Studying Neighborhood Crime Across Different Macro Spatial Scales:

The Case of Robbery in 4 Cities

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Abstract

Whereas there is a burgeoning literature focusing on the spatial distribution of crime events across neighborhoods or micro-geographic units in a specific city, the present study expands this line of research by selecting four cities that vary across two macro-spatial dimensions: population in the *micro*-environment, and population in the broader *macro*-environment. We assess the relationship between measures constructed at different spatial scales and robbery rates in blocks in four cities: 1) San Francisco (high in micro- and macro-environment population); 2) Honolulu (high in micro- but low in macro-environment population); 3) Los Angeles (low in micro- but high in macro-environment population); 4) Sacramento (low in micro- and macro-environment population). Whereas the socio-demographic characteristics of residents further than ½ mile away do not impact robbery rates, the *number* of people up to 2.5 miles away are related to robbery rates, especially in the two cities with smaller micro-environment population, implying a larger spatial scale than is often considered. The results show that coefficient estimates differ somewhat more between cities differing in micro-environment population compared to those differing based on macro-environment population. It is therefore necessary to consider the broader macro-environment even when focusing on the level of crime across neighborhoods or micro-geographic units within an area.

Keywords: spatial scale, neighborhoods, crime, land use.

Bio

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A long line of research has demonstrated spatial clustering of crime events in neighborhoods (Shaw and McKay 1942) or even smaller geographic units (Boessen and Hipp 2015; Groff, Weisburd, and Yang 2010; Weisburd, Bushway, Lum, and Yang 2004). Beyond focusing on how crime clusters in various locations, this literature has also employed neighborhood-level theories to study whether particular characteristics of the environment can explain why crime clusters in some micro-geographic locations and not others (Davies and Johnson 2014; Weisburd, Groff, and Yang 2012), or in some neighborhoods rather than others (Hipp, Tita, and Greenbaum 2009; Sampson and Groves 1989). This research has provided important insights regarding where crime is more likely to occur. However, a limitation is that almost all of these studies focus on crime patterns within a particular city. As a consequence, we are left with the assumption that these observed relationships will occur similarly across all cities, regardless of the unique spatial pattern of the location of residents that characterizes a given city, rather than actually testing this assumption.

Whereas an ideal way to test this assumption of invariance in the spatial patterning of crime events across the various possible spatial socio-demographic distributions of cities would be to collect data for a large number of cities, such a strategy is data intensive and currently infeasible. We instead adopted a case study approach in which we selected four extreme cases based on their spatial patterns of residents and collected robbery data from these four cities. Specifically, these four cities differ based on two dimensions defined by Hipp and Roussell (2013): size of population in the *micro*-environment, and size of population in the broader *macro*-environment. The population of the micro-environment is the number of people that live within some small radius of a person (say ½ mile). The population of the macro-environment is the number of people that live within a larger radius of a person (say 5, 10 or 25 miles). This allows us to relax the assumption of invariance across these cities, and assess the extent to which this is actually the case.

Our strategy entailed selecting four cities that are extreme cases based on population in the micro-environment and macro-environment, with the goal that this will give us the highest probability of detecting differences in the spatial patterning of crime across these cities. We thus selected four cities based on a 2 x 2 table of high and low micro- and macro-environment population: 1) San Francisco (high in micro- and macro-environment population); 2) Honolulu (high in micro- but low in macro-environment population); 3) Los Angeles (low in micro- but high in macro-environment population); 4) Sacramento (low in micro- and macro-environment population). We are then able to compare the robustness of our various structural measures—motivated by routine activities and social disorganization theories—for explaining robbery rates across these four cities with very different micro- and macro-environment population.

SPATIAL PATTERNS AND CRIME

Theories of the Spatial Patterning of Crime

The bulk of studies exploring the patterns of crime in small geographic units employ routine activities theory and its geographic corollary, crime patterning theory (Brantingham and Brantingham 1984; Smith, Frazee, and Davison 2000). Routine activities theory posits that crime events are more likely to occur with the convergence in time and place of motivated offenders and suitable targets along with a lack of guardians (Cohen and Felson 1979; Felson and Boba 2010), which implies that the ambient population at micro-locations during various hours of the day is important for understanding when and where crime is most likely to occur (Brantingham and Brantingham 1995; Roncek and Maier 1991). Thus, we need to know not only where the residential population lives, but we must also know their likely destinations during the day to obtain estimates of the number of people on a block during particular hours of the day, or what is referred to as "ambient population" (Andresen 2011; Malleson and Andresen 2016). Nonetheless, much of the research studying crime in small geographic units focuses only on presence of criminal opportunities at locations, which does not take into account the relative presence of *offenders* at a location, which is an equally important component of the theory (Groff and Lockwood 2014; Stucky and Ottensmann 2009). For example, although a bar provides criminal opportunities, the amount of crime experienced there will likely differ if there are relatively few potential offenders in the surrounding area compared to a bar with a relatively high number of offenders in the surrounding area (Hipp 2016).

Although research in this vein provides much insight into the relative attractiveness of areas such as commercial districts, it leaves unanswered whether these are inviolate patterns that will be observed in all cities. That is, will the presence of an attractive target lead to higher levels of crime in commercial districts across all possible environments? Furthermore, will the size of the relative increase in crime at such locations be similar across different possible environments? Or, will these patterns differ based on the spatial layout of the broader environment?

A key insight of opportunity theory is the need to understand where the convergence of offenders and targets will occur, and the consequences of this for crime at micro locations. We need to know not only where crime opportunities are located, but also where offenders are likely to live. And a challenge is that offenders will typically travel to commit most crimes. Indeed, the journey to crime literature has consistently shown that a spatial distance decay function characterizes the travel to crime behavior for offenders. Rossmo (2000) cites research finding that robbers travel, on average 0.6 miles in Boston; 1.22 miles in Ottawa (for armed robbery); 1.57 miles in Philadelphia; 2.1 miles in Washington, D.C.; 2.14 miles in Indianapolis; 2.67 miles in Eugene, Oregon. Thus, despite the distance decay effect where offenders commit crimes closer to home, they nonetheless travel nontrivial distances that have consequences for studying crime at micro locations. As a further complication, for some crimes, such as robbery, the targets in many instances will also travel. Whereas the opportunities of a micro environment can impact where crime occurs, it is also necessary to account for where offenders and targets might travel. It is notable that of these six cities described by Rossmo, the average distance traveled in the three high population density cities (Boston, Philadelphia, and Washington D.C.) is 1.42 miles whereas the average distance traveled is just over 2 miles in the three low population density cities. Although not a systematic study, this implies that the journey to crime distance may be longer in low population density cities. This leads to our first hypothesis:

H1: The relationship between population density and robberies will extend to longer distance in cities with low micro-environment population.

Understanding where people travel is dependent in part on the spatial distribution of where people live. Where people live and where jobs are located are two key ingredients for understanding where the ambient population is located. The business location literature has shown that retail firms prefer to locate nearer to potential customers (Glaeser 2008), which is based on the idea that residents in general prefer to travel shorter distances when patronizing various retail and amenities. There are also agglomeration effects leading amenities to cluster near one another, such as malls and downtown districts (Glaeser 2008). The consequence is that the relative locations of where residents live and where retail and amenities are located will determine typical ambient population (Hipp 2016). Likewise, the relative location of retail and amenities will affect offender travel behavior (Bernasco 2010; Bernasco and Block 2011), as retail locations provide suitable crime targets. Given that these various options will likely impact where potential targets travel (as well as offenders), the question is whether this will have an impact on the spatial patterning of crime.

These considerations imply the need to focus not only on small geographic units of analysis when studying the location of crime, but also taking into account the surrounding area. This idea underlies the logic of egohoods, which are geographic units with a block at the center and a defined buffer of some distance around it (Hipp and Boessen 2013). As argued by Hipp and Boessen, egohoods better capture the spatial extent of residents' travel patterns, which tend to follow a distance decay effect from their home (Moudon, Lee, Cheadle, Garvin, Johnson, Schmid, Weathers, and Lin 2006; Sastry, Pebley, and Zonta 2002), rather than occurring within a predefined "neighborhood." The result is overlapping units that "wash" across the city, rather than the more common approach of predefined non-overlapping units. In their study of nine cities, Hipp and Boessen (2013) found that aggregating data to egohoods rather than non-overlapping units provided better predictions of the location of crime, and was particularly important for capturing the strong relationship between inequality and crime.

To understand how the micro spatial patterns of egohoods might be affected by the broader macro-environment, we follow Hipp and Roussell (2013) in suggesting that two key dimensions might matter: the population in the micro-environment and the population in the macro-environment. We can consider the micro-environment population of an area: the number of people that live within some small radius of a person (say ½ mile). And we can consider the macro-environment population of an area: the number of people that live within a larger radius of a person (say 5, 10 or 25 miles). Hipp and Roussell (2013) used these ideas in exploring city-level crime rates across a large number of cities. Their work found nonlinear interactions between micro- and macro-environment population in these larger spatial units, which they pointed out was consistent with the idea that in higher density cities the number of offenders and targets increase, but so too does the number of guardians. Their results were also consistent with the possibility that cities with higher macro-environment population have more offenders as a result of increased anomie (Wirth 1938). However, they were constrained to studying city-level patterns, and we extend this idea here by exploring whether similar patterns are detected at smaller spatial scales of blocks and egohoods.

The question then is whether the spatial locations of residents, workplaces and amenities impact where crime occurs within particular cities. On the one hand, if the presence of commercial districts is all that determines the level of crime within small geographic units, then the presence of commercial districts on a local street block, or within some nearby area, will entirely determine the amount of crime in that block. On the other hand, given the broader travel patterns of offenders, it may be that the broader spatial pattern of residents, workplaces and commercial districts will impact the amount of crime in a block (beyond the effect of the characteristics of the local block and nearby surrounding area). If offenders have more opportunities in denser environments, and therefore travel shorter distances, this should be detected in the spatial effects that are estimated. This implies our next hypothesis:

H2: The spatial effects of commercial districts on robberies will be stronger in cities with low micro-environment population.

Spatial effect of socio-demographic characteristics

Beyond the simple presence of persons—based on where they live and where they work or shop—are the insights of social disorganization theory in which some neighborhoods have more disorder and hence less ability to provide informal social control (and guardianship) and therefore more crime (Hipp 2007b; Krivo and Peterson 1996; Sampson and Groves 1989). These characteristics include concentrated disadvantage, racial/ethnic composition and heterogeneity, residential instability, or the presence of vacant units.

Whereas social disorganization theory focuses on crime at the neighborhood level, there are competing perspectives regarding how the particular macro context might impact this ability to provide informal social control. On the one hand, it may be that the social structure of a local block and some surrounding area will impact the level of crime similarly regardless of the broader spatial patterns of the city. Indeed, this is the assumption of much existing literature that studies the relationship between neighborhood structural characteristics and levels of crime in a specific city. On the other hand, the population of the micro- and macro-environment in a city may impact how these structural characteristics play out in specific neighborhoods. Nonetheless, only in rare exceptions have researchers studied the relationships between socio-demographic characteristics of neighborhoods and crime across a larger sample of cities (Chamberlain and Hipp 2015; Peterson and Krivo 2010). For example, whereas the presence of attractive targets in a nearby neighborhood may increase crime there (Chamberlain and Hipp 2015; Mears and Bhati 2006), it could also be that multiple nearby areas with attractive targets will "compete" with each other for offenders and hence result in a smaller increase in crime in each (Hipp 2016).

This possibility that the context at a larger spatial scale can impact crime in smaller units has only been considered in a few studies. As one example, Peterson and Krivo (2010) posited and found that crime rates were higher for all neighborhoods in cities with high levels of residential segregation; crime was higher in all neighborhoods in these cities regardless of the racial composition of the neighborhoods. In a study using cities as the units of analysis, Hipp

(2011) tested and found that the level of economic segregation combined with the level of inequality in a city had consequences for the overall level of crime. He pointed out that the combination of economic inequality and economic segregation in a city has consequences for the level of inequality in the constituent neighborhoods, and across the neighborhoods, which might lead to crime within and across neighborhoods. He found a similar positive relationship for cities with high levels of racial/ethnic heterogeneity and segregation; the fact that this city-level analysis found a positive relationship, along with the Peterson and Krivo study that found increased crime across all neighborhoods in the city, may speak to the tendency of offenders to often travel distances farther than the boundaries of a census tract.

Neighborhood socio-demographic characteristics and crime in different macro contexts

Although the existing literature has typically not compared the results for the relationship between social structural characteristics and crime across cities, we can glean some insights from existing literature studying single cities. We organize this discussion around how the results for a particular covariate differ across cities based on the city's level of micro- or macro-environment population.

Regardless of the level of micro- or macro-environment population, the level of concentrated disadvantage in a neighborhood is consistently associated with higher crime rates. Numerous studies have found this effect whether measuring small geographic units (Bernasco and Block 2011; Groff and Lockwood 2014; Stucky and Ottensmann 2009) or meso-units such as neighborhoods (Bellair 2000; Krivo and Peterson 1996; Sampson, Raudenbush, and Earls 1997). Another important structural characteristic of neighborhoods is the racial/ethnic composition. Studies have typically found that the presence of more minority residents (often measured as the percent African American) or the presence of more racial/ethnic heterogeneity are associated with higher levels of crime, regardless of the micro- or macro-environment population of the city (Browning, Byron, Calder, Krivo, Kwan, Lee, and Peterson 2010; Haberman and Ratcliffe 2015; Warner and Rountree 1997). Therefore we hypothesize:

H3: The effects of concentrated disadvantage and racial/ethnic composition will not differ over cities based on micro- or macro-environment population.

Although the level of residential stability in a neighborhood is posited to enhance the level of cohesion, increase informal social control ability, and lead to lower levels of crime, the existing research seems to tell a mixed story based on the micro-environment population of the city. In low micro-environment cities, research commonly finds a negative relationship between residential stability and crime rates in Indianapolis (Stucky and Ottensmann 2009), Rochester and Tampa/St Petersburg (Bellair 1997), Atlanta (McNulty 2001), Columbus, OH (Browning et al. 2010), or Cincinnati (Wooldredge 2002). However, in relatively higher density cities of Boston (Warner and Pierce 1993), Chicago (Sampson and Raudenbush 1999) or Miami (Nielsen and Martinez 2003) the relationship was nonsignificant or positive depending on the crime type. Therefore we hypothesize:

H4: Residential stability will have a stronger negative effect in cities with low micro-environment population.

There is also mixed evidence for the role of retail areas in impacting crime. On the one hand, there are relatively consistent results from high density cities of a positive relationship between retail areas and crime levels. This finding has been detected in Seattle (Wilcox, Quisenberry, Cabrera, and Jones 2004), and Chicago (Bernasco and Block 2011). On the other hand, the results are mixed for lower density cities. Whereas a positive relationship was detected in Indianapolis for small geographic units (Stucky and Ottensmann 2009) a negative relationship was detected in Columbus (Browning et al.) for census tracts. Likewise, the effect of population density differs depending on the macro context. Whereas studies have typically found a positive relationship between local population density and crime rates in lower density environments such as Indianapolis (Stucky and Ottensmann 2009) and Austin (Hannon 2002), the results are mixed in higher density environments. Although a negative relationship was detected in Seattle (Hannon 2002; Kubrin, Squires, Graves, and Ousey 2011) and Chicago (Sampson and Raudenbush 1999), a nonsignificant relationship was found in Philadelphia (Groff and Lockwood 2014), and a study of Chicago using small units (blocks) actually found a positive relationship (Bernasco and Block 2011). Therefore we hypothesize:

H5: The presence of commercial districts will have a stronger positive relationship with robbery in cities with high micro-environment population.

H6: Higher population in the block and nearby area will have a stronger positive relationship with robbery in cities with low micro-environment population.

Given these differences in the existing literature, our study is well poised to assess whether the micro- or macro-environment population impacts these relationships. By systematically varying the micro- and macro-environment across a wide range of values, we are better able to assess whether such differences exist. We next turn to our research design, and then describe our data and methods.

Research Design

Our analytic strategy was to obtain crime and sociodemographic data for four cities with distinct spatial distributions of residents along two dimensions: what Hipp and Roussell (2013) refer to as population in the micro-environment and the macro-environment. We therefore chose two cities with high levels of population in the micro-environment—that is, high levels of density in the neighborhoods within the city. These were San Francisco and Honolulu, and Table 1 shows that the mean population density of San Francisco blocks is 133.2 per square mile and those in Honolulu is almost 94; note that this measure is capturing the average density experienced by a person, and therefore implicitly accounts for large empty areas (see Hipp and Roussell 2013 for a discussion of this issue). We pair these with two cities with more spatially diffuse patterns that are consistent with the more recent type of ecological development observed in the Sunbelt: Sacramento and Los Angeles. Los Angeles blocks have an average population density of 79 and Sacramento's blocks have an average of just 48.

But these four cities also differ in their level of population in the macro environment: that is, the population within some larger radius around a resident's neighborhood. Thus, the average population within 5 miles of each neighborhood is much higher in Los Angeles (almost 800,000) and San Francisco (about 725,000) compared to Sacramento (about 300,000) and Honolulu (about 270,000). Thus, Honolulu—by virtue of its location on an island surrounded by water—and Sacramento—by virtue of its location in the California delta area in which it is largely surrounded by farmland—result in a much smaller number of persons within the macro environment of their residents than the other two cities. These macro-environment population patterns are even more extreme when viewing the population within 25 miles of each tract in these cities. Thus, we have a 2 x 2 design of a city with high micro- and macro-environment population (San Francisco), a city with high micro- and low-macro environment population (Honolulu), a city with low micro- and high macro-environment population (Los Angeles), and a city with low micro- and macro-environment population (Sacramento).

<<<Table 1 about here>>>

DATA AND METHODS

Data

The data used in the present study come from four police departments, the U.S. Census Bureau, and the Mint business data source. We constructed the crime and socio-demographic variables at the block level to capture micro-processes, as well as within various sized spatial buffers to capture broader spatial effects. Crime data were collected from 2009 to 2011. U.S. Census data and the American Community Survey (2007-11 five year estimates) were used to generate variables in both blocks and buffers of various sizes. For all variables, we aggregated measures to: 1) the block; 2) the ¼ mile buffer surrounding the block; and 3) the area between ¼ mile and ½ mile from the block. We constructed measures of population within the area: 4) between ½ mile and ¾ mile from the block; 5) between ¾ mile and 1 mile from the block; 6) between 1 mile and 1¼ mile from the block; 7) between 1¼ mile and 1½ mile from the block; 8) between 1½ mile and 2½ miles from the block. For all buffer variables, we also included information from blocks in the area surrounding our research site, to avoid boundary problems.

Measures

Outcome Variable

Based on the Uniform Crime Reports provided by each police agency, we coded robbery events, and then geocoded and aggregated them to the constituent blocks. The outcome variable refers to the computed totals over the three years (2009-11) in order to smooth year-to-year fluctuations in robberies. We used robberies because: 1) they are usually a well-reported crime type; 2) reporting typically provides relatively accurate day and time information on the incident; 3) both offenders and targets typically move prior to a robbery event, so it is a particularly spatially influenced crime type.

Key Predictor Variables

We account for the presence of persons in the nearby environment in several manners. First, we take into account the number of residents by constructing a measure of the block-level population as *logged population*. We capture nonlinear effects by also including the quadratic version of this variable (we tested a cubic functional form, but this term was never statistically significant). The daytime population is impacted by the presence of employees in the area, so we constructed a measure of total employees in the area as *logged total employees* (Boessen 2014; Steenbeek, Völker, Flap, and Oort 2012). We also included the quadratic version of this variable to capture nonlinearities. The employee data comes from Mint Business data, which provides the address and North American Industry Classification System (NAICS) codes for businesses across the U.S. We geocoded the establishments and placed them in the representative census block. Given that retail employees not only represent persons in the area, but also represent many other persons in the form of patrons of these stores, we constructed a measure of the retail employees in the area (2-digit NAICS codes 44 and 45) as *logged retail employees*. Although shops themselves can be targets, we focus on the number of employees given that they operate as a proxy for the ambient population in an area, which is of particular interest to us here. Although some existing research has focused on specific types of retail locations as potential "risky facilities", we do not do so here because 1) creating many categories of establishments is outside the scope of the present research; and 2) existing research typically indicates that risky facilities have a very micro effect on the local block and therefore would be less likely to have an effect at broader scales as tested here. We also constructed a quadratic version of this variable to test for nonlinear effects.

We included measures to capture the characteristics of people in the block and nearby area. We capture the possible effect of *concentrated disadvantage* with a measure that combines four variables using factor analysis to create factor scores: the percent at or below 125% of the poverty level, the percent single parent households, the average household income, and the percent with at least a bachelor's degree (the latter two are reverse coded) (α= .77 in blocks and α = .86 in the surrounding area). Given that only the single parent household variable is available at the block level, the other measures are imputed using the synthetic estimation approach described in Boessen and Hipp (2015).[1] *Residential stability* is captured with a measure that standardized and combined variables of the percent homeowners, average length of residence, and the percent same house five years previously (α= .70 in blocks and α = .80 in the surrounding area). The presence of racial minorities is captured with measures of *percent Black*, *percent Latino*, and *percent Asian* residents (with *percent White and other races* as the reference category). *Racial/ethnic heterogeneity* is measured based on the Herfindahl Index combining five racial/ethnic groups (Asian, Black, Latino, White, and other race). Given that vacant units can be crime attractors (Boessen and Hipp 2015: 402), we include a measure of the *percent vacant* units. We account for the prime offending ages by including a measure of the *percent aged between 15 and 29.*

A measure of *income inequality* is constructed in four sized egohoods: ¼ mile, ½ mile, ¾ mile, and 1 mile. Egohoods are constructed based on the block, and then constructing a buffer around the block of various sizes in which all blocks within the buffer are included, but do not include a distance decay effect. We used egohoods rather than buffers given evidence from

[1] In this approach, a prediction model is estimated at the block group level in which the outcome variable is a variable unavailable at the block level, and the parameter estimates from that model are used in a regression framework at the block level to compute estimated values for the block. The variables used in the imputation model were: percent owners, racial composition, percent divorced households, percent households with children, percent vacant units, population density, and age structure (percent aged: 0-4, 5-14, 20-24, 25-29, 30-44, 45-64, 65 and up).

previous research that inequality shows a much stronger relationship with crime when measured in egohoods rather than with a distance decay (Hipp and Boessen 2013). This measure was constructed by first assigning household incomes to the midpoint of their reported range, log transforming these values, multiplying them by the number of observations in each bin, computing the mean logged household income, and then computing the standard deviation of income based on these values. We tested these measures in separate models to assess which sized egohood provided the strongest results.

Analytic Plan

Cross-sectional negative binomial regression models were estimated to assess the differences in the spatial processes across these four cities. Whereas one approach includes logged population in the model with the parameter constrained to 1 (an exposure term), we relax this assumption and freely estimate this parameter. We first estimated the model separately on each of the four cities. To test for statistical significance, we then estimated models in which the data were stacked up for two cities at a time, and an indicator variable for one city was included as well as interactions between the city indicator variable and each of the variables in the model (analogous to a Chow test). This allowed us to perform joint tests of the statistical significance of the difference in the coefficients across these cities across the pairs of cities. Whereas a chi square test is a common strategy for such tests, we have inordinate statistical power given our large number of blocks which would almost certainly return a significant result suggesting different coefficients across the two cities. As a consequence, we argue that using the Akaike Information Criterion (AIC) to assess differences is more appropriate.

We assessed whether there was any additional spatial autocorrelation in the residuals from the models presented in Table 3 and found no such evidence. Specifically, The Moran's I values of residuals in the models were very small: .04 in Honolulu, .02 in Sacramento, and 0 in Los Angeles and San Francisco. This indicates that the models adequately control the spatial clustering. The Moran's I values for robbery in the models presented in Table 3 ranged from 0.16 in Sacramento to 0.38 in Honolulu suggesting spatial clustering of crime events, which was effectively accounted for by conditioning on the variables in the models. For the models in Table 3 we initially estimated models including all nonlinear variables and spatial buffer variables. We also tested models with socio-demographic variables in buffers at further distances but they were not statistically significant. Therefore, nonlinear and spatial buffer variables with nonsignificant parameters were excluded from the models. Although variance inflation factor (VIF) values are sometimes used as a diagnostic for multicollinearity, VIFs are just one of four components in the standard error calculation, as the other three are: 1) the degree of variability in the variable of concern, 2) the sample size, and 3) the proportion of variance explained by the model (O'Brien 2007). Using O'Brien's approach to calculate the degree to which standard errors are inflated, we found no evidence of problematic results.[2]

RESULTS

Descriptive Statistics

The means and standard deviations of all study variables are presented in Table 2. San Francisco blocks experienced the most robberies in the study period, and Sacramento blocks experienced the fewest. Although Sacramento blocks have less than half as many retail employees as blocks in the other cities, the gap is narrower when viewing the number of retail

[2] For example, in Honolulu the largest VIF was 10.5 for the percent Asian in the surrounding area, but this is comparable to estimating a simple regression with just a single variable, an R-square of .25, and a sample of 305 (a size that clearly provides enough power for estimation). In Los Angeles, the largest VIF was 15.1 for percent Latino in the surrounding area, but this is comparable to estimating a simple regression with a single variable, an R-square of .25, and a sample of 1,977. Thus, the sample size dramatically improves the precision of estimates (Goldberger 1991).

employees within ¼ mile or from ¼ to ½ mile. And whereas Honolulu blocks have as many retail employees on average as San Francisco blocks within the block itself, they have notably fewer within the buffers. A similar pattern is observed for total employees in Honolulu and San Francisco. Thus, there are differences in the spatial patterning of the residences and work places across these four cities. There are also differences in the composition of persons in these cities: given that we constructed the concentrated disadvantage standardized variable using data from the entire U.S., we see that San Francisco blocks have concentrated disadvantage that is .56 standard deviations below the mean of the U.S. At the other extreme, Sacramento blocks have the highest level of concentrated disadvantage across these four cities. Honolulu has a considerably smaller presence of African Americans and Latinos, but a larger representation of Asians. Los Angeles has a higher proportion of Latinos. Honolulu also has a smaller proportion of residents in the high crime prone ages of 16 to 29.

<<<Table 2 about here>>>

Negative Binomial Regression Analyses

We begin by describing our negative binomial regression models estimated separately on the four cities, and displayed in Table 3 (again, nonsignificant polynomials and spatial measures were excluded from the models). We focus first on the results for the residential population of the block and nearby, and plot these results to demonstrate the nonlinear patterns detected. Figure 1 plots the marginal relationship between the residential population of the block (logged) and the count of robberies; for all figures shown we plot the values from the 5^{th} to the 95^{th} percentile (in this and all other figures we plot the marginal effect, rather than predicted effects including mean differences for visual clarity). This figure shows that for all four cities the count of robberies is lower for a modest number of residents in the block. However, there are differences across the cities as the population increases beyond about 50 (logged 3.9). In Los Angeles and Honolulu, robberies drop the most as the block population goes from zero to a modest number, and increase very modestly as the population increases to much larger numbers. Thus, robberies are about 65% lower in Honolulu and 80% lower in Los Angeles for a population of about 50 (compared to no population), but then are about 35% to 40% larger in blocks with very high population compared to blocks with average population. Block population exhibits a pronounced U relationship with robberies in San Francisco, as it is about 65% lower when there is a modest population level (compared to no population) but about 20% higher at the highest population levels. And robberies increase relatively steeply in Sacramento: at the highest values of block population robberies are about 60-70% higher than blocks with no population. Thus, we see mixed evidence for hypothesis 6, as there are indeed stronger block population effects in the two low micro-environment population cities (Sacramento and Los Angeles), although there is an unexpectedly similar positive effect in Honolulu.

<<<Table 3 about here>>>

<<<Figure 1 about here>>>

The pattern for the relationship of population in the area surrounding the block at various spatial scales and robbery differs over these cities. On the one hand, there are similarities across these cities in that the population within ¼ mile is not related to the robbery rate in three of the four cities, whereas a larger population from ¼ to ½ mile is associated with higher robbery rates in all four cities. On the other hand, there are differences across the cities for longer distances. In Honolulu, there is no evidence that the population at longer distances is related to robbery rates. In the other high density city—San Francisco—a larger population from 1¼ mile to 1½ mile is associated with a higher robbery rate. The two more spatially diffuse cities of Los

Angeles and Sacramento exhibit a spatially diffuse effect in which the very distant population between 1.5 and 2.5 miles is associated with more robberies, consistent with hypothesis 1.

We assessed the importance of the presence of a large daytime population based on the total number of employees. In all four cities, the presence of more total employees in the block is associated with higher levels of robbery. The pattern is relatively similar over the four cities, as seen in Figure 2. On the other hand, there are notable spatial differences: Figure 3 demonstrates that in the two high micro-environment population cities there is a positive relationship between the total number of employees within ¼ mile and robberies. This relationship is monotonically positive in San Francisco, whereas Honolulu exhibits an inverted-U relationship in which robberies start falling when a block is surrounded by the very highest number of employees. In the two low density cities—Los Angeles and Sacramento—there is a negative relationship between the total number of employees in the surrounding ¼ mile and robberies. Furthermore, Los Angeles is the only city in which the number of employees within ¼ to ½ mile is related to the number of robberies, and it is a strong negative relationship for this sprawling city.

<<<Figures 2 and 3 about here>>>

We proxy the presence of more customers in an area (and hence persons) with the presence of more retail employees in an area. The pattern is relatively similar in the two *low* micro-environment population cities, Los Angeles and Sacramento, consistent with hypothesis 2: these cities have the steepest positive relationship between retail employees in the block and robberies (especially in Sacramento)—see Figure 4—and a similar positive relationship between retail employees within ¼ mile and robberies (see Figure 5). These cities have about 70% more robberies in blocks with very many retail employees (around the 95th percentile) compared to those with none, and 60-80% more robberies when they are surrounded by very many retail employees compared to none. The relationship is weaker in the two high density cities: In Honolulu, there is a modest positive relationship between retail employees in the block and robberies, and a nonlinear positive relationship with retail employees in the surrounding ¼ mile that is only present at the highest concentrations of nearby retail employees. The relationship between retail employees in the nearby area and robberies is weakest in San Francisco, although there is a positive relationship within the block. These results are in contrast to hypothesis 5 and the existing literature in which the positive relationship between retail establishments and crime is typically more robust in high density environments.

<<<Figures 4 and 5 about here>>>

Turning to the socio-demographic variables, we see that blocks with more disadvantage, and those with more disadvantage in the surrounding ¼ mile, generally have more robberies. There is an additional positive relationship between higher levels of disadvantage between ¼ and ½ mile and robberies for three of the cities, with Honolulu being the exception. This consistency across cities is consistent with hypothesis 3. The negative relationship between residential stability on the block and robbery is observed in Los Angeles, whereas residential stability in the surrounding ¼ mile is associated with fewer robberies in Sacramento and San Francisco. Thus, our results parallel the existing literature in that residential stability exhibits the most robust negative relationship with robberies in lower density environments, but is more mixed in higher density environments (hypothesis 4). In fact, residential stability in Honolulu in the surrounding ¼ mile is actually associated with *more* robberies. Vacant units also exhibit a micro spatial effect, as the presence of more vacant units on the block is associated with more robberies in all four cities. In Los Angeles there is an additional positive effect from vacant units within ¼ mile, whereas in Honolulu there is a positive relationship with vacant units from ¼ to ½ mile.

The spatial patterns for the racial composition measures are most pronounced in the two cities with larger *macro-environment* population—Los Angeles and San Francisco. Whereas the presence of more African Americans on the block is associated with more robberies in three of the cities (not Honolulu, which has a low percentage of this group in general), it is only in Los Angeles that the presence of more African Americans in the surrounding ¼ mile and ¼ to ½ mile band is associated with more robberies. And only in San Francisco do we observe a spatial relationship in which more Latinos in the surrounding ¼ mile are associated with more robberies. Likewise, there are spatial effects for Asians as more Asians within ¼ mile are associated with fewer robberies in Los Angeles and Honolulu, but more Asians from ¼ to ½ mile in San Francisco are associated with more robberies.

Finally, we tested the models in Table 3 for each city by progressively including measures of income inequality in successively larger egohoods and assessing model fit. We selected the model with the best overall fit. We found that whereas inequality was not related to robberies in San Francisco, the strongest positive relationship (based on the t-value) was detected in ¼ mile egohoods in Los Angeles and Honolulu. In the low micro- and macro-environment population city of Sacramento, the strongest positive effect was detected in one mile egohoods.

Testing Differences across the 4 Cities

To assess how different the results were across cities we performed a series of joint tests on pairs of cities in the analyses. The largest difference in coefficients was observed across the two large macro-environment population cities that differed based on micro-environment population: Los Angeles and San Francisco. The AIC measure improved 262.2 when allowing the coefficients to differ across the two cities, compared to the model constraining them to be equal. The second largest difference occurred between the city with high micro and macro-environment population (San Francisco) and the city with low micro and macro-environment population (Sacramento), with an AIC improvement of 172.2. The third largest difference was between the cities that differed based on macro-environment population (Los Angeles and Sacramento), as the AIC improved 78.4 when allowing the coefficients to differ. At the other end of the spectrum, an oddity is that there appeared to be little difference (based on the AIC) in the coefficients between a city with high micro-environment population and low macro-environment population (Honolulu) and a city with the opposite population pattern (Los Angeles). The coefficients based on the change in the AIC were only modestly different between Honolulu and either San Francisco (26.9) or Sacramento (52.7).

Thus, on balance it appears that micro-environment population has a stronger effect on the differences in coefficient sizes across our cities compared to the macro-environment. On average, the AIC improves 119.8 across the four city comparisons that differ based on micro-environment population when allowing the coefficients to vary across cities, whereas the improvement is a little more than half that amount (67.4) for the four city comparisons that differ based on macro-environment.

DISCUSSION

Whereas much existing research has focused on the micro-processes of crime within the context of a single city, this study has compared these patterns across four very different spatially oriented cities. We have selected four cities that differ along two dimensions: the size of micro-environment population and the size of macro-environment population (Hipp and Roussell 2013). Micro-environment population is the population density experienced by the residents of the average neighborhood in the city. Macro-environment population captures the average number of people within some larger radius of each block in a city (e.g., within 10 or 20 miles). Our results demonstrated that there are some differences in how the micro spatial processes of crime in place play out given the particular macro environment of the city.

We found that the socio-demographic composition beyond ½ mile was not important for explaining the location of robberies. Thus, the composition of the local block and the surrounding ¼ mile was usually important, and the composition of the area within ¼ to ½ mile sometimes was related to the number of robberies. However, the sociodemographic composition further than this was not related to levels of robbery. This has implications for the general question regarding the appropriate size of neighborhoods (Hipp 2007a). In this study, socio-demographic characteristics further away than ½ mile did not impact the level of crime. Nonetheless, it is worth highlighting that broader spatial patterns were detected when accounting for the actual *number* of people at much greater distances than is typically done in studies.

Although the socio-demographic composition of persons beyond ½ mile was not related to robbery rates, the number of persons beyond ½ mile *was* related to the level of robberies in three of the four cities. Given the spatial patterning of offenders, in which it is not unusual to travel 1-2 miles to commit a robbery, this should not be surprising (Bernasco 2010; Bernasco and Block 2009). We suggested in hypothesis 1 that in a relatively low micro-environment population, offenders may be more likely to travel longer distances. Consistent with this, the broadest spatial pattern was observed in the two cities with relatively low micro-environment population: in Los Angeles and Sacramento a higher population within 1.5 to 2.5 miles was associated with higher robbery rates. It is worth emphasizing that although studies focusing on the micro location of crime typically do not consider the possible impact of such spatially distant locations, our results demonstrate that researchers should account for this broader spatial effect induced by the journey to crime of offenders and emphasizes these same points made by Hipp (2016). In San Francisco, the spatial pattern was not as broad, but it was nonetheless the case that a larger population from 1¼ to 1½ miles was associated with more robberies. It was only in the very unusual circumstance of a high micro-environment population and low macro-environment population environment of Honolulu that the presence of more residents further than ½ mile away did not impact the number of robberies. Thus, consistent with the existing literature, nearby population is positively related to robbery rates when it occurs in cities that generally have lower population density, whereas this relationship is weaker in high population density cities.

The effect of job concentration as measured by the total number of employees differed based on the micro-environment population of the city. In the low micro-environment population cities, the presence of more total employees within ¼ mile had a depressing effect on robberies, whereas the opposite was observed in the high micro-environment population cities. In the existing literature, a robust positive relationship between retail areas and crime is typically observed in high population micro-environments, but less so in lower density environments, which led us to our hypothesis 2. We instead found this effect for our total jobs measure rather than for retail employees; it is worth highlighting that most existing research accounting for the retail environment does not simultaneously account for the presence of other jobs, as we did here. When accounting for the total number of jobs, we found that the presence of more retail jobs showed a relatively robust positive relationship with robberies across these cities. However, contrary to hypothesis 5, we found that the strongest positive relationship between retail employees (as well as total employees) and robberies occurred in the low micro-environment population cities of Sacramento and Los Angeles. Thus, even the relationship between work locations and robberies appears impacted by the overall population structure of the city.

Consistent with the existing literature and hypothesis 4, residential stability exhibited the most robust negative relationship with robberies in the lower density cities of Los Angeles and Sacramento. In the two high density cities the results were mixed, with a negative relationship in San Francisco but a positive relationship in Honolulu. These results imply that more theoretical consideration needs to be given to how residential stability might impact crime: whereas some research has suggested that it may operate in a multiplicative fashion with other structural neighborhood characteristics hypothesized by social disorganization theory (Warner and Pierce 1993; Warner and Rountree 1997), or that it is dependent on the mix or owners and renters (Boggess and Hipp 2010), the results here suggest that a useful theoretical consideration is how the macro environment might impact this relationship.

We found that the differences in coefficients across cities were greater in cities that differed based on micro-environment population compared to cities that differed based on the macro-environment. For example, the largest difference in coefficients was observed for two cities with high macro-environment population (Los Angeles and San Francisco), but differed based on micro-environment population. While we cannot say how much of this difference in coefficients is due to the differences in micro-environment population across the cities, the pattern of results is certainly suggestive that this may be an important dimension. The fact that inequality in a larger egohood was most salient for robbery rates in the low micro-environment population of Sacramento (compared to the smaller egohoods in the higher density cities) is also consistent with this idea. The relationship between the location of jobs and robberies differed across these two high macro-environment population cities, which is consistent with these spatial differences. In Los Angeles, total employment may act as a crime generator, and therefore this would result in a negative spatial correlation given that their presence pulls crime away from nearby blocks. In San Francisco, the relative ubiquity of employment may diminish their spatial effect, and explain why we did not detect such an effect. We cannot be certain of this explanation, but it does suggest that the larger context may have important consequences for what occurs in micro-locations. Notably, the other pair of cities with very large differences in coefficient estimates were the two cities that differed based on both micro- and macro-environment: San Francisco and Sacramento, which was as expected. However, an oddity was that the other two cities that differed based on both micro- and macro-environment population had very similar coefficient estimates. It is hard to imagine two cities with more different spatial patterns than Honolulu and Los Angeles, and yet they yielded very similar coefficient estimates. There were some differences, to be sure: for example, the population beyond ½ mile of the block had virtually no effect on robberies in Honolulu, which differed from the other cities. Nonetheless, the other coefficients were effectively the same between Honolulu and Los Angeles. This suggests a possibly complicated relationship between micro- and macro-environment population and robbery rates, and requires more careful theorizing in the future.

We note some limitations to the present study. One challenge is that whereas we have chosen four cities that differed along the major dimensions of micro- and macro-environment, they nonetheless differ along other dimensions as well, which can potentially confound the analyses. This limits our ability to say for certain whether differences in micro-environment population or macro-environment population are indeed the reasons for the differences that are observed. Nonetheless, our strategy was to assess how different the spatial patterns of crime are across four cities that are extreme cases along these two dimensions to maximize the possibility of detecting differences. A second limitation is the cross-sectional nature of our study design, which limits our ability to make causal claims. Our focus instead was on demonstrating the spatial patterns that are observed between these structural characteristics and crime in city blocks. Third, we lacked data capturing other characteristics of neighborhoods, such as cohesion, social ties, and collective efficacy. Exploring these measures, especially at various spatial scales, would be a useful direction for future research.

In conclusion, this study contributes to the literature focusing on crime in neighborhoods or micro locations by moving away from focusing on a single city and instead exploring these relationships across four cities with very different spatial arrangements. This provides an added corrective to the ecology of crime literature that rarely considers the larger setting, and suggests that the broader context may matter as well. Consistent with some recent research (Boessen and Hipp 2015), we detected spatial effects in which the characteristics surrounding the block impact the level of crime in the block. However, the present study also highlighted that these spatial effects likely differ based on the macro environment as we found differences across these four cities that differed based on micro- and macro-environment population. An important finding was that a very broad population effect was detected in which the population within an area up to 2.5 miles from the block impacted the amount of crime in the block, particularly in the two sites with lower levels of micro-environment population; this broader area is almost never considered in the ecology of crime literature, although it should be given the well-known spatial patterns of offenders (Rossmo 2000). Thus, the ecology of crime literature, while making great progress in understanding the spatial location of crime in neighborhoods or small geographic units, would be well served to also consider the characteristics of the broader spatial environment as well.

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Tables and Figures

Table 1. Population gradient for four cities: Population density, average population within 5 miles, average population within 25 miles

	Population density			Population within 5 miles			Population within 25 miles	
	Mean	Std Dev		Mean	Std Dev		Mean	Std Dev
San Francisco	133.2	163.6		726,027	109,714		3,166,741	171,448
Honolulu	93.7	189.8		268,057	33,281		872,859	21,212
Los Angeles	78.9	110.9		791,737	335,403		8,027,527	1,600,766
Sacramento	47.8	57.0		304,209	56,016		1,802,946	46,652

Table 2. Summary statistics for variables used in analyses across four different cities

	Los Angeles		Sacramento		San Francisco		Honolulu	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Robberies	0.33	1.03	0.18	0.65	0.64	2.53	0.25	2.26
Population (logged)								
Block	3.49	2.17	2.96	1.91	3.22	2.34	3.18	2.38
Within 1/4 mile	9.08	1.64	8.49	1.78	9.79	1.72	8.81	2.19
1/4 to 1/2 mile	9.53	1.08	8.88	1.04	10.12	1.00	9.23	1.51
1/2 to 3/4 mile	9.54	0.92	8.88	0.72	10.09	0.87	9.18	1.35
3/4 to 1 mile	9.54	0.82	8.86	0.49	10.06	0.87	9.18	1.16
1 to 1.25 mile	9.53	0.75	8.83	0.41	10.04	0.84	9.12	0.99
1.25 to 1.5 miles	9.52	0.69	8.78	0.39	9.99	0.85	9.06	0.79
1.5 to 2.5 miles	10.88	0.64	10.07	0.37	11.24	0.58	10.22	0.58
Total employees (logged)								
Block	2.23	1.80	1.55	1.70	2.38	1.98	2.33	2.14
Within 1/4 mile	7.82	1.68	7.23	1.94	8.73	1.93	7.74	2.58
1/4 to 1/2 mile	9.01	1.30	8.57	1.64	9.79	1.69	9.04	2.16
Retail employees (logged)								
Block	0.63	1.11	0.31	0.80	0.67	1.18	0.68	1.26
Within 1/4 mile	5.20	1.96	4.16	2.01	6.18	2.13	4.88	2.71
1/4 to 1/2 mile	6.60	1.52	5.68	1.47	7.39	1.91	6.39	2.30
Socio-demographic variables								
Concentrated disadvantage	0.08	1.02	0.28	0.95	-0.56	0.82	-0.35	0.68
Residential stability	0.08	0.98	-0.25	1.07	-0.11	0.97	0.10	0.99
Percent black	10.33	19.55	11.54	13.75	16.44	21.43	1.20	4.15
Percent Latino	40.17	32.16	25.11	19.03	14.35	15.29	5.11	6.67
Percent Asian	9.89	13.69	16.55	17.69	30.92	23.58	60.79	21.01
Racial/ethnic heterogeneity	0.41	0.20	0.56	0.18	0.36	0.27	0.49	0.17
Income inequality in 1/4 mile egohood	0.91	0.12	0.86	0.13	0.96	0.11	0.88	0.14
Percent vacant units	6.14	9.27	8.66	10.79	7.16	9.22	6.17	10.93
Percent aged 16 to 29	20.65	10.87	22.11	12.80	20.12	11.92	17.70	9.80
Number of blocks	30,691		7,632		7,386		2,844	

Table 3. Robbery models estimated across four cities (including 1/4 mile and 1/2 mile buffers)

	Los Angeles		Sacramento		San Francisco		Honolulu	
Concentrated disadvantage								
Block	0.0853	**	0.033		0.1045	**	0.1518	
	(0.023)		(0.058)		(0.038)		(0.116)	
Within 1/4 mile	0.3358	**	0.1966	*	0.5037	**	0.6205	**
	(0.039)		(0.092)		(0.079)		(0.215)	
1/4 to 1/2 mile	0.0965	**	0.1431	*	0.1868	**	0.0252	
	(0.023)		(0.057)		(0.038)		(0.085)	
Residential stability								
Block	-0.1023	**	-0.0428		0.0009		0.053	
	(0.018)		(0.042)		(0.032)		(0.090)	
Within 1/4 mile	0.0283		-0.1302	*	-0.1629	*	0.4205	**
	(0.028)		(0.064)		(0.069)		(0.160)	
1/4 to 1/2 mile	-0.0182		-0.0554		-0.0969	*	0.0623	
	(0.017)		(0.042)		(0.042)		(0.060)	
Percent black								
Block	0.0049	**	0.0066	*	0.0099	**	0.01	
	(0.001)		(0.003)		(0.002)		(0.024)	
Within 1/4 mile	0.0049	*	-0.007		0.0026		0.076	
	(0.002)		(0.007)		(0.006)		(0.070)	
1/4 to 1/2 mile	0.0034	†	-0.0099	*	0.0044		0.0068	
	(0.002)		(0.005)		(0.005)		(0.015)	
Percent Latino								
Block	0.0057	**	-0.0003		0.0036	†	0.0101	
	(0.001)		(0.003)		(0.002)		(0.010)	
Within 1/4 mile	-0.0012		0.0047		0.0184	**	0.0015	
	(0.002)		(0.005)		(0.004)		(0.056)	
1/4 to 1/2 mile	-0.0026	†	0.0009		0.0002		0.0154	†
	(0.001)		(0.004)		(0.003)		(0.009)	

Percent Asian								
Block	0.0043	**	0.0006		-0.0024		0.0015	
	(0.002)		(0.003)		(0.002)		(0.005)	
Within 1/4 mile	-0.0066	**	-0.0064		0.0002		-0.0321	*
	(0.002)		(0.005)		(0.003)		(0.015)	
1/4 to 1/2 mile	0.0001		0.0003		0.0001	*	-0.0002	*
	(0.000)		(0.000)		(0.000)		(0.000)	
Racial/ethnic heterogeneity								
Block	0.4134	**	-0.2299		0.0604		-1.0464	†
	(0.106)		(0.293)		(0.199)		(0.602)	
Within 1/4 mile	0.1149		1.4225	*	0.2122		-2.2269	†
	(0.160)		(0.636)		(0.409)		(1.341)	
1/4 to 1/2 mile	-0.3418	**	0.9794	*	-0.9466	**	-0.6634	
	(0.125)		(0.469)		(0.363)		(0.554)	
Income inequality								
1/4 mile egohood	0.3572	*			-0.2781		2.215	**
	(0.144)				(0.301)		(0.736)	
1 mile egohood			1.8706	*				
			(0.730)					
Percent vacant units								
Block	0.0048	**	0.0039		0.0052	*	0.0108	*
	(0.002)		(0.004)		(0.002)		(0.005)	
Within 1/4 mile	0.0123	**	0.0036		0.0071		0.0114	
	(0.004)		(0.009)		(0.007)		(0.009)	
1/4 to 1/2 mile	0.0023		0.002		-0.008		0.0154	**
	(0.003)		(0.006)		(0.006)		(0.005)	
Percent aged 16 to 29								
Block	-0.0029	*	0.003		0.0027		0.0112	†
	(0.002)		(0.003)		(0.002)		(0.006)	
Within 1/4 mile	0.0074	**	0.0071		-0.0152	**	0.0065	
	(0.003)		(0.006)		(0.005)		(0.014)	
1/4 to 1/2 mile	-0.002		-0.011	*	-0.0009		0.0037	
	(0.002)		(0.004)		(0.004)		(0.007)	

Population, logged								
Block	-0.501	**	-0.1277		-0.4846	**	-0.3836	†
	(0.052)		(0.150)		(0.100)		(0.211)	
Block, squared	0.0746	**	0.0517	**	0.0917	**	0.0562	**
	(0.006)		(0.017)		(0.012)		(0.022)	
Within 1/4 mile	0.013		-0.1593	*	-0.0487		0.1244	
	(0.032)		(0.077)		(0.064)		(0.114)	
1/4 to 1/2 mile	0.3592	**	0.375	**	0.2188	*	0.4038	**
	(0.051)		(0.112)		(0.102)		(0.154)	
1/2 to 3/4 mile	0.0977		0.1989		0.1894		*(b)*	
	(0.065)		(0.140)		(0.117)			
3/4 to 1 mile	0.0546		0.1169		-0.2303	†	*(b)*	
	(0.072)		(0.164)		(0.118)			
1 to 1.25 mile	-0.1844	*	0.0561		0.2623	†	*(b)*	
	(0.082)		(0.169)		(0.155)			
1.25 to 1.5 miles	0.1168		-0.0683		0.4651	**	*(b)*	
	(0.079)		(0.172)		(0.128)			
1.5 to 2.5 miles	0.2613	**	0.3641	*	*(b)*		*(b)*	
	(0.060)		(0.169)					
Total employees, logged								
Block	0.369	**	0.4339	**	0.1934	**	0.2369	†
	(0.029)		(0.062)		(0.048)		(0.121)	
Block squared	-0.0222	**	-0.0303	**	-0.0033		-0.0043	
	(0.004)		(0.009)		(0.006)		(0.014)	
Within 1/4 mile	-0.2514	**	-0.3184	**	0.1852		0.4012	
	(0.090)		(0.118)		(0.134)		(0.340)	
Within 1/4 mile squared	0.0128	*	0.0176	*	-0.008		-0.0312	
	(0.005)		(0.007)		(0.007)		(0.020)	
1/4 to 1/2 mile	-0.0938	**	-0.0062		-0.0611	†	0.1007	
	(0.020)		(0.039)		(0.035)		(0.077)	

Retail employees, logged											
Block	0.1913	**		0.3513	**		0.2087	**		0.2072	†
	(0.026)			(0.064)			(0.038)			(0.113)	
Block squared	0.0163	**		0.0119			-0.0046			-0.009	
	(0.006)			(0.012)			(0.008)			(0.020)	
Within 1/4 mile	0.1105	**		0.0869	**		0.0327			-0.078	
	(0.015)			(0.028)			(0.026)			(0.153)	
Within 1/4 mile squared	*(b)*			*(b)*			*(b)*			0.0218	†
										(0.013)	
Intercept	-8.687	**		-14.0076	**		-9.7214	**		-8.9515	**
	(0.571)			(1.924)			(0.975)			(2.335)	
Pseudo r-square	0.222			0.269			0.231			0.328	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .10 (two-tail test). Standard errors in parentheses.*

(b): coefficient tested in ancillary models and not statistically significant, and therefore excluded.

Figure 1.

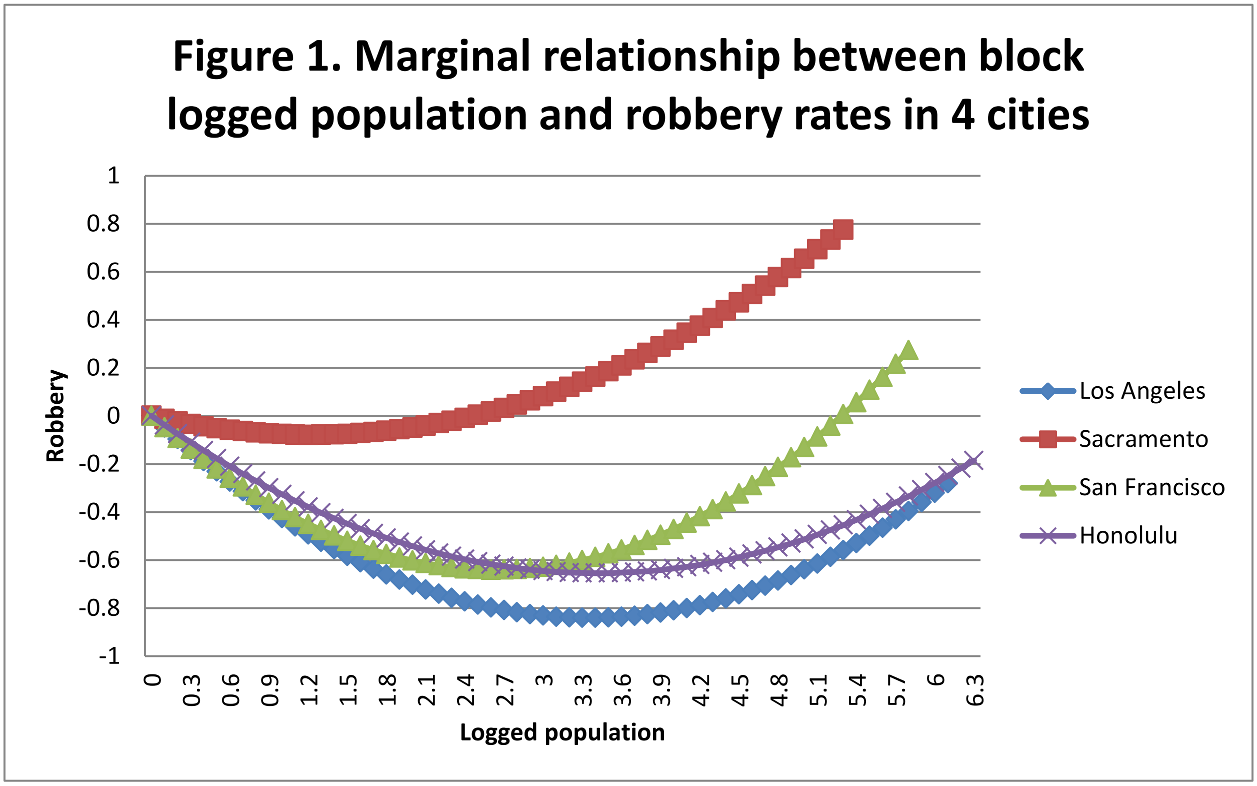
Figure 1. Marginal relationship between block logged population and robbery rates in 4 cities
Robbery
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
0
0.3
0.6
0.9
1.2
1.5
1.8
2.1
2.4
2.7
3
3.3
3.6
3.9
4.2
4.5
4.8
5.1
5.4
5.7
6
6.3
Logged population
Los Angeles
Sacramento
San Francisco
Honolulu

Figure 2.

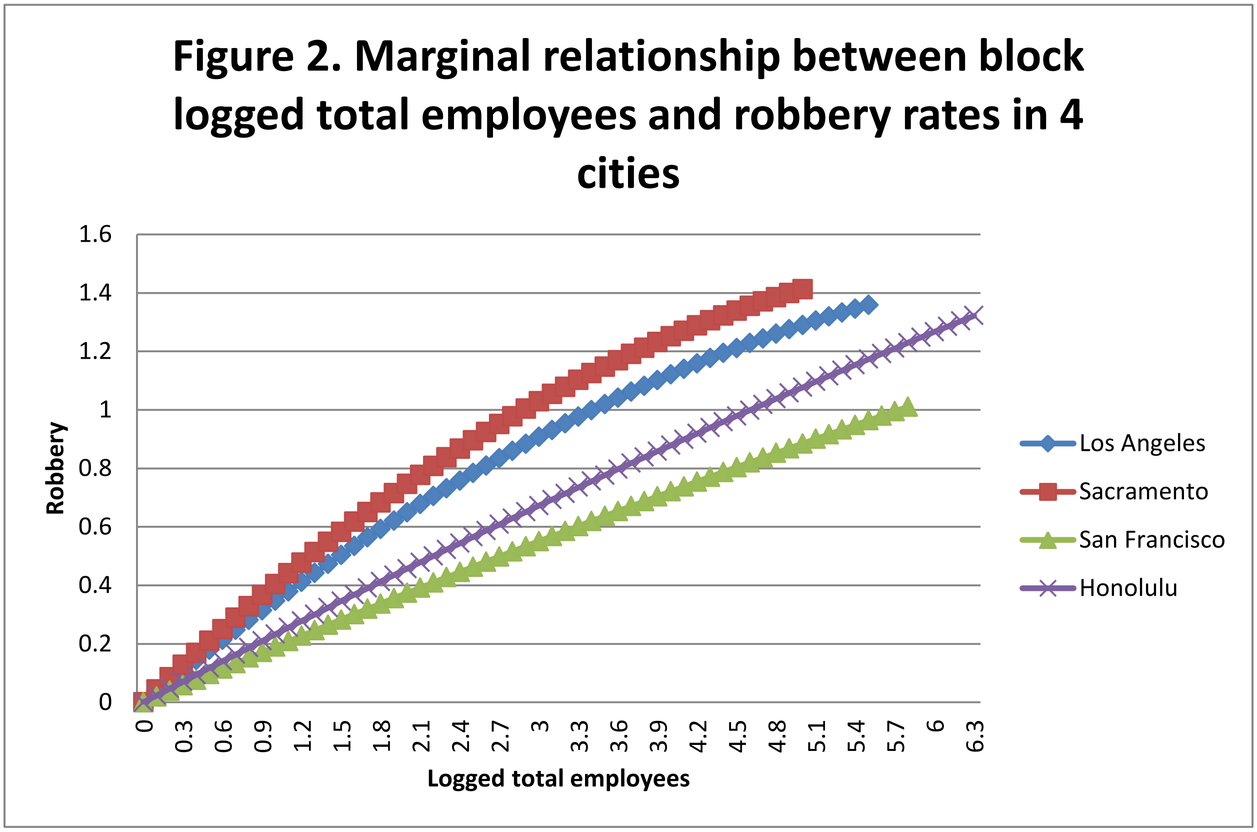
Figure 2. Marginal relationship between block logged total employees and robbery rates in 4 cities
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Robbery
0
0.3
0.6
0.9
1.2
1.5
1.8
2.1
2.4
2.7
3
3.3
3.6
3.9
4.2
4.5
4.8
5.1
5.4
5.7
6
6.3
Logged total employees
Los Angeles
Sacramento
San Francisco
Honolulu

Figure 3.

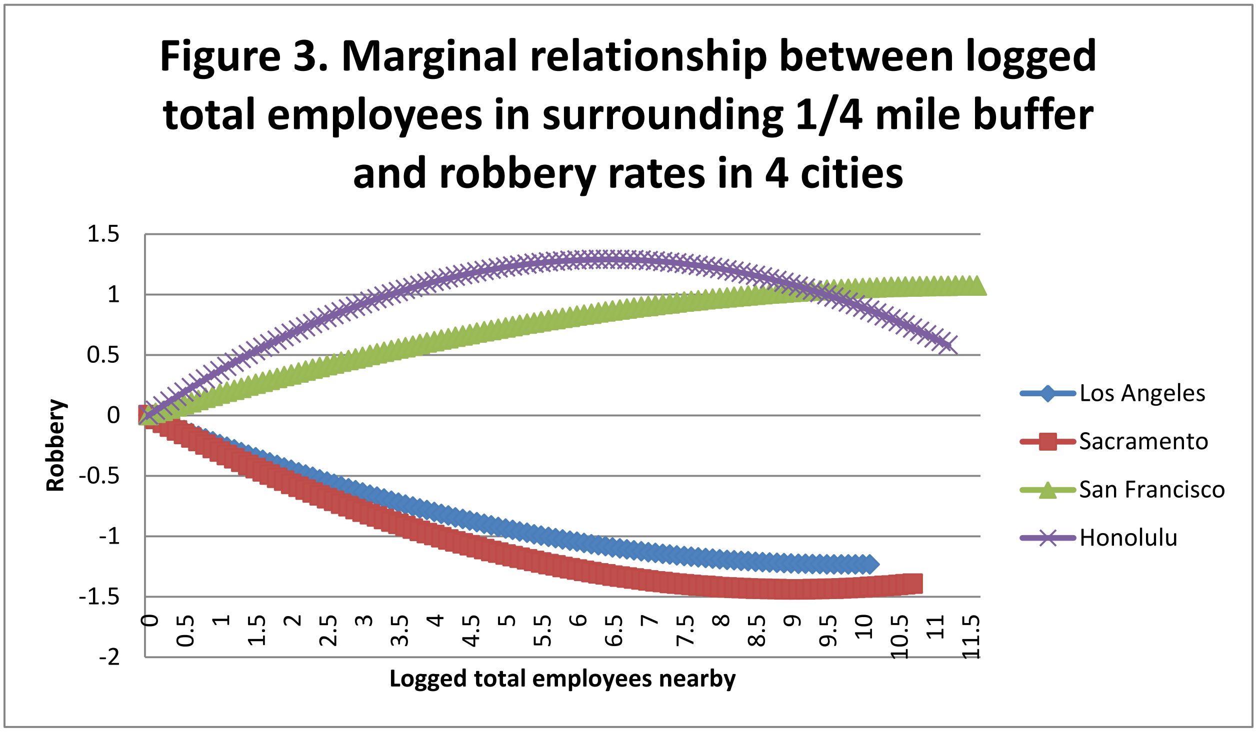
Figure 3. Marginal relationship between logged total employees in surrounding 1/4 mile buffer and robbery rates in 4 cities
Robbery
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8
8.5
9
9.5
10
10.5
11
11.5
Logged total employees nearby
Los Angeles
Sacramento
San Francisco
Honolulu

Figure 4.

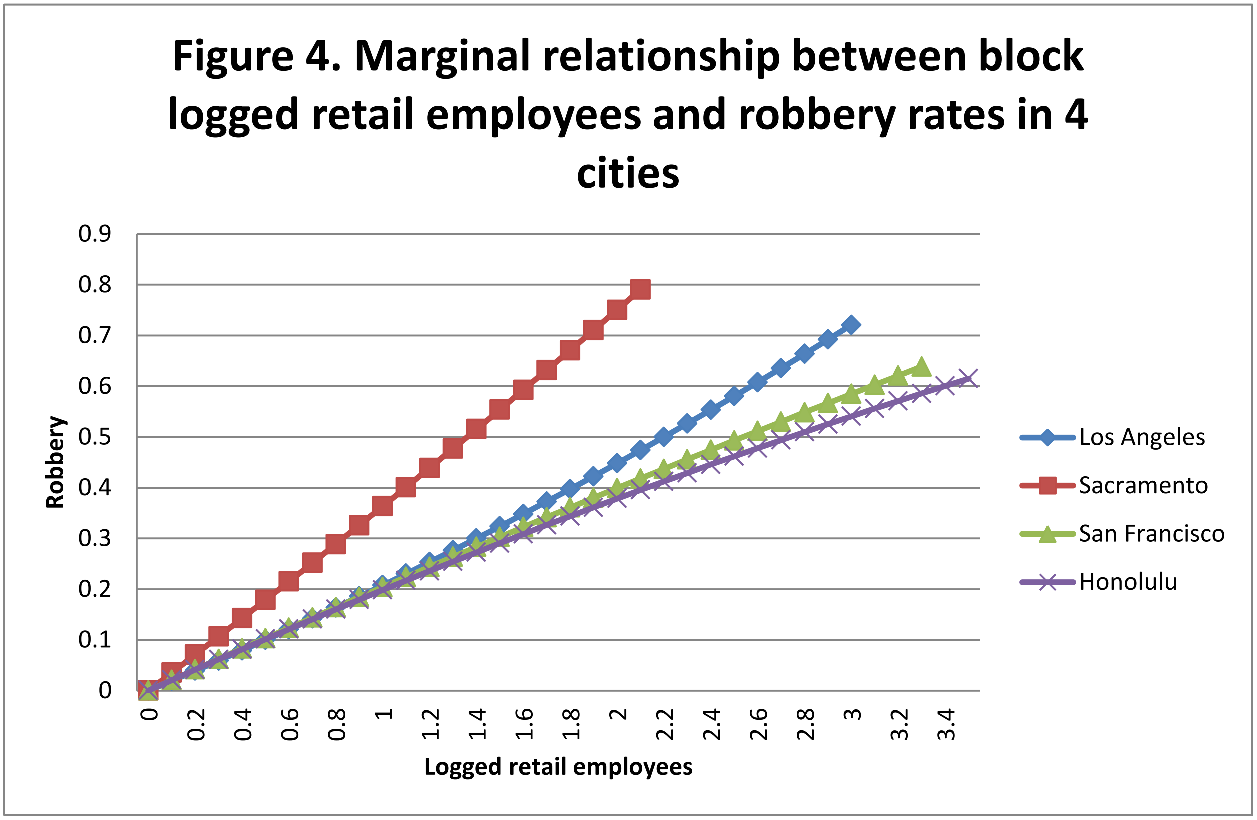
Figure 4. Marginal relationship between block logged retail employees and robbery rates in 4 cities
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Robbery
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
2.8
3
3.2
3.4
Logged retail employees
Los Angeles
Sacramento
San Francisco
Honolulu

Figure 5.

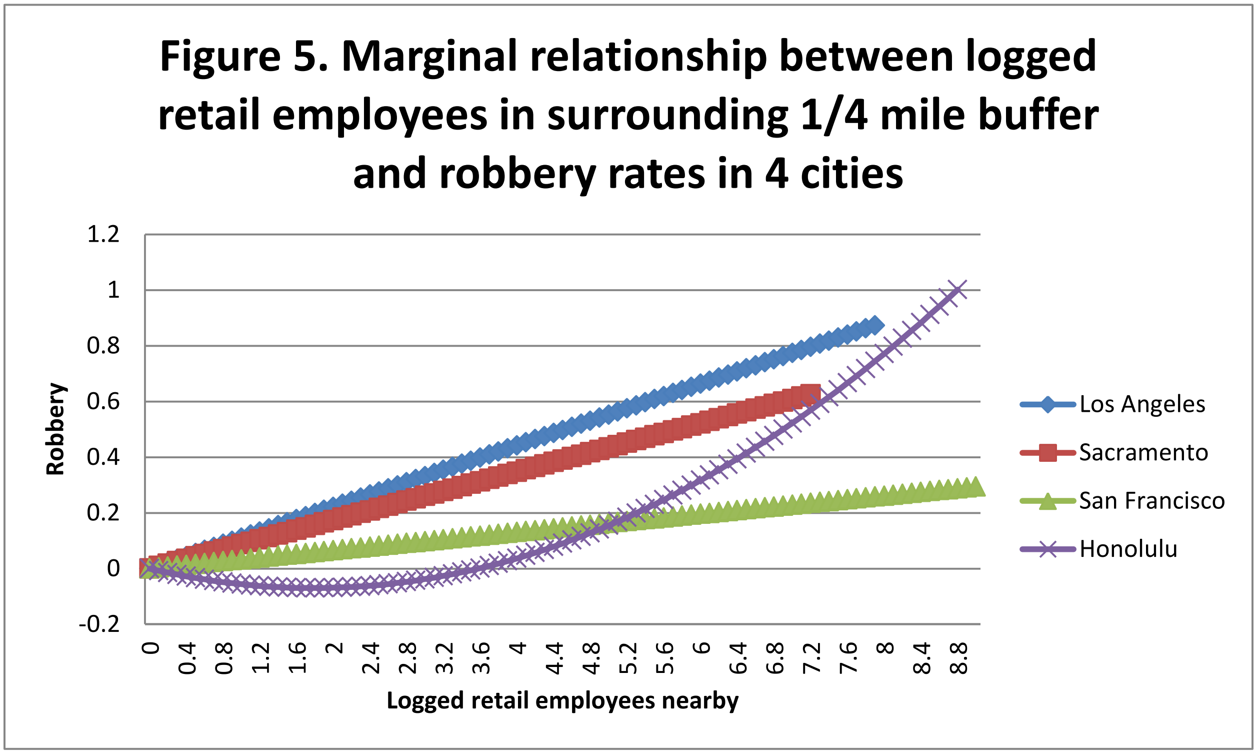
Figure 5. Marginal relationship between logged retail employees in surrounding 1/4 mile buffer and robbery rates in 4 cities
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
Robbery
0
0.4
0.8
1.2
1.6
2
2.4
2.8
3.2
3.6
4
4.4
4.8
5.2
5.6
6
6.4
6.8
7.2
7.6
8
8.4
8.8
Logged retail employees nearby
Los Angeles
Sacramento
San Francisco
Honolulu