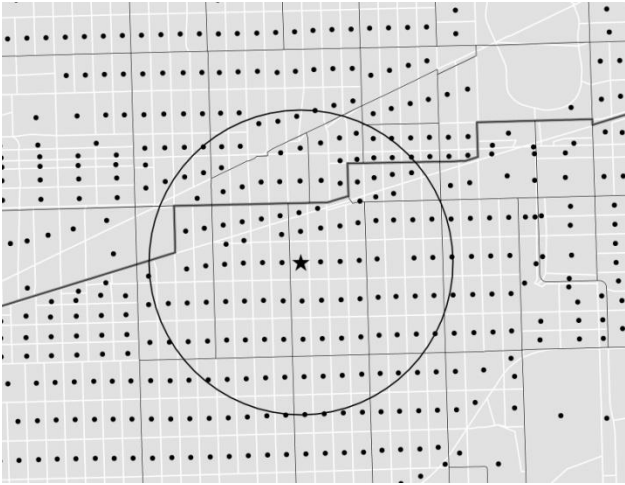|	Aggravated assault	Robbery	Homicide	Burglary	Motor vehicle theft	Larceny
Vacancies	0.018 **	0.006	0.016	0.005 †	-0.004 †	-0.004
	(4.700)	(1.058)	(1.634)	(1.884)	-(1.671)	(0.040)
Owners	-0.011 **	-0.021 **	-0.009	-0.009 **	-0.012 **	-0.021 **
	-(6.982)	-(11.002)	-(1.622)	-(7.453)	-(10.069)	-(17.055)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

Measuring egohoods

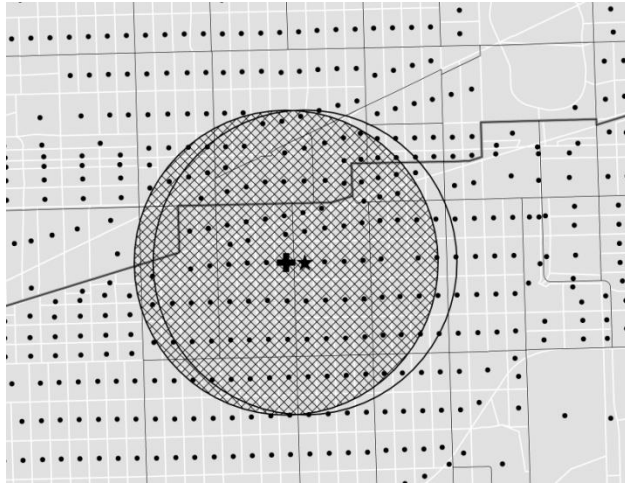-(22.755)   -(20.384)   -(11.943)   -(24.290)   -(21.167)   -(15.120)

*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*
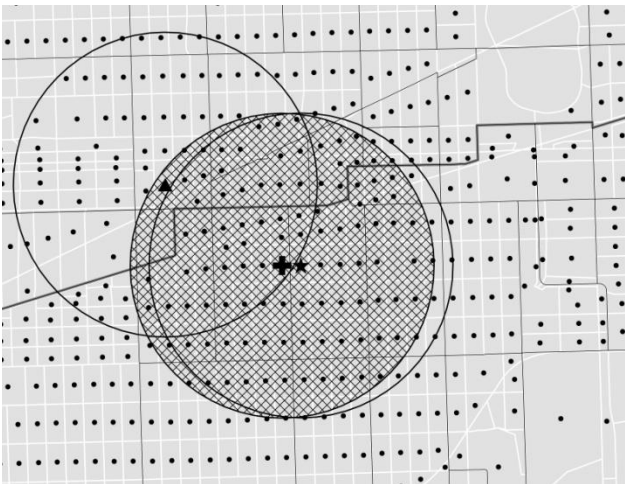
Measuring egohoods
Figure 1

A

B

C

Measuring egohoods

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