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Street Egohood: An Alternative Perspective of Measuring Neighborhood and Spatial Patterns of Crime

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Bio

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Abstract

Objectives
The current study proposes an approach that accounts for the importance of streets while at the same time accounting for the overlapping spatial nature of social and physical environments captured by the egohood approach. Our approach utilizes overlapping clusters of streets based on the street network distance, which we term street egohoods.
Methods
We used the street segment as a base unit and employed two strategies in clustering the street segments: (1) based on the First Order Queen Contiguity; and (2) based on the street network distance considering physical barriers. We utilized our approaches for measuring ecological factors and estimated crime rates in the Los Angeles metropolitan area.
Results
We found that whereas certain socio-demographics, land use, and business employee measures show stronger relationships with crime when measured at the smaller street based unit, a number of them actually exhibited stronger relationships when measured using our larger street egohoods. We compared the results for our three-sized street egohoods to street segments and two sizes of block egohoods proposed by Hipp and Boessen (Criminology 51(2):287–327, 2013) and found that two egohood strategies essentially are not different at the quarter mile egohood level but this similarity appears lower when looking at the half mile egohood level. Also, the street egohood models are a better fit for predicting violent and property crime compared to the block egohood models.
Conclusions
A primary contribution of the current study is to develop and propose a new perspective of measuring neighborhood based on urban streets. We empirically demonstrated that whereas certain socio-demographic measures show the strongest relationship with crime when measured at the micro geographic unit of street segments, a number of them actually exhibited the strongest relationship when measured using our larger street egohoods. We hope future research can use egohoods to expand understanding of neighborhoods and crime.

Street Egohood: An Alternative Perspective of Measuring Neighborhood and Spatial Patterns of Crime

Introduction

The neighborhood is one of the fundamental elements of a city, and a city is composed of multiple neighborhoods. Ecological studies of crime have revealed that some neighborhoods have more crime than others within a city. Studies have empirically found that the tendency of spatial crime concentration occurs, at least in part, due to the social (Hipp, 2007a, 2007b; Kubrin, 2003, 2009; Sampson & Groves, 1989; Sampson, Raudenbush, & Earls, 1997; Warner & Pierce, 1993) and physical environment (Block & Block, 1995; Brantingham & Brantingham, 1993, 1995; Weisburd, Groff, & Yang, 2012) of the neighborhood. Studies focusing on the social environment often invoke social disorganization theory, in which certain structural characteristics of neighborhood such as economic disadvantage, residential instability, and racial/ethnic heterogeneity impede the formation of social ties and cohesion, and thus reduce the level of informal social control among residents to keep the communities safe from crime and disorder. And studies focusing on the physical environment often cite criminal opportunities theory, based on the mixture of motivated offenders, potential victims, and the presence or absence of capable guardians (Cohen & Felson, 1979; Felson, 1987; Felson & Boba, 2010).

An ongoing challenge for this research is the actual definition of the neighborhood unit. We propose an approach that builds on the insights of a body of research in which the street segment is a fundamental geographic unit, and combines them with insights regarding the typical spatial patterns of residents in urban areas—that is, their activity space. An activity space is structured based on three main components: (1) home and movement near the home, (2) daily activity locations and movements around those locations, and (3) movement and travel between the daily activity locations (Golledge & Stimson, 1997). Additionally, a few recent studies have explored temporally dynamic patterns of crime and various activity nodes (restaurants, bars, shopping malls, etc.) during particular hours of the day and days of week (Bernasco, Ruiter, & Block, 2016; Haberman & Ratcliffe, 2015; Hipp & Kim, 2019). Therefore, residents' activity space constructed by their daily routine activities (i.e., work, school, and shopping) are not physically restricted to their own residential areas only (Inagami et al., 2006; Zenk et al., 2008; Zenk et al., 2011; Hipp & Boessen, 2013). Indeed, some empirical studies found that even people residing in the same block have different definitions of their neighborhoods and the individualized neighborhood definitions can largely influenced by residents' different perceptions on surrounding spaces, boundaries of routine activities, and social and physical contexts that they are situated in (Lee et al., 1991; Guest and Lee, 1984; Logan and Collver, 1983; Coulton et al., 2001).

To account for the inherent uncertainty in the social and physical environment of the neighborhood, some previous studies introduced a concept of egocentric neighborhood definition – "egocentric buffers" (Duncan et al., 2014; Forsyth et al., 2012; Boruff et al., 2012; Oliver et al., 2007). This approach defines a neighborhood as the area surrounding a particular location (or a person) within a distance radius and some particular distance decay function. Findings of these studies imply that a spatial buffer approach is theoretically congruent with residents' typical behavior and therefore a reasonable definition of neighborhood. For example, Hipp & Boessen (2013) utilized an "egohood" approach defined as overlapping concentric buffers that surround each Census block. Whereas researchers using spatial buffers typically employ a distance decay effect under the assumption that the surrounding area "acts upon" the block at the center, the egohood approach does not use a distance decay but instead assumes that the buffer as a whole operates as a neighborhood. Hipp & Boessen (2013) found that measures aggregated to egohoods explained more variation in crime than models aggregating to block groups or tracts.

We extend the egohoods approach by explicitly incorporating information about the street network to develop neighborhoods we term "street egohoods." As we discuss shortly, our approach links directly to the criminology literature focusing on crime at micro places that focuses on street segments, and combines it with the literature focusing on residents' daily activity patterns. Despite the insights provided by the egohood approach, a remaining question is how limited the egohood approach based on straight line Euclidean distances is for defining the neighborhood. This is because using straight line distance does not explicitly account for the actual street geography. Arguably, distances based on the street network configuration are more relevant to the real-life environment because they account for the actual street geography and physical barriers; consequently, they are more predictive of physical activity than Euclidean distance. Indeed, studies have revealed that street-network distance is conceptually and empirically more appealing than straight line distance or other boundaries of Census units for understanding neighborhood effects on residential location choice (Guo & Bhat, 2007), land use and walkability (Oliver et al. 2007; Boruff et al., 2012), youths' access to tobacco retailers (Duncun et al. 2013), and accessibility to food and recreational facilities (Forsyth et al., 2012).

In sum, the current study proposes an approach that accounts for the importance of streets while at the same time accounting for the overlapping spatial nature of social and physical environments captured by the egohood approach. Our approach utilizes overlapping clusters of streets based on the street network distance, which we term *street egohoods*. To do this, we used the street segment as a base unit because it is the smallest street based unit frequently used in previous studies. Specifically, we employed three sized street egohoods: (1) based on the First

Order Queen Contiguity (FOQC); and (2 and 3) based on ¼ mile or ½ mile street network distance considering physical barriers (i.e., interstate freeways). We utilized our street egohoods approach for measuring ecological factors and crime rates. Our study area is the Los Angeles County (the urbanized area in the county of Los Angeles as defined by the Census in 2010).

The primary goal of the current study is not to determine the *best* definition of neighborhood. Rather, the current study empirically examines the theoretically driven argument of considering the street network and the overlapping aspect when measuring neighborhood to more directly incorporate real-life geography. We attempt to draw attention to the fact that the field should pay more attention to the real-life geography such as street network configuration and overlapping characteristics, and give more careful consideration when measuring neighborhood and choosing the size of it. By doing so, we suggest an alternative way to look at neighborhood and attempt to enhance the methodological techniques drawing from theoretically more relevant neighborhood definitions. In the following sections, we discuss the theoretical motivations of our approach and then explicitly illustrate how street egohoods are constructed. We then compare the results for our three different-sized street egohoods to street segments and two sizes of block egohoods proposed by Hipp & Boessen (2013) for illustrative purposes.

The Theoretical Importance of Streets in Urban Life

Streets, more specifically, areas on both faces of streets, are important parts of urban environments because they comprise the majority of spaces in cities, and thus play an important role in shaping urban daily life (Appleyard, 1981; Jacobs, 1993; Jacobs, 1961). A primary function of streets is that they are major public utilities through which people move to reach different locations in a city for social, economic, and cultural activities. Moreover, streets themselves are the spaces for various social and leisure activities. Streets function as a public locus of social interactions by providing opportunities for contacts between people. Sociability is one of primary reasons for a city, and streets are major public spaces for that sociability to develop. Therefore, streets are the most vital organs of a city (Jacobs, 1961). If streets are at the core of urban life, and a neighborhood is the elementary form of cohesion in urban life (Park, 1926), then, arguably, a definition of the neighborhood should be based on streets.

A common definition of a street is a road relatively wider than a lane or alley. It is the linear surface along which movement occurs between the adjacent areas. However, a street is not just a linear surface of road but a three-dimensional space including the buildings located on the adjacent faces. For many decades, streets have been the framework of public open space for urban residents. Jane Jacobs emphasized the importance of the physical details of streets and building design. “Streets and their sidewalks, the main public places of a city, are its most vital organs. Think of a city and what comes to mind? Its streets. If a city’s streets look interesting, the city looks interesting; if they look dull, the city looks dull” (Jacobs, 1961:39). She posited that the breakdown of law and order in cities is due to replacement of streets by large building blocks that create more anonymity in places. She specified how the streets can be self-regulating through more eyes on the street facilitating the level of natural surveillance on the street. In her view, streets that have more users on them fairly continuously will provide effective eyes on the street and increase the willingness of people in buildings along the street to watch the street.

Streets facilitate the movement of people, vehicles, or goods to sustain the economic activities among people in the city. Also, streets have a function of communication and interaction that link people, thus serving to bind residents together as a local urban community. People use streets as sites for casual social interaction, recreation, conversation, and entertainment. Streets serve as a locus where a group of people (i.e., neighbors) interact and get to know each other. Therefore, as spaces shared by a group of people, streets can be seen to some extent as closed social systems that have distinct social and physical boundaries with the communal characteristics of neighborhoods. Moreover, although Census administrative boundaries generally follow visible and identifiable features, including roads, street-based units may be theoretically better given that people tend to interact with others who live on the same street, or those on immediately adjacent streets, but less with people on the street segment that backs up to theirs. Thus, a theoretical weakness of administrative boundaries is that they assume that people socially interact with others on these backing streets, but not with those who live across the street on the same street as them. If this is indeed true and if a neighborhood is the elementary form of cohesion in urban life, then, arguably, it is more plausible to define a neighborhood based on streets than any other administrative boundaries (i.e., block group, tract). Yet, the existing ecological studies have typically not constructed “neighborhoods” based explicitly on streets.

Street Segment: Too Small to be a Neighborhood?

Although not directly addressing the issue of measuring neighborhood based on streets, the street segment is frequently employed in studies of criminology of place and may be one possible candidate as a street-based neighborhood unit. The street segment is defined as both faces of a street between two intersections. Street segments can be seen as social locations that contain the characteristics of communities (Taylor, 1997). Wicker (1987) argued that street segments are small-scale social communities (behavior settings) where people know each other, get familiar with others’ routines, and develop and share their own norms. Moreover, street segments are as temporally dynamic as other geographic units as people constantly move in and out and land use can change (Taylor, 1997). Some empirical studies have found that there is street-to-street variability and spatial heterogeneity of crime as well as the social structural characteristics such as residential property values, land use, racial heterogeneity, and physical disorder (Braga & Clarke, 2014; Groff & McCord, 2012; Groff & Lockwood, 2013; Kim, 2016; Weisburd & Amram, 2014; Weisburd et al., 2012). For example, in a recent study, Kim (2016) empirically tested whether social structural characteristics have significant effects on crime in street segments. He found that structural characteristics are important factors in understanding crime patterns at the street segment level.

Some scholars studying the ecological distribution of crime have suggested that a very small street-based unit (i.e., street segment) can operate as possible neighborhoods because although it is spatially very small, a street segment contains all the social and physical characteristics of a community as presented in social disorganization theory and criminal opportunities theories (Groff & LaVigne, 2001; Groff, Weisburd, & Yang, 2010; Weisburd, Bushway, Lum, & Yang, 2004; Weisburd, Lum, & Yang, 2004; Weisburd, Groff, & Yang, 2012). Particularly, Taylor (1997) has justified the use of a street segment as a reasonable unit to capture social environments within a city. Given the theoretical propositions, it is not completely implausible to think that street segments can be seen as communities that contain the structural characteristics of communities presented in social disorganization theory. Weisburd and colleagues also suggested that "if the street segment can be seen as a type of 'micro community,' then social disorganization theory would seem to have direct relevance to the understanding of the criminology of place" (Weisburd et al. 2012: p.45).

If the theoretical argument for the street segment as a social community is indeed true, then an important empirical question is whether it is too small to be a "*neighborhood*." Some studies argue that a street segment is *theoretically* and *methodologically* preferred. Theoretically, residents' behaviors are influenced by physical and social environment only insofar as they can perceive these environments with their senses, or so-called "naked eyes" (Sherman, Gartin, & Buerger, 1989); and these environments are arguably small (Oberwittler & Wikstrom, 2009). However, when it comes to measuring neighborhood, such small-scale units can miss important social processes given that residents' perception of their neighborhood is not necessarily geographically, physically, socially, and psychologically restricted to a given street segment. Moreover, a neighborhood requires collective settings of social life based on the social network among people who share the common interests in that area. Thus, to the extent that empirical evidence shows that social ties extend to streets outside one's own particular street segment (Boessen, Hipp, Butts, Nagle, & Smith, 2017), the street segment will be too small a unit to capture the "neighborhood." Indeed, recent scholarship has shown that there are strong spatial patterns present in which the characteristics of the surrounding area have additional effects on the level of crime beyond the characteristics of the segment itself (Boessen & Hipp, 2015; Kim, 2016).

Although some scholars employ the methodological argument that street segments are preferred because their small size results in more homogeneity of social and physical characteristics, this focus on small units can miss crucial heterogeneity in the spatial landscape. That is, if the spatial patterns of residents are larger than the street segment, ignoring differences in nearby segments can miss important consequences (Hipp & Boessen, 2013). If these heterogeneous aspects of neighborhoods (i.e., racial heterogeneity, land use mix, socioeconomic difference among residents, etc.) are important, defining units based on spatial homogeneity may capture an incomplete picture of the neighborhood. In sum, although a body of studies has suggested that the street segment can be a social community that contains the characteristics of neighborhood, and it may be one possible candidate of a street-based neighborhood, it may be sized too small to be a neighborhood.

Street-based Overlapping Neighborhoods: *Street Egohoods*

As just discussed, a street segment may be too small as a street-based unit to appropriately capture various characteristics of a neighborhood. Thus, we propose using a larger street-based unit based on clusters of street segments incorporating some amount of the surrounding area. Furthermore, previous studies highlighted that the spatial boundaries of neighborhoods are quite unclear, given that residents are not just part of a single neighborhood but many others through their daily routine activities that lead them to travel in the area near their home (Sastry, Pebley, & Zonta, 2002). This implies that an overlapping neighborhood boundary approach may be preferred.

The egocentric buffer approach has a direct relevance to developing a street based neighborhood unit because streets are shared public spaces so one's street can be others' at the same time. This implies an overlapping characteristic of streets. Therefore, we propose extending the egohood approach by taking into account the actual street geography, configuration, and certain physical barriers using street network buffers rather than circular buffers based on straight-line Euclidean distances. Prior studies used the egohood approach with a circle radius around a centroid of a focal area (i.e., block), which is functionally easier to create and less computationally demanding. However, previous empirical studies found that buffers based on the street-network are more relevant to human geography because they take into account the actual street network configuration and physical barriers (Guo &Bhat, 2007; Oliver et al. 2007; Boruff et al., 2012; Forsyth et al., 2012; Duncun et al. 2013).

In sum, prior studies have typically not defined neighborhoods explicitly based on the street network, despite the importance of streets in urban daily life. Although some research has focused on the micro unit of street segments, this may be too small a unit to capture social and communal aspects of neighborhood as theorized. Additionally, an important aspect that should be incorporated when defining neighborhood is overlapping boundaries of neighborhoods. Although the egohood approach proposed in prior studies is a substantial contribution, one drawback is that it may be less relevant to actual human geography given that it does not explicitly consider the actual street geography, configuration, and physical barriers. To fill the intellectual gaps in the field of neighborhood and crime, herein we propose a concept of *street egohood* as an alternative perspective of measuring neighborhood based on urban streets. In the subsequent section, we specifically discuss how we constructed the street egohoods at various levels.

Constructing Street Egohoods

Given the above discussion, the strategy we adopt employs four different neighborhood definitions in constructing measures of neighborhood characteristics and crime to explore their relationships. We do not propose that any one definition is ideal, but rather start with the presumption that a good strategy is to use the street segment as a unit on which to construct neighborhoods, and then assess whether there are important consequences depending on the defined spatial scale. We therefore first constructed the data at the street segment level as a baseline unit and then aggregated to larger units. So beyond our models with data measured at the street segment level, we constructed street egohoods of three sizes in which the street segment was combined with: (1) nearby segments based on First Order Queen Contiguity (FOQC), which defines neighbors when at least one point of a street segment is shared with at least one point of its neighbors; (2) nearby segments within ¼ mile (which typically includes segments within 3 segments of the focal segment); (3) nearby segments within ½ mile.

To do this, we created a street network dataset in ArcGIS 10.3 using the 2010 TIGER street line shapefile. Then we utilized the Origin-Destination (OD) Cost Matrix Analysis function in the network analysis toolbox in ArcGIS 10.3. All the centroids of street segments in the study area were the origins and destinations in the OD cost matrix analysis when calculating the spatial distances along the street network from each street segment to the neighboring segments accounting for physical barriers (i.e., freeways). For comparison, we also constructed traditional egohoods centered on the block and computing distance based on straight line at two scales: 1) ¼ mile; 2) ½ mile. We employed the same method as Hipp and Boessen (2013) when creating block egohoods. First, we draw a circle buffer around a center block with a ¼ or ½ distance radius based on straight line distance for all blocks in the study area. Note that the OD cost matrix analysis is not required to generate block egohoods given that they are not constructed based on street network distance. We illustrate the street egohoods based on the FOQC strategy in Figure 1. As shown there, street segment S_1 shares the two intersection points with other 6 neighboring segments ($S_2, S_3, S_4, S_5, S_6, S_7$). Therefore, using the FOQC strategy, a street egohood 1 is comprised of 7 street segments (S_1 to S_7) and overlaps with the neighboring street egohoods such as street egohood 2 (S_5 and S_7).

<< Figure 1 about here >>

Our two larger neighborhood definitions measured a street egohood as a cluster of segments within one quarter (or one half) mile distance from a given segment including the focal segment. Figure 2 shows an example of ¼ mile distance street egohood 1. As shown, street egohood 1 consists of 33 street segments within one quarter mile street network distance from the focal street segment, which is overlapping with the adjacent street egohood 2. We used distances of one quarter mile and one half mile to define the neighborhoods because these relatively short distances constitute a proximal neighborhood environment according to prior studies (Colabianchi et al., 2007; Duncan et al., 2014; Timperio, Crawford, Telford, & Salmon, 2004).

<< Figure 2 about here >>

Some previous simulation studies found that using too large a spatial unit will bring about potential underestimation of neighborhood effects when measuring variables based on the first moment (e.g., averages or proportions) (Spielman & Yoo, 2009; Spielman, Yoo & Linkletter, 2013). Therefore, the selection of neighborhood size should not be too large. We considered the average walking distances of American adults when choosing the sizes of our street and block egohoods for the following reasons. First, in previous emperical studies, 400-800 meters (0.25-0.5 miles or a 5-10-minute walk) have been considered to be the distance that the average American will walk rather than drive (Atash, 1994; Yang & Diez-Roux, 2012). For example, Yang & Diez-Roux (2012) found that 65% of walking trips from a large nationally representative sample covered about 0.25 miles to 1 mile. Moreover, importantly, walking is closely associated with features of the physical and social environments because fixed neighborhood environmental features can be spatially perceived within walking distance of the residents. Also, Hipp & Boessen (2013) found that the strongest effects for the relationship between neighborhood characteristics and crime were generally observed for the ¼ and ½ mile radii for their egohoods. The average length of street segment is about 985 feet (300 meters). As shown in Figure 1, a FOQC street egohood consists of a focal street segment and 5 surrounding segments. Thus, the average length of a FOQC street egohood is about three times larger than a typical street segment, which is about to be 3,000 feet. The average length of other larger street/block egohoods are about to be ¼ and ½ mile given that they are explicitly constructed based on street network distance as shown in Figure 2.

Data and Methods

The study area is Los Angeles County, which is the largest county in the U.S. We combined multiple data sources to construct various measures. The crime data come from the Southern California Crime Study (SCCS). For the land use measures, we utilized the Southern California Association of Government (SCAG) 2008 land use data. The business data come from Reference USA (Kane, Hipp, & Kim, 2017).

Dependent variables

The dependent variables of the present study are the number of violent and property crime incidents in 2010. The crime data come from the Southern California Crime Study (SCCS). As part of this larger project, SCCS researchers contacted each police agency in the Southern California region and requested address-level incident crime data for the years 2005-2012. The crime data obtained cover roughly 84 percent of the region's population. Police agencies of cities in the study area reported incident crime data with geographic information such as addresses or 100 blocks.[1] The SCCS classified crime events into six Uniform Crime Report (UCR) categories: homicide, aggravated assault, robbery, burglary, motor vehicle theft, and larceny. The number of violent crime events is the sum of the counts of homicide, aggravated assault, robbery, while that of property crime events is the sum of the counts of burglary, motor vehicle theft, and larceny. Crime events were geocoded for each city separately to latitude–longitude point locations using ArcGIS 10.2, and subsequently aggregated to the various abovementioned street based units (i.e., street segments and three types of street egohoods at various levels) or block egohoods. In the current study, we use the crime incident data in 2010. Unlike previous studies that simply drop all crime incidents at intersections, we evenly assigned them to contiguous street segments (Kim, 2016, Kim & Hipp, 2017). For example, if a crime incident occurred on a typical intersection where two roads cross, each of four segments is given 0.25 of a crime incident.

Independent variables

To measure the social environment (structural characteristics) of street egohoods, data collected at the street segment level is preferred, yet such data are hard to obtain. Alternatively, in a recent study, Kim (2016) proposed two unique methods for imputing existing Census data at the block level to street segments: Simple Average (SA) and Segment Weighted Average (SWA). The results confirmed that the two imputation methods are generally valid compared to data actually collected at the street segment level, and thus the simpler method (SA) is

[1] For crime incident data with exact street address, Southern California Crime Study (SCCS) researchers geocoded crime incidents to longitude and latitude points using the address information. If 100 block addresses rather than exact street addresses were provided, SCCS geocoded at the random street addresses within the 100 block, which is essentially similar to geocoding to the center of the 100 block. We believe that this process should not affect to the aggregation to the various units because our base unit is street segment which is identical to 100 block in the geocoding process

effectively preferred. Therefore, we employ the SA method to impute the 2010 Census block data to street segments to measure structural characteristics. The SA method calculates the average values of these two blocks to apportion the data of the blocks to the street segment, which takes following form:

$$SA = \frac{\sum_{j=1}^{J} V_j}{J} \tag{1}$$

where J is the number of contiguous blocks associated with a given street segments, V_j is value of Census data of block j. The imputation method employed in the current study may contain measurement errors. Kim (2016) proposed this imputation approach given the difficulty of collecting segment-level data. As Weisburd et al. (2012) stated, the most significant limitation of their study and the field of criminology of place is data collection at street segment level. Whereas we ideally would have data at the segment level, the question is whether the imputation methods are effective despite their imperfections. Kim (2016) attempted to empirically test the validity of the spatial imputation methods by using point level home value data compared to the segment-level data imputed from adjacent Census blocks. He found that the imputation methods generally worked fine at least in the study area and for the home values as proxy measures of socioeconomic status of the places. Furthermore, given that a block is also very small geographic unit, it is reasonable to think that the majority of blocks in a city would not have substantially heterogeneous structural characteristics within each, which may provide confidence that the imputation methods are useful for detecting the general patterns between structural characteristics and crime at the street segment level within a city (or cities).

To test the effects of structural characteristics of street segments, the current study includes Census indicators of the three structural determinants of social disorganization. First, we constructed a *concentrated disadvantage index*, which is a factor score computed after a factor analysis of four measures: (1) percent at or below 125% of the poverty level; (2) percent single-parent households; (3) average household income; and (4) percent with at least a bachelor's degree. The last two measures had reversed loadings in the factor score.[2] The current study includes the presence of racial/ethnic minorities in street segments as the percent African-American and the percent Latino/Hispanic. To capture the level of *racial/ethnic heterogeneity*, a Herfindahl index based on five racial/ethnic groups (white, African-American, Latino, Asian, and other races) was computed. Besides the variables included above, this study also accounted for *population (logged)* of the street segments. The percent *occupied units* is used to measure vacancies, and the percent *home owners* for residential stability.

We also included measures of land use characteristics to capture physical environments of the street egohoods. Using the Southern California Association of Government (SCAG) 2008 Land use data, we constructed measures of the percent of the land area that is: 1) industrial; 2) office; 3) residential; and, 4) retail. "Other land use types" is the reference category. Given the possibility that the mix of land uses in an area has consequences for crime levels, we constructed a measure of land use mixing based on a Herfindahl index of five categories (residential, retail, office, industrial, and other land use types).

We employed another set of the measures of physical environment using detailed characteristics of business facilities in locations. We utilized Reference USA business data in 2010 which include a wealth of information such as addresses, types of businesses by North American Industry Classification System (NAICS) code, the number of employees, year of establishment, the business revenues, etc. In order to properly obtain the information of businesses in street segments, we geocoded addresses of businesses to latitude–longitude point

[2] We decided to use one factor that had an eigenvalue of 1.00 or higher. Eigenvalues of the concentrated disadvantage index across all units are greater than 2.

locations using ArcGIS 10.2 and then aggregated to street segments. The current study includes the number of employees of 1) retail, 2) restaurants, 3) groceries, 4) bars, and 5) liquor stores. The measures of number of employees are used instead of the number of facilities because they are better proxy measures of (1) existence of the business facilities, (2) the size of the facilities, and (3) the magnitude of people moving in-and-out. Note that the measures of the structural characteristics (social environment), land use, and business employees (physical environment) were constructed at the street segment level first, then aggregated to the various levels of the street egohoods.

Analytic Strategy

The summary statistics are presented in Table 1. As expected, the standard deviation for each variable tends to decrease as the size of the geographic unit increases. We highlight that the two distributional measures—racial/ethnic heterogeneity and land use mix—have larger mean values as the size of the unit increases. Thus, such larger units can sometimes better capture the heterogeneity present in the landscape given that smaller units can tend to be more homogeneous.

<<< Table 1 about here >>>

One question is how similar the measures are across our four different sized street segments. To answer this question, we conducted a correlational analysis. These correlations are shown in Table 2, and illustrate that there can be considerable differences. On the one hand, the highest correlations across the geographic units occur for the socio-demographic variables: the average correlation with segments of the three street egohood measures is .96 for percent Latino, .935 for percent black, .93 for concentrated disadvantage, and .90 for percent owners.

The average correlations with population are lower (.62). The correlations of the land use measures across geographic scales are lower (the average correlations for measures of street segments with the street egohoods range from .69 to .82). The measures capturing the presence of employees are very different across spatial scales: the average correlation of the segment measures with the street egohood measures range from just .25 to .34.

<<< Tables 2 about here >>>

Next, we estimated the same models at the four different levels of street based units (street segment and the three sizes of street egohoods) and two sizes of block egohoods. We estimated the models as negative binomial regression models, which capture the overdispersion in the count variable outcomes, with logged population as an offset measure (Osgood, 2000). To compare the size of the coefficients across the different models, we need to place them in a similar metric. To do so, we interpret the marginal changes in crime as a percentage change based on a one standard deviation change in the exogenous variable of interest. Whereas the full results are presented in Tables 3-4, to compare the relative size of the effect from the different models, we plot the effects as the percentage change in the outcome measure (violent or property crime) for a one standard deviation change in the variable. This accounts for the fact that a standard deviation change varies over the different sized geographic units. We focus on these visual presentations, as they make clearer the pattern of results. We found no evidence of multicollinearity problems across our models given that the variance inflation factor values were all below 5.5.

<<< Tables 3-4 about here >>>

Results

Social Environment of Street Egohoods: Population and socio-demographic measures

The population (logged) of the area reflects the nighttime population.[3] Across all spatial scales, the estimated coefficient was negative. This indicates that the crime rate is lower as the size of the population increases (since population is also included as an offset variable). This negative relationship is strong across all geographies, but is even stronger in the smallest units (Figure 3). For example, we observed that there is a 57 percent decrease in property crime when employing street segment compared to a 38 percent decrease using block egohood ½ mile. The presence of vacant units has a strong positive relationship with the violent crime rate, and this is particularly strong in the larger street egohoods. The relationship between vacant units and property crime is very weak in this study (Figure 3b).

<<< Figure 3 about here >>>

Turning to the socio-demographic measures, we generally find strong relationships, although there are some scale differences. We find that the level of concentrated disadvantage (Figure 3), the presence of renters (Figure 3), or the presence of racial/ethnic minorities measured as percent black and percent Latino (Figure 4) are all positively related to crime rates, regardless of the spatial scale. However, two variables show a stronger relationship when measured at larger geographic scales: although racial/ethnic heterogeneity is negatively related to violent crime rates at all spatial scales (Figure 4), and the presence of more persons aged 16 to 29 is related to higher property and violent crime rates at all spatial scales (Figure 4), these relationships are particularly strong in the largest street egohoods. This finding is consistent with prior research showing that racial/ethnic heterogeneity appears to be more appropriately

[3] We include population as an offset variable (with coefficient constrained to 1) and also include it in the model. This is a straightforward way to handle to possibility that population does not have a 1:1 relationship with crime (which is the assumption when creating crime rates). We prefer our approach as the provided t-test from Stata 13 is for the difference from 1 (which is a reasonable test, given the common assumption of a 1:1 relationship with crime in crime rates), rather than testing whether an estimate is different than zero (which would assume no relationship with population, which is a less interesting test).

measured in larger units (Boessen & Hipp, 2015; Hipp & Boessen, 2013). And the finding for those aged 16 to 29 is consistent with the journey to crime literature showing that offenders tend to travel non-trivial distances, indicating that any measure capturing offenders should operate at a larger spatial scale.

<<< Figure 4 about here >>>

Physical Environment of Street Egohoods: Land Use and Employee Measures

Turning next to the measures of land use, we see in Figure 5 that the percentage of residential land use in the geographic unit has a modestly negative relationship with violent crime in the segments model and the FOQC model, but a strong positive relationship in the ¼ mile and ½ mile street egohood models. The pattern is similar for property crime across the different geographic units. We see a similar pattern for industrial land use in Figure 5, as the composition of this type of land use has a negative relationship with violent crime in segments and in the FOQC model, but reverses to strong positive relationships in the two larger street egohoods. There is a positive relationship between industrial land use and property crime that is even stronger in the larger street egohoods. We see in Figure 5 that retail land use has a consistently positive relationship with both violent and property crime regardless of the geographic unit used, and the relationship is similar across the street egohoods. Thus, it appears that the relationships between residential, industrial, or retail land use and crime in our larger street egohoods are very different compared to the micro measure of street segments.

For office land use, the biggest difference is across crime types. Whereas office land use is positively associated with property crime, particularly in smaller units (Figure 5), it is negatively associated with violent crime in the various street egohoods. The pattern for land use mix shows that the scale at which it is measured is important. For violent crime, the relationship with land use mix is positive in the street egohoods, (Figure 5). For property crime, the negative relationship with land use mix is strongest in the two larger street egohoods, but weaker (or even somewhat positive) in the smaller units.

<<< Figure 5 about here >>>

The geographic scale has differential consequences for the measures of four different types of employees. Retail employees show a consistent positive relationship with both violent and property crime across all spatial scales (Figure 6), with the strongest positive relationship occurring in the smaller geographic units. The presence of more bar and liquor store employees is associated with higher rates of crime regardless of the spatial scale. In contrast, whereas the presence of more restaurant employees or grocery employees exhibit positive relationships with crime across all spatial scales, these relationships are strongest in the largest geographic units.

<<< Figure 6 about here >>>

Street Egohoods vs. Block Egohoods

We next assess whether there are distinct effects for the measures of structural characteristics and physical environment in street egohoods (0.25 and 0.5 mile) compared to block egohoods proposed by Hipp & Boessen (2013). Although the comparison between the two units is useful, we do not necessarily attempt to identify which one is the most proper unit. However, the comparison is meaningful to show how choice of different street-based units can bring about different effects of physical and social environmental features on crime (Hipp, 2007a). First, to see if there is a meaningful difference of relative quality between the two egohood strategies, we compared the correlations between street and block egohoods. The correlation results are presented in Table 5. Correlations of the structural characteristics measures between two strategies are generally high. For example, the correlation of concentrated disadvantage between quarter mile street egohood and block egohood is 0.93 while that of half mile egohoods is 0.70. This implies that two egohood strategies essentially are not different at the quarter mile egohood level but this similarity appears lower when looking at the half mile egohood level. In contrast, population, percent occupied units, and percent aged 16-29 have relatively lower correlations, as are those of measures of the physical environment (land use and business employees). In general, the differences between measures aggregated to street egohoods compared to block egohoods are larger in the ½ mile units compared to the ¼ mile units, which may be because street egohoods are constructed based on the street network distance while taking into consideration physical configuration of the street network and physical barriers such as interstate freeways.

<<< Table 5 about here >>>

Next, we examined whether the spatial patterns of violent and property crime driven by structural characteristics and physical environment can vary across different egohood strategies (street vs. block). We present the results of models aggregated to block egohood in columns 5 and 6 of Tables 3-4. We report the model fit statistics (McFadden's pseudo R-squared)[4] at the bottom of the tables, which indicate that the street egohood models are better fit for predicting violent and property crime compared to the block egohood models. This implies that street egohoods incorporating the street network configuration and physical geography may be methodologically preferred over block egohoods when measuring social and physical environment of neighborhood and studying spatial patterns of crime.

[4] McFadden's pseudo R-squared is calculated as 1- (log likelihood value for the fitted model / log likelihood of the null model). Values closer to 1 indicate better model fit, while conversely closer to 0 suggest less predictive ability.

To more systematically compare the findings of street egohoods to the block egohoods, we plotted the percentage change of violent and property crime by a one standard deviation increase in each independent variable for property crime in Figure 7a and violent crime in Figure 7b. We added the 95 percent confidence interval for each bar so that we can readily distinguish if effects at the street egohood levels are statistically different from block egohoods. Also, Tables 6-7 report a summary of patterns observed in Figures 7a and 7b. Specifically, we reported the ratio of the effect size of street egohood to block egohood. The ratio is calculated as street egohood divided by block egohood. If the ratio is greater than 1, the variable shows a greater effect at the street egohood level than block egohoods. Comparing the percentage change of crime by a one standard deviation increase is effectively standardizing the coefficients of street egohoods and block egohoods. Thus, it is more appropriate than comparing unstandardized coefficients given that the standard deviations between street and block egohoods.

<<<Figures 7a-7b about here>>>

First, we observed that the results of street egohoods generally have similar patterns compared to block egohoods. For example, a one standard deviation increase in population results in 49.5 and 41.9 percent decrease in property crime at the quarter and half mile street egohood levels, but a 42.6 and 38.2 percent decrease at the block egohood levels. We observed very few instances in which the sign of coefficients was opposite in block egohoods compared to street egohoods (OPPs in Tables 6-7). One difference was that whereas a one standard deviation increase in concentrated disadvantage leads to 7.4 and 6.7 percent increase in property crime in quarter and half mile street egohoods it implies a 1.5 and 5 percent reduction in property crime in quarter and half mile block egohoods.

<<<Tables 6-7 about here>>>

We also found that whereas some measures have larger effects at the street egohood levels, others are larger at the block egohood levels. Furthermore, these vary across two different distance bands. For instance, percent occupied units have 73 percent (1-0.27 = 0.73) stronger effects on property crime in quarter mile *block* egohoods while percent home owners have 99 percent (1-1.99 = 0.99) larger effects in quarter mile *street* egohoods. For violent crime, population, racial/ ethnic heterogeneity, percent home owners, percent Black, and percent Latino have larger effects when employing the street egohoods approach regardless of spatial scales (quarter or half mile), whereas percent occupied units and the number of bar employees have larger effects at the block egohood level.

Conclusion

Over the past few decades, many ecological studies have shown that neighborhood context matters in understanding various outcomes such as crime. One great challenge for studies has been how to define a neighborhood. Most previous studies have used various non-overlapping neighborhood definitions such as Census defined block groups or tracts. Using these units, studies have found that crimes are spatially concentrated within certain neighborhoods. Also, they revealed that structural characteristics (i.e., the level of concentrated disadvantage, racial/ethnic heterogeneity, residential instability, etc.) affect the amount of crime in neighborhoods (Chamberlain & Hipp, 2015; Hipp, 2007a, 2007b; Kubrin, 2003, 2009; Sampson & Groves, 1989; Sampson, Raudenbush, & Earls, 1997; Warner & Pierce, 1993). In the present study, we introduced the *street egohood* approach which is an alternative method defining a neighborhood as a cluster of street segments overlapping one another. Thus, a primary contribution of the current study is developing another way to define and measure neighborhoods based on streets.

Although the street egohood approach provides theoretical and methodological insights that the relationships of ecological features with crime vary across different levels, we do not necessarily argue that the field switch to using the street egohood method, or that the smallest or largest differences of coefficients are the standard for evaluating the appropriateness of the spatial unit of analysis. Instead, the current study aims to empirically examine the theoretically driven argument of considering more real-life geography based on the street network and overlapping aspect of neighborhood. Note that the spatial patterns of crime could be inconsistent over different street based units and we do not necessarily seek a consistent pattern.

Instead, the present study proposes another way to assess the effects of physical and social environments of neighborhood while more directly accounting for more real-life geography and comparing various street based-units. Some variables may have larger/smaller effects at one level but others have larger/smaller effects when employing other levels. Note that the primary point of comparison between various street egohoods is not necessarily for identifying the ideal street-based unit. Rather, we intended to show that the spatial effects of the physical and social environmental attributes may have different impacts in terms of effect sizes and directions even when more directly accounting for the street network configuration. Therefore, the primary takeaways of the current study are: 1) proposing alternative ways to measure neighborhood more directly incorporating the real-life geography such as street network, physical barriers, and overlapping aspect of neighborhood; and 2) given the findings of comparison between different sized street-based units, the field should give more careful consideration when measuring and choosing the size of neighborhood. Furthermore, future research may wish to account for how physical features of the environment such as transit locations or various public amenities impact activity spaces and hence, perhaps, the particular dimensions of some street egohoods.

It is worth emphasizing that the coefficients of our various measures of interest often differed quite notably across the four different neighborhood definitions in this study. Whereas the average correlations of the three street egohood measures with the street segment measure is quite high for the sociodemographic variables, the average correlations of the population and the land use measures across geographic scales are lower. Furthermore, the measures capturing the presence of employees are very different across these spatial scales. These results imply that although the sociodemographic measures are relatively stable across different sized street based units, there can be considerable differences in population, land use patterns, and the presence of employees as a proxy measure of the magnitude of people moving in-and-out of the area.

Our findings of negative binomial regression models showed that some variables have stronger effects when larger street egohoods (quarter or half mile street network buffers) are employed while most of the sociodemographic measures show relatively stable effects on crime across different levels of street based units. It is consistent with our expectations that socioeconomic measures, land use patterns in neighborhoods, and their associations with crime in the neighborhood can be better captured when accounting for some part of the area surrounding the focal street segment. For example, racial/ethnic heterogeneity is negatively related to violent crime rates at all spatial scales, but the relationship is particularly strong in the largest street egohoods. This implies that a street segment as a street based unit may be too small to capture a comprehensive picture of racial/ethnic heterogeneity and its effect on crime in the neighborhood. This finding is also consistent with the results of previous studies in which distributional measures such as racial/ethnic heterogeneity show a stronger relationship with crime in ½ and ¼ mile egohoods (Hipp & Boessen, 2013). Likewise, the relationships between residential, industrial, or retail land use and crime were stronger in our larger street egohoods compared to street segments. This may be because offenders target an area larger than simply a street segment when looking for crime-rich target areas.

In contrast, a few variables exhibited stronger effects when smaller sized units are employed. For example, across all spatial scales, population has a negative relationship with crime, but it is even stronger in the smallest units. This may be because the crime reducing effect of more potential guardians provided by the greater residential population may be washed out when using larger street egohoods. This implies that the particular micro processes of population may be captured better at the street segment level than the larger street egohoods (Boessen & Hipp, 2013). Although we suggested some theoretical merits of the street egohood approach, this is not to say that street segments are not also a useful spatial unit of analysis in criminological research given the distinct spatial patterns of crime and the larger effects for certain physical and social environment characteristics observed at the street segment level.

We found evidence that the employee measures and their effects on crime at different spatial scales can vary by business types. Whereas the presence of more restaurant employees exhibits a positive relationship with crime across all spatial scales and this relationship is strongest in the largest geographic units, retail employees showed the strongest positive relationship with crime in the smallest geographic units (street segments). Given that the employee variables are proxy measures of the number of people moving in-and-out, presence and size of businesses, and the number of potential guardians, it may be that it is necessary to know what persons are doing in the area. In this manner, the type of business may provide a clue whether persons are simply coming to a single location, or whether they are spending time at many locations in a general area. Such information would help in specifying the spatial scale at which businesses operate as crime attractors that facilitate an increase of the number of potential offenders, as well as potential victims by attracting more people to a place, or generators that have reputations for criminal opportunities.

We assessed our street egohood approach to two block egohood aggregations (quarter and half mile) to empirically examine whether street egohoods capture meaningfully different qualities of the social and physical environment, and thus predict different spatial patterns of crime. The bivariate correlations indicate that measures aggregate to street or block egohoods can be quite similar. Furthermore, the general pattern of the direction and significance of the coefficients for these measures in the property and violent crime models was similar. There were a few differences for a couple measures, although it is interesting to note that when we compare the size of the standardized coefficients across models, the differences were nearly as big when comparing across spatial scale (i.e., between ¼ and ½ mile egohoods of either street or block egohoods) as compared to ½ mile street vs. block egohoods. The differences between ¼ mile street vs. block egohoods were larger, which may also relate somewhat to spatial scale given that their different forms of distance likely lead to larger differences in the scale of the egohood. These findings highlight that consideration of the spatial scale is important and deserves more attention.

One notable improvement of the street egohood approach is that it attempts to incorporate the real-life street network configuration by employing street network distance when constructing the data at the street egohood level, which scholars have suggested is theoretically and methodologically preferred as discussed above. Furthermore, we observed that models employing street egohoods generally have better predictive ability than block egohoods given the greater pseudo-R squared values. Thus, despite the computational demands of creating street egohoods when examining the relationship between the social and physical environment and crime, our findings suggest that employing street egohoods is a plausible alternative measure of neighborhoods. To the best of our knowledge, this is the first criminological study that explicitly employed a street based overlapping spatial boundaries as a unit of analysis in understanding spatial patterns of crime, which is a primary contribution of the current study.

We acknowledge some limitations to the current study. First, to create street egohoods we used the street segment level data as the building blocks and aggregated to the various street egohood levels. One challenge of constructing the data of structural characteristics is that Census data are not available at the street segment level. To address this, we employed an imputation method to apportion the Census block level data to adjacent street segments developed by Kim (2016). Although Kim (2016) demonstrated the effectiveness of this imputation method, and we suspect that more sophisticated imputation techniques may not make a substantial difference in constructing street egohood measures, it would be preferable to actually have segment-level socio-demographic data.

Second, the current study is designed as cross-sectional. Future research will want to utilize longitudinal data to capture and reflect how the changes of socio-demographic measures and land use patterns at the various street egohoods impact changes in crime over time. Third, our street egohood approach tends to consider more real street network configurations and physical barriers compared to other administrative neighborhood boundaries, yet room for refinement still exists. For example, our street network dataset and the street egohood approach does not consider possible variations in individual travel patterns along the street (routes, time, cost, speed limit, elevation, etc.). We hope future research will consider more detailed information on street network and travel patterns when conceptualizing and constructing street egohoods and assess whether these refinements might help explain the spatial patterns of crime.

Fourth, it is likely that the relationships between street egohood measures and crime can vary by different types of crime. Although we measured property and violent crime rates, an additional distinction in crime types might be necessary to test whether street egohood measures have distinct effects on certain types of crime. Finally, our findings may not be applicable to other city contexts given that we studied a single area (Los Angeles metropolitan area). We hope future studies employ the street egohood approach and assess whether our findings are generalizable to other cities across the U.S.

In conclusion, we proposed the street egohood approach as an alternative way to define and measure neighborhoods based on streets. We emphasized the importance of streets and explained our motivations for constructing street egohoods. We empirically demonstrated that whereas certain socio-demographic measures show the strongest relationship with crime when measured at the micro geographic unit of street segments, a number of them actually exhibited the strongest relationship when measured using our larger street egohoods. Therefore, a primary contribution of the current study is to develop and propose a new perspective of measuring neighborhood based on urban streets. We hope future research can use street egohoods to expand understanding of neighborhoods and crime.

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Table 1. Summary Statistics of Variables used in Analyses

	Street segments			Street egohood FOQC			Street egohood 1/4 mile			Street egohood 1/2 mile			Block egohood 1/4 mile			Block egohood 1/2 mile		
	Mean	**S.D.**	**N**	**Mean**	**S.D.**	**N**	**Mean**	**S.D.**	**N**	**Mean**	**S.D.**	**N**	**Mean**	**S.D.**	**N**	**Mean**	**S.D.**	**N**
Property crime events	0.85	4.25	230987	4.92	12.37	230987	16.60	24.65	230987	67.09	81.92	230987	30.09	39.63	92776	115.80	128.98	92776
Violent crime events	0.20	1.67	230987	1.25	4.66	230987	4.55	9.91	230987	17.70	32.74	230987	9.61	16.18	92776	36.86	55.27	92776
Socio-demographic measures																		
Population (logged)	4.11	2.91	225468	6.14	2.22	225468	7.61	2.02	225468	9.04	1.69	225468	6.88	2.51	92769	8.62	1.44	92769
Racial/ethnic heterogeneity	0.45	0.19	213013	0.46	0.18	213013	0.48	0.17	213013	0.48	0.17	213013	0.47	0.18	92286	0.48	0.17	92286
Concentrated disadvantage	0.00	9.45	210018	0.00	9.51	210018	0.00	9.34	210018	0.00	9.09	210018	0.00	9.05	92134	0.00	8.68	92134
Percent occupied units	94.47	8.21	211924	94.92	6.24	211924	94.89	5.42	211924	94.99	4.37	211924	94.54	5.48	92190	94.58	3.63	92190
Percent owners	65.35	28.98	211436	62.61	28.02	211436	62.66	26.11	211436	63.04	23.75	211436	53.17	26.67	92166	51.75	23.33	92166
Percent black	7.75	15.28	213013	7.92	15.55	213013	7.91	14.94	213013	7.12	13.17	213013	8.25	14.87	92286	8.21	13.92	92286
Percent Latino	38.19	29.64	213013	39.45	29.67	213013	39.46	28.87	213013	39.87	28.45	213013	44.55	29.89	92286	45.10	28.85	92286
Percent aged 15-29	20.08	8.69	213013	20.22	7.74	213013	20.20	6.66	213013	20.19	5.53	213013	21.68	6.99	92286	22.10	6.17	92286
Land use measures																		
Percent residential land use	57.56	39.73	230987	58.80	36.74	230987	58.80	34.73	230987	44.99	37.92	230987	60.83	27.69	92765	57.08	22.16	92765
Percent retail land use	6.13	15.05	230987	6.37	12.93	230987	6.15	10.43	230987	4.62	7.50	230987	8.65	10.64	92765	8.18	6.81	92765
Percent industrial land use	4.13	14.36	230987	4.24	13.23	230987	4.06	11.98	230987	3.04	9.26	230987	7.62	16.18	92765	8.69	14.29	92765
Percent office land use	2.78	9.64	230987	2.90	8.54	230987	2.79	7.17	230987	2.04	5.07	230987	3.99	7.33	92765	3.94	5.19	92765
Land use mix	0.39	0.35	230987	0.42	0.32	230987	0.50	0.31	230987	0.61	0.32	230987	0.43	0.20	92765	0.51	0.16	92765
Employee measures (divided by 1,000)																		
Retail employees	0.00	0.03	197160	0.01	0.08	197160	0.04	0.14	197160	0.15	0.34	197160	96.02	230.03	92629	398.53	596.82	92629
Bar employees	0.00	0.00	197160	0.00	0.00	197160	0.00	0.01	197160	0.00	0.01	197160	1.68	10.55	92629	6.56	25.24	92629
Grocery employees	0.00	0.01	197160	0.00	0.01	197160	0.00	0.02	197160	0.02	0.04	197160	11.82	38.41	92629	47.99	78.83	92629
Liquor store employees	0.00	0.00	197160	0.00	0.00	197160	0.00	0.00	197160	0.00	0.00	197160	1.05	2.74	92629	4.06	6.02	92629
Restaurant employees	0.00	0.01	197160	0.01	0.03	197160	0.02	0.07	197160	0.09	0.18	197160	56.33	116.92	92629	219.97	319.88	92629

S.D. = Standard Deviation

Table 2. Correlations between Segment and the Three Street Egohoods

	Population (logged)	Segment	1	2
1	Street Egohood FOQC	0.75		
2	Street Egohood ¼ mile	0.61	0.69	
3	Street Egohood ½ mile	0.48	0.56	0.85

	Racial/ethnic heterogeneity	Segment	1	2
1	Street Egohood FOQC	0.93		
2	Street Egohood ¼ mile	0.86	0.93	
3	Street Egohood ½ mile	0.82	0.88	0.95

	Concentrated disadvantage	Segment	1	2
1	Street Egohood FOQC	0.96		
2	Street Egohood ¼ mile	0.92	0.96	
3	Street Egohood ½ mile	0.88	0.92	0.96

	Percent occupied units	Segment	1	2
1	Street Egohood FOQC	0.88		
2	Street Egohood ¼ mile	0.72	0.83	
3	Street Egohood ½ mile	0.59	0.69	0.85

	Percent home owners	Segment	1	2
1	Street Egohood FOQC	0.95		
2	Street Egohood ¼ mile	0.90	0.95	
3	Street Egohood ½ mile	0.83	0.88	0.95

	Percent Black	Segment	1	2
1	Street Egohood FOQC	0.97		
2	Street Egohood ¼ mile	0.93	0.96	
3	Street Egohood ½ mile	0.89	0.92	0.97

	Percent Latino	Segment	1	2
1	Street Egohood FOQC	0.97		
2	Street Egohood ¼ mile	0.95	0.97	
3	Street Egohood ½ mile	0.93	0.95	0.98

	Percent aged 16 to 29	Segment	1	2
1	Street Egohood FOQC	0.90		
2	Street Egohood ¼ mile	0.79	0.88	
3	Street Egohood ½ mile	0.69	0.77	0.90

Table 2. Continued

	Percent residential area	Segment	1	2
1	Street Egohood FOQC	0.93		
2	Street Egohood ¼ mile	0.88	0.94	
3	Street Egohood ½ mile	0.55	0.59	0.64

	Percent retail area	Segment	1	2
1	Street Egohood FOQC	0.87		
2	Street Egohood ¼ mile	0.74	0.84	
3	Street Egohood ½ mile	0.45	0.52	0.67

	percent industrial area	Segment	1	2
1	Street Egohood FOQC	0.92		
2	Street Egohood ¼ mile	0.86	0.92	
3	Street Egohood ½ mile	0.66	0.72	0.80

	percent office area	Segment	1	2
1	Street Egohood FOQC	0.88		
2	Street Egohood ¼ mile	0.76	0.86	
3	Street Egohood ½ mile	0.51	0.59	0.72

	Land use mix	Segment	1	2
1	Street Egohood FOQC	0.88		
2	Street Egohood ¼ mile	0.76	0.85	
3	Street Egohood ½ mile	0.51	0.55	0.58

	Retail employees	Segment	1	2
1	Street Egohood FOQC	0.46		
2	Street Egohood ¼ mile	0.28	0.55	
3	Street Egohood ½ mile	0.14	0.31	0.54

	Bar employees	Segment	1	2
1	Street Egohood FOQC	0.42		
2	Street Egohood ¼ mile	0.24	0.50	
3	Street Egohood ½ mile	0.12	0.24	0.48

	Grocery employees	Segment	1	2
1	Street Egohood FOQC	0.44		
2	Street Egohood ¼ mile	0.26	0.50	
3	Street Egohood ½ mile	0.10	0.23	0.43

	Liquor employees	Segment	1	2
1	Street Egohood FOQC	0.41		
2	Street Egohood ¼ mile	0.22	0.47	
3	Street Egohood ½ mile	0.10	0.20	0.42

Table 2. Continued

	Restaurant employees	Segment	1	2
1	Street Egohood FOQC	0.54		
2	Street Egohood ¼ mile	0.33	0.58	
3	Street Egohood ½ mile	0.15	0.32	0.62

Table 3. Negative binomial models of various street based units (exponentiated coefficients) - Property Crime

	Street Segments		Street egohood FOQC		Street egohood 1/4 mile		Street egohood 1/2 mile		Block egohood 1/4 mile		Block egohood 1/2 mile	
Census Variables												
Population (logged)	0.438	**	0.474	**	0.496	**	0.549	**	0.556	**	0.566	**
	[0.433,0.443]		[0.471,0.478]		[0.493,0.499]		[0.545,0.553]		[0.548,0.564]		[0.556,0.577]	
Racial/ethnic heterogeneity	0.954		0.938	**	0.802	**	0.942	**	0.978		1.137	**
	[0.895,1.016]		[0.900,0.978]		[0.773,0.832]		[0.902,0.984]		[0.920,1.041]		[1.055,1.227]	
Concentrated disadvantage	1.011	**	1.011	**	1.008	**	1.008	**	0.998		0.994	**
	[1.009,1.013]		[1.009,1.012]		[1.007,1.010]		[1.006,1.009]		[0.996,1.000]		[0.991,0.997]	
Percent occupied units	0.997	**	0.999		0.996	**	1.003	**	0.982	**	0.975	**
	[0.995,0.999]		[0.998,1.001]		[0.995,0.997]		[1.001,1.005]		[0.980,0.985]		[0.971,0.979]	
Percent home owners	0.993	**	0.991	**	0.988	**	0.989	**	0.995	**	0.995	**
	[0.992,0.993]		[0.991,0.992]		[0.988,0.989]		[0.989,0.990]		[0.994,0.995]		[0.995,0.996]	
Percent Black	1.011	**	1.013	**	1.014	**	1.016	**	1.011	**	1.013	**
	[1.011,1.012]		[1.012,1.013]		[1.014,1.015]		[1.016,1.017]		[1.010,1.011]		[1.012,1.014]	
Percent Latino	1.005	**	1.005	**	1.005	**	1.006	**	1.003	**	1.006	**
	[1.004,1.005]		[1.004,1.005]		[1.005,1.005]		[1.005,1.006]		[1.003,1.004]		[1.005,1.007]	
Percent aged 16 to 29	1.011	**	1.008	**	1.012	**	1.011	**	1.008	**	1.005	**
	[1.009,1.012]		[1.007,1.009]		[1.011,1.014]		[1.009,1.012]		[1.006,1.009]		[1.003,1.007]	
Land Use Variables												
Percent residential area	0.998	**	0.997	**	1.003	**	1.004	**	0.998	**	1.003	**
	[0.998,0.999]		[0.997,0.998]		[1.003,1.004]		[1.003,1.004]		[0.997,0.999]		[1.002,1.004]	
Percent retail area	1.007	**	1.006	**	1.011	**	1.014	**	1.018	**	1.021	**
	[1.006,1.007]		[1.005,1.007]		[1.011,1.012]		[1.013,1.015]		[1.017,1.019]		[1.019,1.024]	
percent industrial area	1		1.002	**	1.002	**	1.005	**	1.004	**	1.007	**
	[0.999,1.001]		[1.002,1.003]		[1.002,1.003]		[1.004,1.005]		[1.003,1.005]		[1.006,1.008]	
percent office area	1.005	**	1.001		1.001	*	0.996	**	0.999	*	0.993	**
	[1.004,1.006]		[1.000,1.002]		[1.000,1.002]		[0.995,0.998]		[0.997,1.000]		[0.991,0.995]	
Land use mix	1.028		0.909	**	0.862	**	0.823	**	0.677	**	0.873	*
	[0.963,1.097]		[0.870,0.950]		[0.826,0.899]		[0.778,0.870]		[0.623,0.736]		[0.768,0.991]	
Number of Employees												
Retail	1.01	**	1.003	**	1.001	**	1.000	**	1.000	**	1.000	
	[1.009,1.011]		[1.003,1.003]		[1.001,1.001]		[1.000,1.000]		[1.000,1.000]		[1.000,1.000]	
Bar	1.029	**	1.008	**	1.002	**	1.001	**	1.002	**	1.000	
	[1.015,1.045]		[1.005,1.011]		[1.001,1.003]		[1.001,1.002]		[1.001,1.003]		[1.000,1.001]	
Grocery	1.002		1.001	**	1.001	**	1.001	**	1.000		1.000	
	[1.000,1.005]		[1.001,1.002]		[1.001,1.002]		[1.001,1.001]		[1.000,1.000]		[1.000,1.000]	
Liquor	1.119	**	1.051	**	1.02	**	1.013	**	1.007	**	1.007	**
	[1.083,1.157]		[1.043,1.060]		[1.017,1.023]		[1.011,1.014]		[1.003,1.010]		[1.005,1.009]	
Restaurants	1.02	**	1.008	**	1.003	**	1.001	**	1.001	**	1.001	**
	[1.018,1.022]		[1.007,1.008]		[1.003,1.003]		[1.001,1.001]		[1.001,1.002]		[1.001,1.001]	
N	191473		191643		191457		196463		92308		92063	
Pseudo R-squared	0.042		0.055		0.053		0.045		0.028		0.018	

*** p < .01(two-tail test), * p < .05 (two-tail test)*

95% confidence Intervals below coefficient estimates.

Table 4. Negative binomial models of various street based units (exponentiated coefficients) - Violent crime

	Street Segments		Street egohood FOQC		Street egohood 1/4 mile		Street egohood 1/2 mile		Block egohood 1/4 mile		Block egohood 1/2 mile	
Census Variables												
Population (logged)	0.459	**	0.502	**	0.555	**	0.640	**	0.65	**	0.668	**
	[0.451,0.467]		[0.496,0.507]		[0.550,0.560]		[0.634,0.646]		[0.640,0.660]		[0.655,0.682]	
Racial/ethnic heterogeneity	0.722	**	0.606	**	0.538	**	0.538	**	0.815	**	0.769	**
	[0.653,0.798]		[0.570,0.645]		[0.513,0.564]		[0.514,0.564]		[0.766,0.867]		[0.719,0.822]	
Concentrated disadvantage	1.033	**	1.034	**	1.023	**	1.033	**	1.022	**	1.029	**
	[1.030,1.037]		[1.031,1.036]		[1.021,1.025]		[1.031,1.035]		[1.019,1.024]		[1.026,1.031]	
Percent occupied units	0.988	**	0.986	**	0.977	**	0.976	**	0.964	**	0.958	**
	[0.986,0.990]		[0.984,0.988]		[0.975,0.978]		[0.974,0.978]		[0.962,0.967]		[0.954,0.962]	
Percent home owners	0.990	**	0.989	**	0.986	**	0.988	**	0.997	**	1.000	
	[0.990,0.991]		[0.989,0.989]		[0.985,0.986]		[0.988,0.989]		[0.997,0.998]		[1.000,1.001]	
Percent Black	1.028	**	1.029	**	1.032	**	1.033	**	1.027	**	1.027	**
	[1.027,1.029]		[1.028,1.030]		[1.032,1.033]		[1.032,1.033]		[1.026,1.028]		[1.026,1.028]	
Percent Latino	1.016	**	1.014	**	1.015	**	1.012	**	1.013	**	1.012	**
	[1.015,1.017]		[1.014,1.015]		[1.015,1.016]		[1.012,1.013]		[1.012,1.014]		[1.011,1.013]	
Percent aged 16 to 29	1.008	**	1.008	**	1.015	**	1.016	**	1.004	**	1.004	**
	[1.006,1.010]		[1.007,1.010]		[1.013,1.016]		[1.014,1.018]		[1.002,1.006]		[1.002,1.006]	
Land Use Variables												
Percent residential area	0.995	**	0.996	**	1.002	**	1.006	**	0.996	**	1.002	**
	[0.994,0.996]		[0.996,0.997]		[1.002,1.003]		[1.005,1.006]		[0.995,0.997]		[1.001,1.003]	
Percent retail area	1.010	**	1.011	**	1.014	**	1.016	**	1.015	**	1.017	**
	[1.009,1.012]		[1.010,1.012]		[1.013,1.014]		[1.014,1.017]		[1.013,1.016]		[1.015,1.019]	
percent industrial area	0.993	**	0.996	**	0.999	**	1.004	**	1.001		1.005	**
	[0.992,0.995]		[0.995,0.997]		[0.998,0.999]		[1.004,1.005]		[1.000,1.002]		[1.004,1.006]	
percent office area	0.997	**	0.992	**	0.987	**	0.983	**	0.986	**	0.982	**
	[0.995,0.999]		[0.991,0.994]		[0.986,0.988]		[0.982,0.985]		[0.985,0.988]		[0.980,0.984]	
Land use mix	1.342	**	1.436	**	1.412	**	1.198	**	0.955		1.063	
	[1.224,1.471]		[1.350,1.527]		[1.340,1.488]		[1.129,1.270]		[0.880,1.036]		[0.950,1.190]	
# of Employees												
Retail	1.004	**	1.001	**	1.000	**	1.000	**	1.000		1.000	**
	[1.003,1.005]		[1.001,1.001]		[1.000,1.000]		[1.000,1.000]		[1.000,1.000]		[1.000,1.000]	
Bar	1.063	**	1.024	**	1.010	**	1.005	**	1.012	**	1.006	**
	[1.045,1.082]		[1.020,1.027]		[1.009,1.011]		[1.005,1.006]		[1.011,1.013]		[1.006,1.007]	
Grocery	1.007	**	1.004	**	1.003	**	1.001	**	1.001	**	1.000	**
	[1.004,1.010]		[1.003,1.004]		[1.002,1.003]		[1.001,1.001]		[1.000,1.001]		[1.000,1.001]	
Liquor	1.269	**	1.126	**	1.057	**	1.026	**	1.027	**	1.016	**
	[1.222,1.318]		[1.114,1.137]		[1.053,1.061]		[1.025,1.028]		[1.023,1.031]		[1.014,1.018]	
Restaurants	1.023	**	1.009	**	1.004	**	1.002	**	1.002	**	1.001	**
	[1.021,1.025]		[1.008,1.009]		[1.004,1.004]		[1.002,1.002]		[1.002,1.002]		[1.001,1.001]	
N	191473		191643		191457		196463		92308		92063	
Pseudo R-squared	0.142		0.141		0.142		0.127		0.088		0.061	

*** p < .01(two-tail test), * p < .05 (two-tail test)*

95% confidence Intervals below coefficient estimates.

Table 5. Correlations: Street Egohood vs. Block Egohood

	¼ mile	*½ mile*
Population (logged)	0.55	0.49
Racial/ethnic heterogeneity	0.88	0.91
Concentrated disadvantage	0.93	0.70
Percent occupied units	0.58	0.65
Percent owners	0.87	0.89
Percent black	0.94	0.95
Percent Latino	0.96	0.97
Percent aged 15-29	0.75	0.76
Percent residential land use	0.73	0.39
Percent retail land use	0.72	0.56
Percent industrial land use	0.80	0.68
Percent office land use	0.66	0.56
Land use mix	0.60	0.31
Retail employees	0.78	0.65
Bar employees	0.75	0.66
Grocery employees	0.55	0.42
Liquor store employees	0.67	0.53
Restaurant employees	0.84	0.76

Table 6. Percent change of crime for one S.D. change in measure (Property Crime)

Property Crime	Percent Change of Crime (1/4 mile)			Percent Change of Crime (1/2 mile)		
	Street Egohood	Block Egohood	Ratio	Street Egohood	Block Egohood	Ratio
Population	-49.5	-42.6	1.16	-41.9	-38.2	1.10
Heterogeneity	-3.5	-0.4	8.75	-0.9	2.3	OPP
Disadvantage	7.4	-1.5	OPP	6.6	-5	OPP
Occupied units	-2	-7.4	0.27	1.2	-7.8	OPP
Home owners	-26.6	-13.4	1.99	-22.4	-10.1	2.22
Black	23.2	16.7	1.39	23.9	19.9	1.20
Latino	15.4	10.7	1.44	17.4	20	0.87
Aged 16-29	8.4	5.1	1.65	6	3	2.00
Residential area	8.4	-4.8	OPP	8.4	6.6	1.27
Retail area	12	20.1	0.60	10.7	15.4	0.69
Industrial area	2.6	5.3	0.49	6	10.2	0.59
Office area	0.6	-1	OPP	-2.1	-3.5	0.60
Land use mix	-2.8	-7.6	0.37	-3.1	-2.1	1.48
Retail Employees	9.4	6.5	1.45	4.3	1.3	3.31
Bar Employees	1.6	2.3	0.70	1.7	1.1	1.55
Grocery Employees	2.9	-0.3	OPP	3.7	1	3.70
Liquor Employees	3.9	1.9	2.05	5.4	4.4	1.23
Restaurant Employees	23.1	19.2	1.20	27.6	24.2	1.14

Ratio = Street Egohood / Block Egohood

OPP = Opposite direction

Table 7. Percent change of crime for one S.D. change in measure (Violent Crime)

Violent Crime	Percent Change of Crime (1/4 mile)			Percent Change of Crime (1/2 mile)	
	Street Egohood	Block Egohood	Ratio	Street Egohood	Block Egohood
Population	-43.6	-33.5	1.30	-33.2	-28.9
Heterogeneity	-9.5	-3.6	2.64	-9	-4.5
Disadvantage	21.3	21.2	1.00	31	27.8
Occupied units	-10.7	-14.4	0.74	-8.6	-12.9
Home owners	-31.3	-6.7	4.67	-24.1	0.6
Black	60	47.7	1.26	52.8	45.2
Latino	53.9	47.2	1.14	41.1	40.6
Aged 16-29	10	2.7	3.70	8.9	2.3
Residential area	6.3	-9.6	OPP	13	3.8
Retail area	14.3	16.2	0.88	12.3	12.2
Industrial area	-1.5	0.9	OPP	5.4	6.9
Office area	-8.7	-9.3	0.94	-9.3	-9.2
Land use mix	6.8	-0.9	OPP	2.9	1
Retail Employees	1.2	0.2	6.00	-1.5	-1.6
Bar Employees	6.7	13.6	0.49	7.6	16.8
Grocery Employees	5.5	2	2.75	6.1	3.3
Liquor Employees	11.2	7.6	1.47	11.3	10.1
Restaurant Employees	33.1	27.4	1.21	33.8	21.8

Ratio = Street Egohood / Block Egohood

OPP = Opposite direction

Figures

Figure 1.

Figure 2.

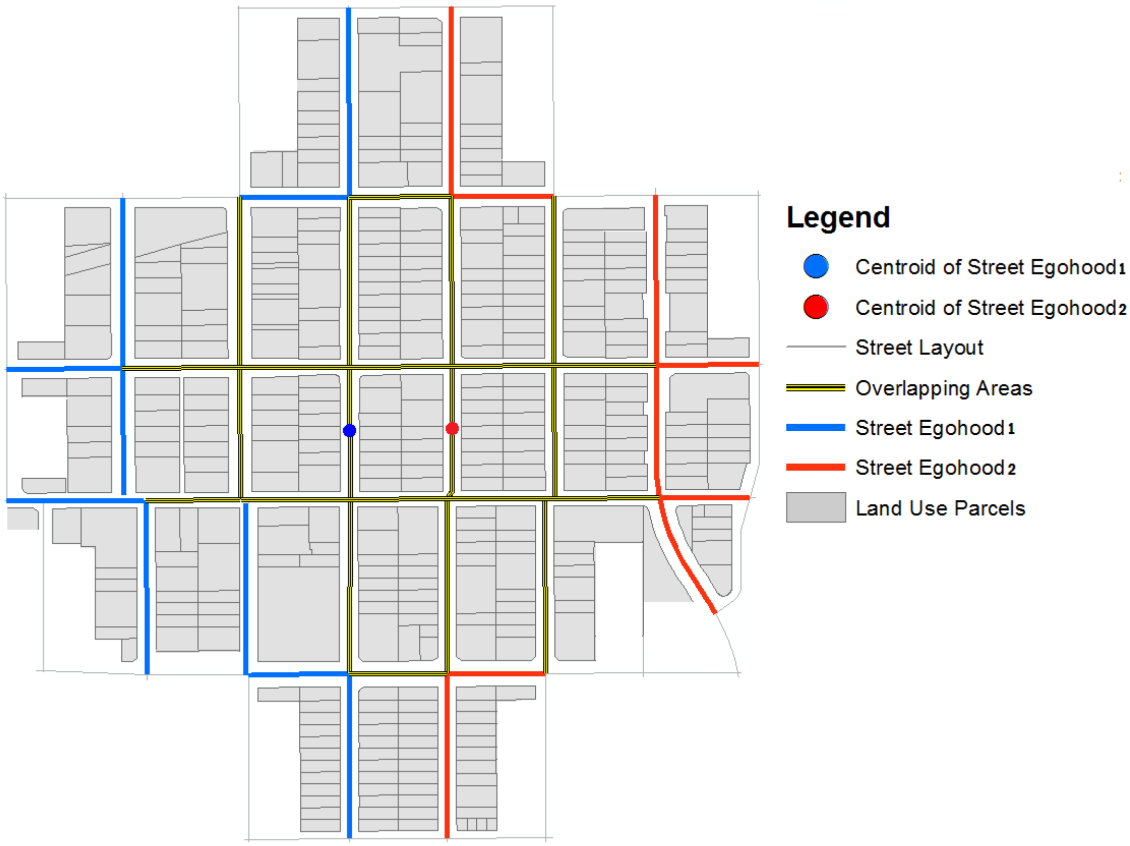
Legend
Centroid of Street Egohood1
Centroid of Street Egohood2
Street Layout
Overlapping Areas
Street Egohood1
Street Egohood2
Land Use Parcels

Figure 3. Structural Characteristics and Crime at Various Levels of Street Egohoods (1)

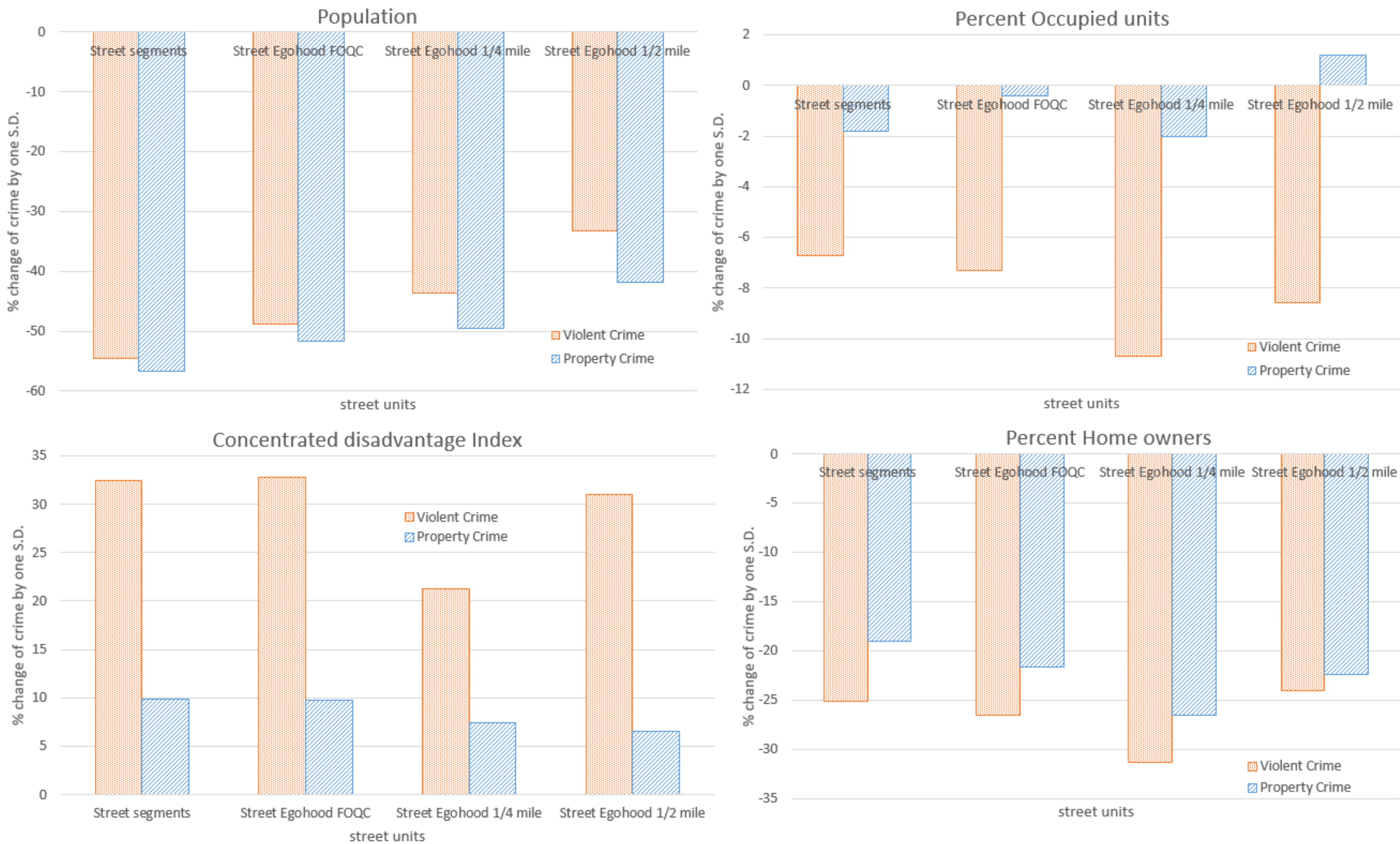

Figure 4. Structural Characteristics and Crime at Various Levels of Street Egohoods (2)

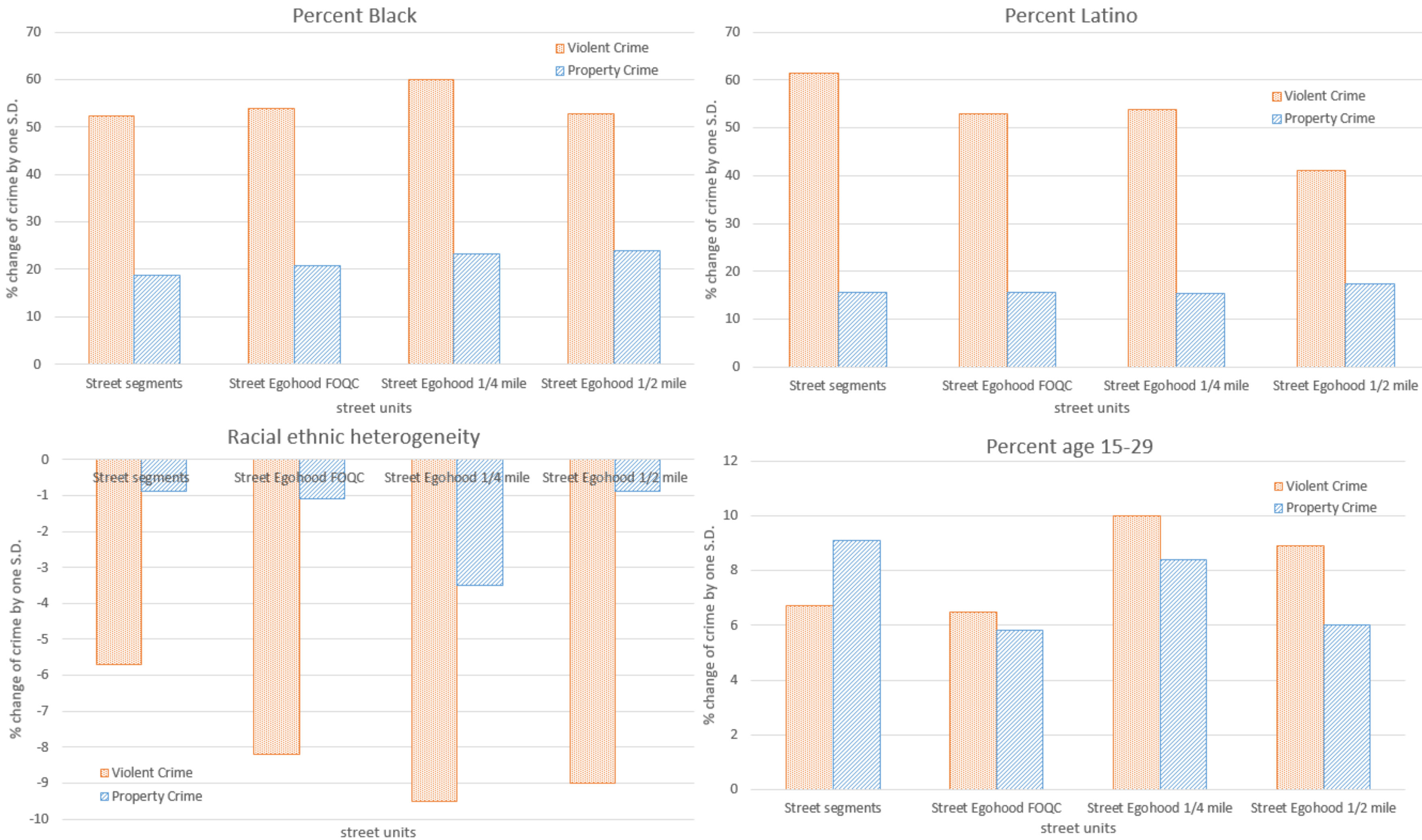

Figure 5. Land Use Characteristics and Crime at Various Levels of Street Egohoods

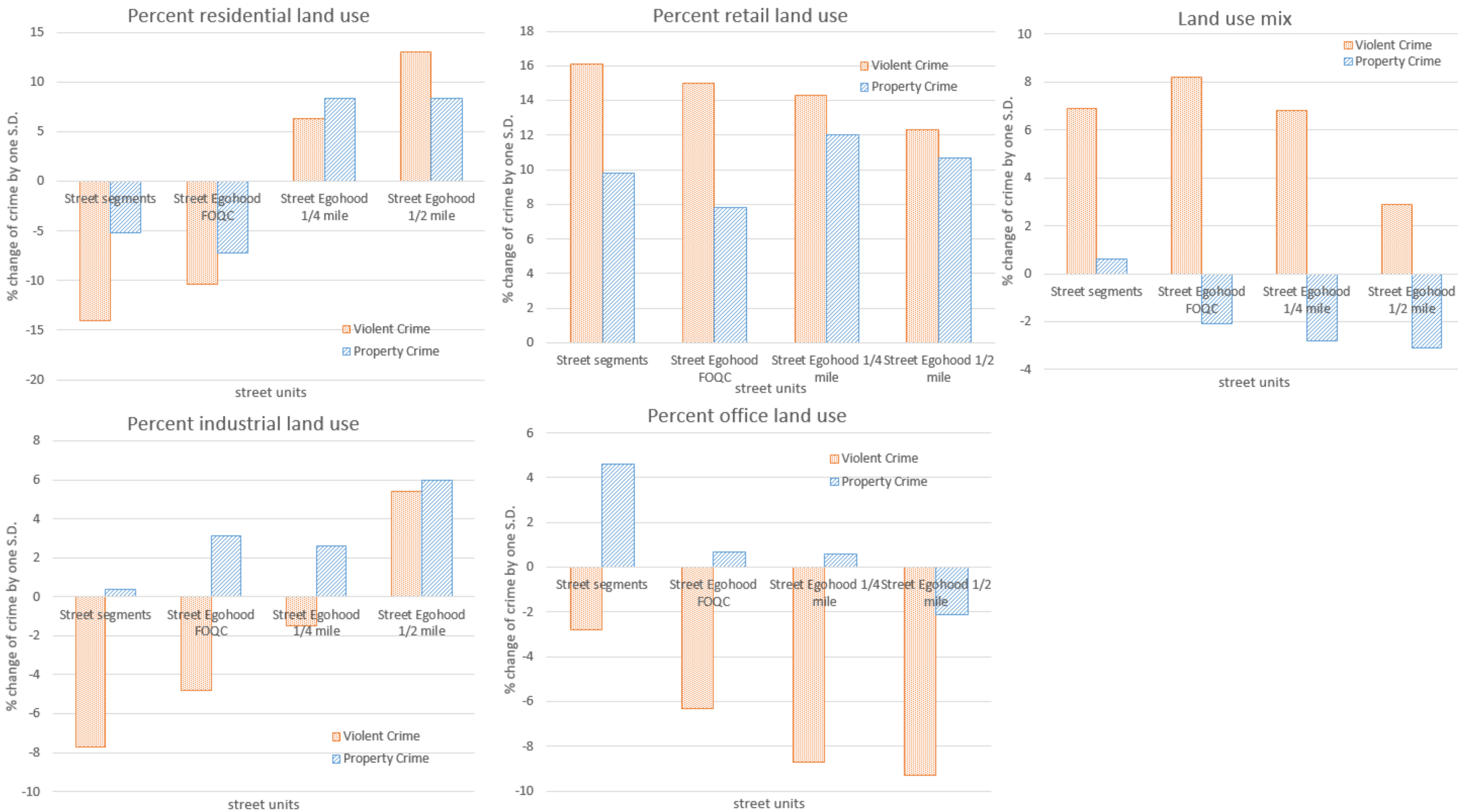

Figure 6. Employee Measures and Crime at Various Levels of Street Egohoods

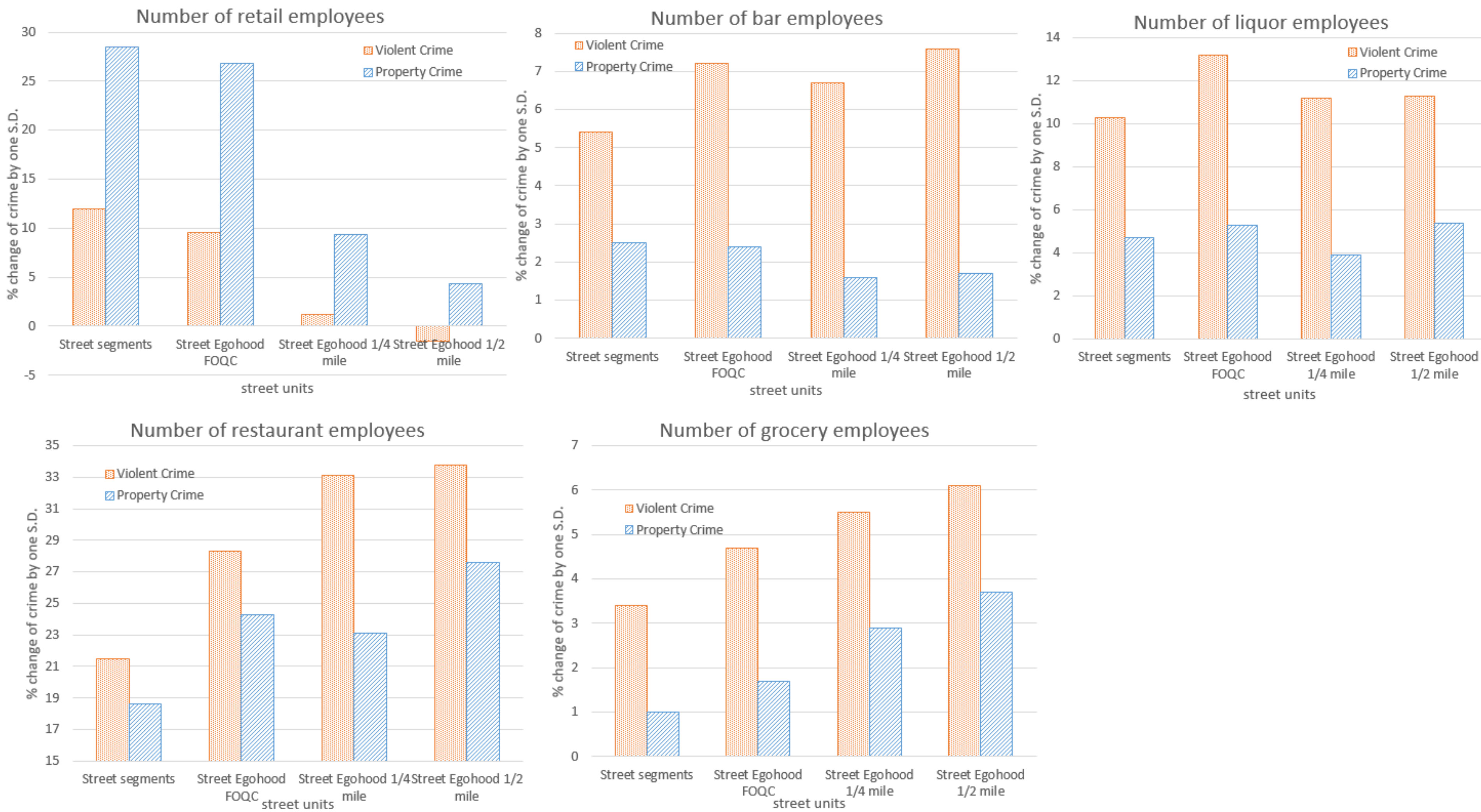

Figure 7a. Street Egohood vs. Block Egohood (Property Crime)

Figure 7b. Street Egohood vs. Block Egohood (Violent Crime)

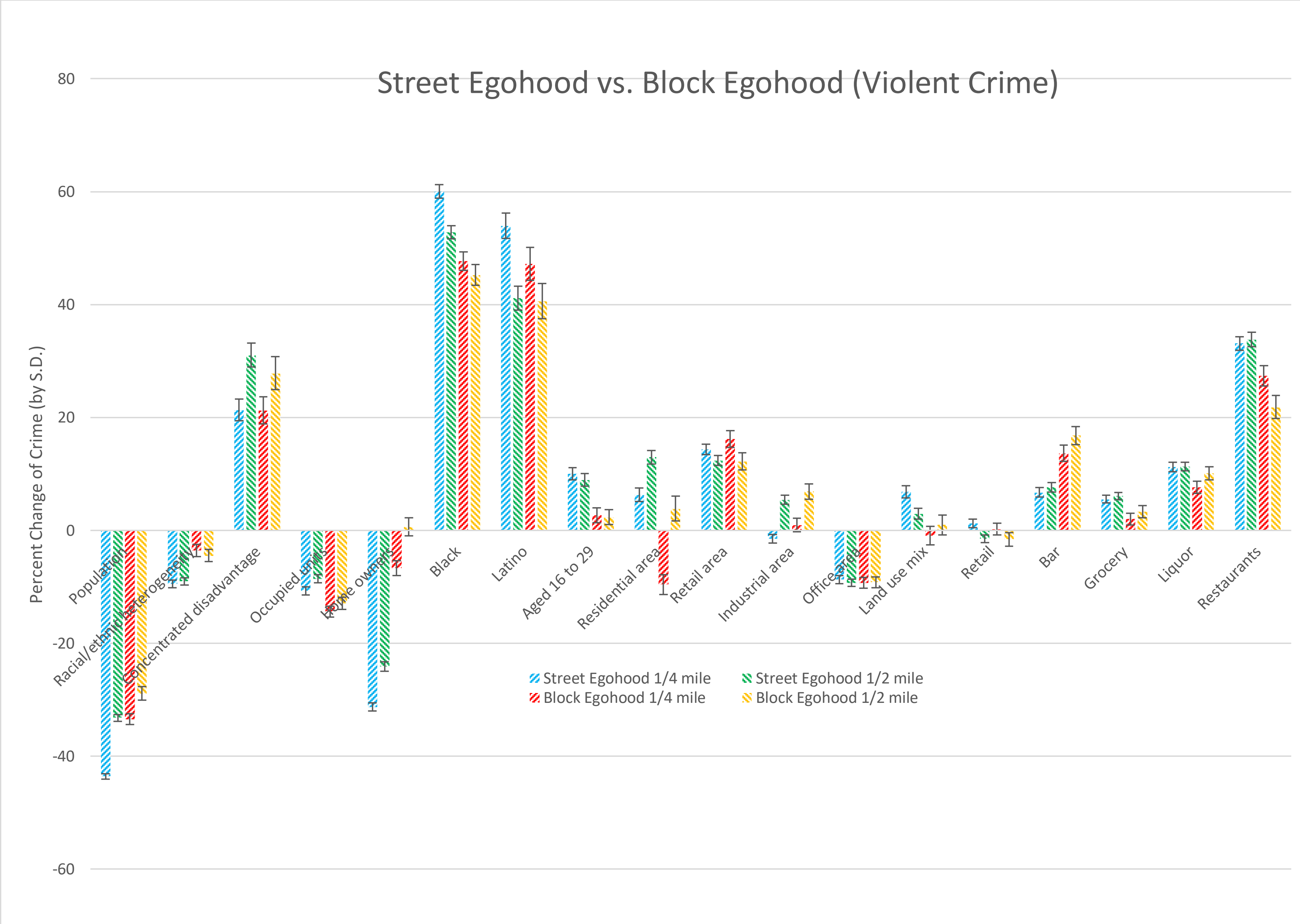

Table A1. Negative binomial models of various street based units (standardized coefficients) - Property Crime

	Street Segments	Street egohood FOQC	Street egohood 1/4 mile	Street egohood 1/2 mile	Block egohood 1/4 mile	Block egohood 1/2 mile
Census Variables						
Population (logged)	-0.257 **	-0.060 **	-0.028 **	-0.007 **	-0.014 **	-0.004 **
	-142.091	-194.530	-209.834	-151.308	-82.047	-58.348
Racial/ethnic heterogeneity	-0.003	-0.001 **	-0.001 **	0.000 **	0.000	0.000 **
	-1.463	-3.032	-11.607	-2.661	-0.690	3.338
Concentrated disadvantage	0.029 **	0.008 **	0.003 **	0.001 **	0.000	0.000 **
	9.605	14.402	11.542	8.368	-1.532	-3.856
Percent occupied units	-0.005 **	0.000	-0.001 **	0.000 **	-0.002 **	-0.001 **
	-3.267	-1.151	-6.285	3.466	-14.201	-12.115
Percent home owners	-0.065 **	-0.020 **	-0.013 **	-0.003 **	-0.004 **	-0.001 **
	-30.212	-53.339	-72.155	-49.111	-20.351	-12.599
Percent Black	0.053 **	0.016 **	0.008 **	0.003 **	0.004 **	0.001 **
	30.845	52.393	65.171	58.735	26.314	25.423
Percent Latino	0.044 **	0.012 **	0.006 **	0.002 **	0.003 **	0.001 **
	15.751	24.079	25.640	24.207	10.256	14.584
Percent aged 16 to 29	0.027 **	0.005 **	0.003 **	0.001 **	0.001 **	0.000 **
	13.906	14.101	21.535	12.716	8.274	4.335
Land Use Variables						
Percent residential area	-0.016 **	-0.006 **	0.003 **	0.001 **	-0.001 **	0.000 **
	-6.244	-13.567	17.010	15.703	-4.680	5.151
Percent retail area	0.029 **	0.006 **	0.005 **	0.001 **	0.005 **	0.001 **
	14.949	18.440	33.224	26.970	27.639	18.810
percent industrial area	0.001	0.003 **	0.001 **	0.001 **	0.001 **	0.001 **
	0.680	8.070	7.918	16.378	8.329	13.102
percent office area	0.014 **	0.001	0.000 *	0.000 **	0.000 *	0.000 **
	7.927	1.886	2.141	-6.499	-1.977	-5.796
Land use mix	0.002	-0.002 **	-0.001 **	0.000 **	-0.002 **	0.000 *
	0.821	-4.258	-6.879	-6.906	-9.142	-2.095
Number of Employees						
Retail	0.077 **	0.020 **	0.004 **	0.001 **	0.002 **	0.000
	18.728	37.326	19.594	9.369	8.334	1.606
Bar	0.008 **	0.002 **	0.001 **	0.000 **	0.001 **	0.000
	3.933	6.038	4.793	4.311	4.102	1.684
Grocery	0.003	0.001 **	0.001 **	0.000 **	0.000	0.000
	1.698	4.725	10.322	11.612	-0.622	1.686
Liquor	0.014 **	0.004 **	0.002 **	0.001 **	0.000 **	0.000 **
	6.772	12.195	12.810	16.138	3.906	7.835
Restaurants	0.053 **	0.018 **	0.008 **	0.003 **	0.004 **	0.002 **
	24.482	47.160	51.495	48.956	23.959	23.035
N	191473	191643	191457	196463	92308	92063
Pseudo R-squared	0.042	0.055	0.053	0.045	0.028	0.018

*** p < .01(two-tail test), * p < .05 (two-tail test)*
t-values below coefficient estimates.

Table A2. Negative binomial models of various street based units (standardized coefficients) - Violent Crime

	Street Segments	Street egohood FOQC	Street egohood 1/4 mile	Street egohood 1/2 mile	Block egohood 1/4 mile	Block egohood 1/2 mile
Census Variables						
Population (logged)	-0.886 **	-0.200 **	-0.060 **	-0.012 **	-0.025 **	-0.006 **
	-87.958	-122.049	-128.840	-92.397	-54.384	-40.050
Racial/ethnic heterogeneity	-0.066 **	-0.025 **	-0.010 **	-0.003 **	-0.002 **	-0.001 **
	-6.343	-15.927	-25.815	-26.002	-6.471	-7.713
Concentrated disadvantage	0.317 **	0.085 **	0.020 **	0.008 **	0.012 **	0.004 **
	17.937	28.605	24.170	32.579	18.957	21.002
Percent occupied units	-0.079 **	-0.023 **	-0.012 **	-0.003 **	-0.010 **	-0.002 **
	-9.758	-15.566	-27.193	-21.580	-27.620	-21.839
Percent home owners	-0.325 **	-0.092 **	-0.039 **	-0.008 **	-0.004 **	0.000
	-26.986	-46.723	-69.463	-48.810	-9.666	0.780
Percent Black	0.474 **	0.128 **	0.049 **	0.013 **	0.024 **	0.007 **
	55.382	88.322	121.420	109.774	68.196	58.264
Percent Latino	0.538 **	0.126 **	0.045 **	0.010 **	0.024 **	0.006 **
	32.256	46.510	58.570	45.513	38.188	30.018
Percent aged 16 to 29	0.072 **	0.019 **	0.010 **	0.003 **	0.002 **	0.000 **
	7.250	10.899	18.937	16.225	4.080	3.485
Land Use Variables						
Percent residential area	-0.169 **	-0.033 **	0.006 **	0.004 **	-0.006 **	0.001 **
	-13.065	-14.627	10.696	22.597	-10.018	3.439
Percent retail area	0.168 **	0.042 **	0.014 **	0.004 **	0.009 **	0.002 **
	18.222	25.797	32.138	29.163	23.136	16.818
percent industrial area	-0.090 **	-0.015 **	-0.002 **	0.002 **	0.001	0.001 **
	-9.910	-9.561	-3.803	14.018	1.563	10.084
percent office area	-0.032 **	-0.019 **	-0.010 **	-0.003 **	-0.006 **	-0.002 **
	-3.278	-11.904	-22.794	-26.608	-17.893	-17.730
Land use mix	0.075 **	0.024 **	0.007 **	0.001 **	-0.001	0.000
	6.290	11.479	12.867	6.034	-1.108	1.072
Number of Employees						
Retail	0.127 **	0.027 **	0.001 **	0.000 **	0.000	0.000 **
	8.889	12.998	3.240	-4.376	0.420	-2.611
Bar	0.060 **	0.021 **	0.007 **	0.002 **	0.008 **	0.003 **
	6.792	13.613	16.546	18.400	19.783	22.195
Grocery	0.038 **	0.014 **	0.006 **	0.002 **	0.001 **	0.001 **
	5.016	10.122	16.543	18.417	3.762	6.085
Liquor	0.110 **	0.037 **	0.011 **	0.003 **	0.004 **	0.002 **
	12.332	22.389	27.415	30.328	14.527	17.981
Restaurants	0.219 **	0.074 **	0.030 **	0.009 **	0.015 **	0.004 **
	24.768	42.705	62.304	58.392	33.594	23.256
N	191473	191643	191457	196463	92308	92063

Pseudo R-squared	0.142	0.141	0.142	0.127	0.088	0.061

*** p < .01(two-tail test), * p < .05 (two-tail test)*
t-values below coefficient estimates.