Title

Micro- and Macro-Environment Population and the Consequences for Crime Rates

Journal

Social Forces, 92(2)

ISSN

0037-7732

Authors

Hipp, JR
Roussell, A

Publication Date

2013-12-01

DOI

10.1093/sf/sot091

Micro- and macro-environment population and the consequences for crime rates*

John R. Hipp[1]

Aaron Roussell[2]

June 21, 2013

Post-print. Published in Social Forces 2013. 92(2): 563-595

Word count: 9,360

Running Head: "Population density and crime"

[1] Department of Criminology, Law and Society and Department of Sociology, University of California, Irvine. Address correspondence to John R. Hipp, Department of Criminology, Law and Society, University of California, Irvine, 3311 Social Ecology II, Irvine, CA 92697; email: john.hipp@UCI.edu.

[2] Department of Criminal Justice and Criminology at Washington State University, Pullman

* We would like to thank Malcolm Holmes, Marisa Omori, and Akhila Ananth for their helpful comments on drafts of the manuscript. The authors remain solely responsible for the analyses, interpretations, and opinions presented herein.

Biography

John R. Hipp is a Professor in the departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He has published substantive work in such journals as *American Sociological Review, Criminology, Journal of Quantitative Criminology, Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

Aaron Roussell is an Assistant Professor in the Department of Criminal Justice and Criminology at Washington State University, Pullman. One major branch of his research focuses the ways that crime relates to geography, place, and shifting demographics and the implications for social theory and policy. He publishes in the fields of sociology, criminology, and socio-legal studies.

Micro- and macro-environment population and the consequences for crime rates

Abstract

Few studies have explored Louis Wirth's propositions regarding of the independent effects of population size and density due to the conceptual difficulty in distinguishing between them. We directly address this conundrum by conceptualizing these as micro-population density and macro-population density. We propose two novel measures for these constructs: population density exposure to capture micro-density, and a measure of population within a 20 mile radius to capture macro-density. We combine the theoretical insights of Wirth with routine activities theory to posit and find strong nonlinear effects of micro-density on crime rates, as well as the moderating effect of macro-density. We find strong evidence of macro social processes for population size including: 1) its strongest effect occurred for crimes generally between strangers (robberies and motor vehicle thefts); 2) virtually no effect for homicides, a type of crime that often occurs among non-strangers. For micro-density, our findings include: 1) strong curvilinear effects for the three types of property crime; 2) diminishing positive effects for robbery and homicide; and 3) a strikingly different pattern for aggravated assault. The effects for micro-density are stronger than for macro-density, a finding unexplored in the extant literature. We discuss the implications of these results within the context of Wirth's theoretical framework as well as routine activities theory, and suggest ways to extend these findings.

Micro- and macro-environment population and the consequences for crime rates

Introduction

Although there is general agreement among scholars that compositional measures such as the socioeconomic and racial/ethnic composition of human developments strongly influence crime volume, less certain is whether such basic aggregations as population size and density affect crime rates. In his seminal urban sociology tract, Louis Wirth (1938) proposed that three key characteristics of human developments help shape the volume and character of social interaction: 1) population size, 2) population density, and 3) heterogeneity. Wirth argued that these structural characteristics can deter social interaction and result in a sense of anomie. Chicago School scholars argued that this led to a subsequent increase in neighborhood-level crime and delinquency (Shaw and McKay 1942). Heterogeneity has become a standard crime covariate, yet the numerous studies testing the propositions regarding population size or density and crime have provided no conclusive results. Indeed, few studies have found even modest evidence for a density-crime relationship when accounting for population size (Liska, Logan, and Bellair 1998; Messner and Sampson 1991), and most studies find essentially no effects for density (Bailey 1984; Kovandzic, Vieratis, and Yeisley 1998; Messner 1983; Messner and Sampson 1991; Williams 1984). Consequently, some scholars argue that population size and density do not independently explain crime patterns, but simply co-occur with those contextual characteristics such as socio-economic disadvantage that truly explain patterns of city crime (Fischer 1981; Gans 1962). Some who do believe in the importance of these measures combine them into a single construct, obscuring their independence (Land, McCall, and Cohen 1990).

We argue that conclusions regarding the irrelevance of population size and density for the level of crime in cities are premature given certain limitations of the literature. We suggest that neither Wirth's propositions nor the population-related propositions of routine activities theory have been adequately tested. These limitations comprise both conceptual/measurement issues and theoretical issues. Measurement challenges stem from the difficulty of conceptually distinguishing between population size and density. Careful consideration of these constructs reveals the considerable conceptual and mathematical overlap that explains inconsistencies in previous studies. Below, we argue that it is more productive to distinguish instead between the population of the *micro-environment* and the *macro-environment*. Furthermore, we provide novel measures of each of these constructs. Our results demonstrate that the insights of Wirth are more robust than one would conclude from a perusal of the existing sociological literature, suggesting that our conceptual innovations are important and may have implications for other social outcomes apart from crime.

Second, a crucial theoretical insight from routine activities theory that we introduce below is the expectation of a nonlinear relationship between population density and crime rates. We also elaborate how this nonlinear relationship may behave differently depending on the population size of the larger constituent area. This nonlinear hypothesis requires a sample containing ecological units with a broad range of densities, yet previous work has often focused either on metropolitan areas (high density) or rural areas (low density), obscuring the broader population-crime relationship. We construct a dataset of all U.S. cities to better approximate the nation's entire density spectrum. Our approach allows a granulated exploration of population size, density, and crime rates.

In this paper, we first conceptually disentangle the concepts of population size and density. Our approach distinguishes between population in the local *micro-environment* and the broader *macro-environment*. We then discuss the insights of Wirth and routine activities theory that underpin the relationship between human population dispersion and crime. We then describe the empirical evidence regarding these relationships currently in the literature. Next, we describe our data and our novel operationalization of both the population size and density concepts. Finally, we present evidence of a strongly nonlinear density effect on crime while simultaneously accounting for the population size of communities, and conclude. Our findings highlight that it is important to simultaneously account for both the population in the local micro-environment and that of the broader macro-environment, as they have multiplicative, nonlinear effects on the rates of various crime types. Thus, conclusions that population density can be ignored when studying crime in ecological units are premature.

Theoretical background

Population density and population size: The micro- and macro-environment

Structural theories hypothesize that population size and population density affect social interactions and therefore crime rates, but demonstrating this relationship is challenging. Measuring population size, population density, and rates of crime inherently involves teasing apart population and physical area. Population size and density inextricably intertwine in the calculation of crime rates: the rate of crime in a locality (C/P) is equal to the number of crime events (C) for a given population (P) in a specific geographic area (A). Population is inherently geographically bounded— i.e., it is meaningless to discuss the size of the population without knowing the specific geographic area. Thus, we must define the given area for which we wish to measure population size (P), rendering population size as the number of people over an *implicit* area, which is usually rather large (e.g., a city). On the other hand, population density is *explicitly* computed as the ratio of this population to the actual physical area under consideration (P/A), often rather small (e.g., a square mile). Population size and density are thus intricately related. Nonetheless, density represents the number of people within physical proximity to an individual, and directly impacts issues of social control, strain, and opportunity (Stark 1987). Population size, on the other hand, relates more to potential, rather than actual, interactions (Mayhew and Levinger 1977). Both of these concepts combine people and space in different fashions with different effects. In choosing, for unrelated reasons, to collapse population size and density into a single index (Baller, Anselin, Messner, Deane, and Hawkins 2001; Land, McCall, and Cohen 1990), scholars lose these distinct effects .

Because of the conceptual overlap between population size and density, analysts must carefully consider geographic area when measuring these constructs. We suggest conceptualizing population density and population size as two explicit dimensions: the micro-environment and the macro-environment. This renders the micro-environment as an immediate area containing a household (alternatively, a “neighborhood”). Setting aside debates regarding size and definition of neighborhoods (Coulton, Korbin, Chan, and Su 2001; Hipp 2007a), we tap into Wirth’s (1938) conception of a localized environment which creates social “friction” (p. 16) through spatial competition and regular physical contact. This micro-environment captures the number of persons in, for example, a one-mile radius, and arguably captures the persons whom a resident might conceivably experience on a daily basis.

Population size, on the other hand, measures the macro-environment; that is, the number of persons in some larger area akin to the city or larger resident community. Following Wirth (1938), this area captures the persons a resident would likely encounter within a broader social context than a neighborhood. Thus, selecting some particular geographic area (e.g., 20 mile radius) and measuring the number of persons captures Wirth’s notion of population size. Wirth suggested that population size affects the proportion of persons in a macro-environment that a resident can know—in a small city, only a fraction of the 20 mile radius would contain persons, whereas the remainder of the area might constitute open land. Residents living in a neighborhood within a small city can potentially know nearly everybody, rarely encountering strangers. On the other hand, in a larger city there will be population throughout a much larger portion of this 20-mile radius containing a nearly inexhaustible supply of residents to enter the social space of an individual.

This raises an important issue: although the existing macro level crime literature often uses city population size, what this actually measures is unclear, given that cities have politically determined boundaries. In other words, analyses determined by geo-political boundaries can compare cities of similar population sizes yet with wildly different areas. Furthermore, this approach makes the untenable assumption that residents orient their interactions around these boundaries, rather than by physical proximity. Individuals in a city of 20,000 surrounded by farmland have a different potential for social interaction than a city of 20,000 surrounded by other cities. Following Wirth, we argue that the population of some particular radius around a neighborhood is more important than the population size of some arbitrarily defined political unit.[1]

Theories explaining the relationship of population and crime in the micro- or macro-environment

Various theoretical models posit a relationship between population in the micro- or macro-environment and the amount of crime. Turning first to the macro-environment, two related perspectives stand out: 1) the anomie created in highly populated macro-environments as postulated by Wirth (1938); 2) the sheer number of available social ties in highly populated macro-environments as postulated by Mayhew and Levinger (1977). Wirth (1938) regarded population size and density as related but separate concepts that play key roles in determining the context for social interaction. The sheer size of large populations multiplies the range of potential differentiation between individuals. Mayhew and Levinger (1977) formalized this notion of multiplicative growth in social ties, demonstrating that, as the population of the macro-environment grows, an individual's number of ties can grow exponentially, but that at the same time, the amount of possible time devoted to each tie plummets at a decreasing rate. To the extent that crime is a function of these elements, the expected relationship is distinctly non-linear, rising sharply with population before leveling off at some upper limit. This underlines Wirth's sense of anomie, which suggests higher crime rates, since anomic individuals may be less restrained from criminal behavior. This suggests a monotonic positive effect of population in the macro-environment on crime rates.

In theorizing about the micro-environment (population density) one must consider three main perspectives: 1) theories of overcrowding and anti-social behavior fostered by high levels of density (Choldin 1978); 2) Louis Wirth's (1938) insight that physical contacts intensify as density increases; and 3) routine activities theory (Cohen and Felson 1979). The first perspective describes a psychological mechanism rooted in animal studies which demonstrate increased violence and mortality in overcrowded conditions (e.g., Calhoun 1962). It generally implies a monotonic linear relationship between population density and crime. In the second perspective, Wirth posits that physical contacts increase within high density micro-environments. Thus, higher density creates increased competition for urban space with resultant interpersonal friction and, potentially, higher crime rates—another monotonic positive relationship. Indeed, psychological work suggests that social density relates to aggression and social withdrawal, providing microlevel support for macrosocial Chicago School theories (c.f., Regoeczi 2003).

The third micro-environmental perspective to consider is routine activities theory (Cohen and Felson 1979), which emphasizes that crime is an ecological event that occurs within time and space. In the seminal statement on the importance of social ecological processes, Cohen and Felson (1979) posited that crime events occur with the temporal confluence of three spatial factors: 1) the presence of motivated offenders; 2) the presence of suitable targets; and 3) the absence of guardians who might intervene. What is often overlooked, we argue, is that routine activities theory implies multiplicative effects. As Cohen and Felson point out (1979:604): "the effects of the convergence in time and space of [target, offender, and absence of guardians] may be multiplicative rather than additive," meaning that a crime event requires the confluence of all three characteristics and is not simply a sum of the probabilities of each. There is no expectation of crime events in a location with numerous motivated offenders but no suitable targets. Against whom would they commit crime? Likewise, there will be no crime in a location comprising numerous suitable targets but no motivated offenders. Thus, we argue that simply summing these three factors does not in itself provide insight into the expected level of crime. We suggest accounting for this multiplicative function with the construction of interaction variables.

Accounting for the changing presence of offenders, guardians, and targets throughout the micro-environment gives rise to nonlinear hypotheses. First, a greater density of persons within micro-environments indicates a larger number of potential targets, which could raise the crime rate irrespective of anomic effects. Greater density also potentially increases the number of motivated offenders in proximity to these suitable targets, who may commit more than one crime. These two factors combine to work multiplicatively to increase the crime rate. However, greater density also increases the probability of a proximate guardian who may intervene in the event of a crime. Additional guardians should help to lower the rate of crime, particularly if they oversee more than one target or deter more than one offender. Indeed, this idea underlies Jane Jacobs' notion of "eyes upon the street" (Jacobs 1995). Given these complicated predictions, the effect on crime of increasing the number of offenders, targets, and guardians (i.e., the number of people) in a micro-environment is not obvious.

After accounting for these separate issues, a further question concerns the conditioning effect that the population of the macro-environment may have on the effect of population in the micro-environment. That is, the effect of neighborhood density may depend on its location within a metropolitan area as opposed to a small town. We consider two hypotheses. First, the effects of the micro- and macro-environment may be most clear when the other dimension is effectively moot. In other words, the positive effect of an increasing population density in the local micro-environment might be strongest at the smallest populations of the macro-environment. Likewise, the positive effect of an increasing population size of the macro-environment might have its strongest effect when it contains relatively sparse micro-environments. In contrast, when higher levels of both micro- and macro-population are present the effects of each may “crowd-out” the other (an example of *diminishing returns*). This implies that whereas each may be important, their combined effect weakens as both are present at larger levels. This suggests a *negative interaction* between these two dimensions—that is, differential effects of both variables are strongest when one is at its lowest level and the other is at a higher level while weakest when both are at high or low levels.

The second hypothesis is that the multiplicative implications of routine activities theory may differ depending on the population size of the macro-environment (Wirth 1938). Wirth posits that population density works together with population size to complicate and diversify the urban division of labor in an organic Durkheimian sense. Specifically, Wirth’s insights suggest increases in macro-environment population will differentially affect *rates* of offenders and guardians through increased anomie. Increased anomie should decrease guardianship norms, and simultaneously increase the rate of potential offenders by weakening social norms against crime. In sum, because of anomie and normative shifts, people should behave differently in a low population macro-environment than in a larger one . Specifically, the same people who would act as guardians in a small macro-environment do so at lesser rates in a larger macro-environment, while those less inclined to crime might be more inclined at larger macro-environments than smaller ones. This implies a *positive interaction* between the population size of the micro- and macro-environments.

Empirical evidence of population size, density, and crime

Despite our theoretical exposition regarding the importance of population size and density for crime rates, the empirical evidence appears quite mixed. Many studies have tested the effect of population size, but ignored the effect of population density (examples include Ousey 1999; Sampson

1987). Other studies have tested the effect of population density, but ignored effects of population size (examples include Hipp, Bauer, Curran, and Bollen 2004; Kposowa, Breault, and Harrison 1995).[2] Studies testing both simultaneously have found a stronger effect for population size and almost no effect for population density (Bailey 1984; Kovandzic, Vieratis, and Yeisley 1998; Land, McCall, and Cohen 1990; Messner 1983; Messner and Sampson 1991; Williams 1984), although occasional studies have found modest evidence for a density-crime relationship (Liska, Logan, and Bellair 1998; Messner and Sampson 1991). Overall, there is very little evidence that population density affects crime when accounting for population size.

We explain these weak findings theoretically: although the theories we have described imply nuanced and highly non-linear relationships, the literature mostly comprises tests of linear hypotheses. Few studies have explicitly explored possible nonlinear population effects, and none have explored the conditioning effect of macro-environment population on the micro-environment. For example, Osgood and Chambers (2000) charted nonlinear relationships between the juvenile population and youth violence in selected non-metropolitan counties and one study posited, but did not detect, such an effect for preincarceration methamphetamine use among selected rural prisoners (Roussell, Holmes, and Anderson-Sprecher 2009). A study of all U.S. counties in 1980 found positive relationships between density and homicide or violent crime for the entire sample, but no effect for rural counties only, which suggests nonlinearity over the density spectrum (Kposowa, Breault, and Harrison 1995). Finally, Regoeczi (2003) found significant curvilinear relationships between household density and self-reported psychological aggression and withdrawal as well as significant interaction effects between the density of *households* and *neighborhoods*.

In short, the empirical evidence regarding the nonlinear relationship between population density and crime, and the potential moderation by area population size, is too sparse to draw conclusions. The present study addresses this lacuna.

Data and Methods

Data

We aggregate demographic data for all cities ("places") in the U.S. from the 2000 Census, and crime data comprising serious reported crime events from the FBI's Uniform Crime Report (UCR). It can be difficult to distinguish between police survey non-responses and areas with genuinely no crime for smaller police departments (Lott and Whitley 2003). Because these smaller areas are important to this analysis, rather than blanket omission, we adopted an inclusive yet conservative approach for handling cases with no reported crime in 2000. First, we computed the number of crime events reported by a unit in 1970, 1980, 1990, and 2000. Then we omitted cases if they 1) contained no reported crime data from 1970-1990, 2) consistently reported zeros for 1970-1990, or 3) contained either zeros *or* missing data for 1970-1990, or 4) the total crime events in any year from 1970-1990 totaled more than 10, as a fairly conservative cut-off. The included cases therefore reported some mixture of zeros and/or very low numbers of crimes for the previous decades, suggesting that the "true" values for those places were very small or actually zero for the years in question. We estimated models both with and without these "compromise" zeros and found similar results (available upon request). The final dataset thus comprised 7,990 units of observation, including the compromise zeros.

Outcome Variables

We created averaged counts of the violent crimes of aggravated assault, robbery, and homicide over 1999, 2000, and 2001 (aggregating three years smoothes over yearly fluctuations) and then rounded to the nearest integer.[3] Similarly, we created measures of burglary, automotive theft, and larceny events.

Independent Variables

Our key independent variables measure various iterations of population spatial composition. To capture the population density in the local micro-environment experienced by the average person in a geographic area, we computed a *population density exposure* variable. Although places typically have more uniform density within them than do counties, they vary nonetheless. To illustrate, suppose a city is 90% developed with a relatively uniform level of density, but the other 10% of the land is relatively uninhabited. This 10% would improperly affect the overall level of measured density in the city in a traditional P/A expression. We relaxed the homogeneous density assumption across neighborhoods within a city and instead computed the density experienced by the average person within these smaller units by computing the density in each block group, and then combining these to create a measure of population density exposure, weighted by block group population size.[4] Henceforth, when we refer to population density, we are referring to the population of the micro-environment.

We created a measure of the total population within the macro-environment by combining the population of the place itself with the places whose geographic midpoints were within a 20-mile radius of that place's central geographic point. We then log-transformed this measure given the expectation of a diminishing effect of increasing population.[5] Henceforth, when we refer to population size, we are referring to the population of the macro-environment.

We also measured two other types of density. To measure crowding within private space, we followed prior literature (Chilton 1964; Crutchfield 1989; Roncek 1981; Roncek and Maier 1991) in defining household crowding as more than one person per room within a household unit, and then computing the proportion of households in the area exceeding this threshold. By partialling out household crowding in the models, we render the micro-environment population a measure of public space crowding. Prior research also suggests that vacant units within a geographic area will increase crime (Hipp 2007b; Krivo and Peterson 1996; McNulty and Holloway 2000). Although vacant units are implicitly included in the measure of population density insofar as the vacant units occupy space but do not add to the population count, criminological theory posits that such units exert an additional effect on crime rates by providing a haven for delinquent behavior (Stark 1987). We therefore computed the proportion of vacant housing units. We also tested polynomials of each of these measures to assess nonlinearity.

To minimize spurious effects, we also included other measures that the literature suggests might affect crime rates. Given the propensity for adolescents and young adults to commit crime, we computed the population proportion aged 15-29 (Cohen and Land 1987). We measured *socio-economic disadvantage* by combining the following measures through factor analysis: 1) percent unemployed, 2) percent in poverty, 3) per capita income, and 4) percent single parent households ($\alpha = .82$). We measured the racial/ethnic composition by including measures of the percent African American, Latinos, Native Americans, Asians, and "other race" (whites are the reference category due to their numerical preponderance). Additionally, we computed a Herfindahl index of *racial/ethnic heterogeneity*, defined as:

$$\mathrm{EH}_k = 1 - \sum_{1}^{j=J} G_j^{\;2}$$

where G represents the population proportion of ethnic group *j* out of *J* ethnic groups (using the same groupings as the composition measures) in place *k*. To capture effects of immigration apart from ethnic composition, we included a measure of the *proportion immigrant*. We measured *residential stability* via a factor analysis of the following measures: 1) percent homeowners, 2) the proportion living in the same housing unit five years previously, and 3) the average length of time in the same residence ($\alpha = .80$) . As a proxy for informal social control capacity, we constructed a measure of the ratio of those aged 30-64 to those aged 16-29, given that this younger group represents those at the highest risk of being offenders whereas the older group is more likely to provide informal social control action given that it tends to be in more conventional societal roles (and perhaps have more physical ability, on average, to respond to disorderly events than those who are even older). Finally, we controlled for Southern states, given research suggesting a Southern "culture of violence."[6] Our regression diagnostics produced no evidence of collinearity (all variance inflation values were below 5 for models without polynomials), and no influential observations. The summary statistics for all variables included in the analyses are presented in Table 1. Given that our covariates are based on administrative data obtained from the U.S. Census, we do not have any missing data beyond that of the crime measures (described above).

<<<Table 1 about here>>>

Methods

Given that our outcomes are count variables, we estimated negative binomial regression models (a Poisson distribution with an overdispersion term). To effectively model crime *rates*, we use the population size of the geographic unit as an offset variable for five of the crime types. For the motor vehicle theft models we included the number of motor vehicles in the city as the offset variable, as well as a covariate in the model to capture any possible nonlinear effects.[7] This variable of total vehicles was taken from the 2000 U.S. Census. We account for the nonlinearity introduced through the Poisson estimation procedure by plotting all of our results.

We tested the nonlinearity of population density on the various types of crime by adding polynomials of density exposure measure until they no longer improved the model fit.[8] Thus, we do not impose a traditional assumption of linearity on this relationship, but instead allow for nonlinearity in a parametric fashion. This is roughly analogous to propensity score approaches that adopt a completely nonparametric approach in estimating the shape of a relationship over the points of support in the data. We also included all interactions between population size and the various polynomials of density that significantly improved the fit of the model.[9]

Results

We begin by estimating models that imitate those in the extant literature, specifying traditional measures of population size and density in an additive linear model. We include all control variables in these models, but for the sake of comparison present only micro- and macro-population results in Panel 1, Table 2. The mixed results for population density mimic prior research: although density shows a positive relationship with robbery and motor vehicle theft, it shows a negative relationship with burglary and larceny, and no relationship with aggravated assault and homicide. Also consistent with previous findings, population size shows a more dependably positive relationship with all six outcomes.

<<<Insert Table 2 about here>>>

In the second panel of Table 2, we substitute our measures of micro- and macro-environment population (population density exposure and logged population size in the surrounding 20 miles) for the traditional measures. In these models, population density exposure is more consistent than the traditional measure, producing a significant positive effect for four of the crime types, although there is still a negative effect for larceny and no effect for burglary. The effect of the macro-environment is more mixed than the traditional measure, exhibiting a positive relationship with robberies, motor vehicle thefts, and larcenies. However, it has a negative relationship with aggravated assault and no relationship with the burglaries and homicides.

Based on our earlier theoretical discussion, we next tested the interaction between the population of the micro- and macro-environments. We display the interaction results when using the traditional measures of population size and density (panel 3) and when using our proposed measures (panel 4). Two features can be seen in these two panels: 1) the results are quite different from one another; 2) the results when including the interaction term and our proposed measures are more robust. With the exception of robbery, for which the two main effects and interaction are all significant and in the same direction, for virtually all of the other 15 coefficients the results are different across the two panels (either losing significance, or of opposite sign). Notably, the results remain mixed when using the traditional measures (panel 3). The traditional population density measure is significantly negative for four crime types, positive for another, and insignificant for the last. The traditional population size measure is significantly positive for three, negative for two, and insignificant for the last. The interaction term also shows a mix of significant positive and negative results. On the other hand, for virtually all crime types, specifying a linear interaction between our measures yields a robust pattern (panel 4). We consistently find a significant positive main effect for the population of the micro-environment and a consistent negative effect between the micro- and macro-environment population interaction for all crime types. Thus, our theoretically refined measures appear to provide more robust results.

The general pattern of these interactions when using our proposed measures is similar regardless of crime type, and we display a representative pattern (robbery) in Figure 1. For this and all subsequent figures, we plot population sizes one standard deviation below the mean, the mean, one standard deviation above the mean, and at the 90th percentile (very large), over *only* the range observed for that particular population size in our sample. The left side of Figure 1 demonstrates that at low levels of population in the micro-environment the population of the macro-environment has little effect on the robbery rate. Only at mid-range levels of micro-environment population (the center of this Figure), does a larger population in the macro-environment negatively affect the robbery rate. Although this interaction is significant, it can be seen in this figure that the substantive effect is not particularly dramatic. This will change as we next turn to the models accounting for nonlinearities.

<<<Figure 1 about here>>>

We extend our analyses by testing the nonlinearities in these relationships that our theoretical exposition predicts. Given the non-independence of the polynomials and interaction terms for the models in Table 4, we visually display the results by graphing them in figures 2 through 7. Figure 2 demonstrates that the effects of micro-environment population on robbery rates differ from those in the linear model when we relax linear assumptions. For robbery, we see a generally positive relationship for micro-environment population that levels off at higher levels of density. At lower levels of density, the robbery rate increases at a strong steady rate regardless of the size of the macro-environment, but beyond about 8,000 persons per square mile increasing levels of density do not impact the robbery rate. Furthermore, at lower levels of density, cities with larger macro-environment populations have higher robbery rates; however, this difference effectively evaporates by about 5,000 persons per square mile. Note that this figure differs considerably from Figure 1, highlighting the importance of accounting for such nonlinear effects in these models.[10]

<<<Figure 2 about here>>>

For aggravated assault, the effect of the micro-environment population is steepest for places with the smallest macro-environment population (Figure 3). This effect weakens and in the largest macro-environment populations the level of density has only a modest effect.

<<<Figure 3 about here>>>

Homicide on the other hand, demonstrates a strong nonlinear effect for population density, yet there is no effect for the size of the population in the macro-environment (Figure 4). The monotonic positive relationship between micro-environment population and homicide slows at higher population densities but never levels off completely. At low levels of population density we see that homicide rates increase sharply as density rates increase. Thus, homicide varies most strongly with the level of population density in the micro-environment.

<<<Figure 4 about here>>>

Types of Property Crime

Turning to the results for property crime types, we find that the functional form for motor vehicle theft sharply contrasts with that for the other property crime types, suggesting that the process through which population affects this type of crime is unique. The effect of population density on motor vehicle theft rates differs considerably depending on the size of the macro-environment population (Figure 5). In small and mid-sized macro-environment populations, the relationship between micro-environment population and motor vehicle thefts accelerates increasingly. However, in larger macro-environment populations, the positive relationship slows until it inflects between 8 and 9,000 persons per square mile and begins decreasing.

<<<Figure 5 about here>>>

We see a pronounced nonlinear relationship between density and burglary rates in Figure 6, and a similar one for density and larceny rates in Figure 7. For small places, there is a very strong positive relationship between density and burglary or larceny rates. For mid-sized places, there is a slowing positive relationship as burglary or larceny rates level off at about 4,000 persons per square mile. For large places, the effect of density on burglary or larceny rates is only positive at lower density levels, and exhibits a negative relationship beyond about 4,300. Although we do not observe a similar decreasing effect for small and mid-sized places, this may be because they simply do not reach density levels this high in our sample. This split demonstrates why studies composed of only rural (low density) or urban (high density) units may obtain diametrically opposed estimates of the density/burglary relationship. Furthermore, there is little evidence that macro-environment population increases burglary rates.

<<<Figures 6 and 7 about here>>>

Turning to the two other types of population density in our models, we observe effects generally consistent with expectations (the coefficients are displayed in Table 3; the results were also graphed, although not shown). Whereas places with a higher proportion of crowded households exhibit a diminishing negative relationship with the larceny rate and the motor vehicle theft rate, they have a linear positive relationship with the other four crime types. The percentage vacant units—a measure of the distribution of density—shows positive effects for four of the crime types, and a U-shaped effect for two of them. There is a slowing positive effect between the vacancy rate and the aggravated assault rates, whereas the vacancy rate has a slowing positive effect on the homicide rate with an inflection point around 21% beyond which it exhibits a slight negative trend. The vacancy rate shows a generally linear positive relationship with burglary and motor vehicle theft rates. Finally, the vacancy rate shows a U-shaped relationship with the robbery and larceny rates in which these crime rates are highest in places with very low or very high vacancy rates. Thus, consistent with Stark (1987), vacant housing units have important theoretical implications for crime above and beyond the effects of simple social density.

<<<Table 3 about here>>>

It is worth emphasizing the differences between the results in Table 3 using our measures of population in the micro- and macro-environment, and their nonlinear interactions, with those obtained in the first models in Table 2 using the traditional measures of population size and density as linear functions. Whereas the aggravated assault model using the traditional measures of population size and density found no significant effects, Figure 3 demonstrated strong nonlinear effects for population density. And whereas the traditional robbery model found a positive effect for both population size and density, Figure 2 showed a more nuanced picture, particularly for the population of the macro-environment. The homicide findings are particularly notable: whereas adopting the traditional approach made it appear that population size has a positive effect and density has no effect, Figure 4 highlights that there is in fact no effect for the macro-environment population, whereas the micro-environment effect is a nonlinear positive one. For both the burglary and motor vehicle theft models, the puzzling opposite sign effects for the traditional population density and size measures become clearer when viewing the strong nonlinear interaction effects in Figures 5 and 6. Finally, although one would conclude from the models using the traditional measures that both population size and density have negative effects on the larceny rate, Figure 7 paints a starkly different picture in which the effects of population in the micro-environment have sharply divergent effects depending on the size of the population in the macro-environment.

We briefly note that the control variables generally performed as expected. The proxy for informal social control capacity (the ratio of those aged 30-64 to those aged 16-29) exhibited the expected negative effect for five of the six crime types. For the racial composition, cities with higher proportion black have higher rates of all of these crime types, cities with higher proportion Latino have higher property crime rates, and the proportion Native American generally has a negative effect, once controlling for the other variables in the model. Places with higher racial/ethnic heterogeneity, more concentrated disadvantage, and less residential stability have higher rates of nearly all crime types. Notably, we see that cities with a higher proportion of immigrants actually have lower rates of all of these crime types, suggesting a negative effect on crime rates from an influx of immigrants when controlling for these other city characteristics.

Sensitivity analyses

As an assessment of the robustness of our findings, we estimated identical ancillary models with 1990 data (these results are displayed in an electronic Appendix on this webpage: TO ADD). All variables were constructed similarly as the 2000 data, and we estimated the models similarly in a stepwise fashion to determine the proper shape of the functional form based on significance of the parameters. The shapes of these nonlinear curves, as well as the moderating effects of population size, were quite similar over both of these decades for all crime types. The only modest differences were that the effect of population density on aggravated assault rates was more curvilinear in the 1990s (and macro-environment population no longer showed a negative effect). The nonlinear effects we chart are not simply an artifact of the data at a single point in time, but appear to represent a more general social phenomenon.

Mediating effect of informal social control

Given that the posited effects of the micro- and macro-population on the presence of motivated offenders, suitable targets, and guardians are complex and nonlinear, a preferable strategy would directly measure each of these constructs; however, this is difficult to do. As a proxy for guardians, we included the ratio of those aged 30 to 64 to those aged 15 to 29. The effect of this proxy on the results was determined by re-estimating our main models but excluding this informal social control proxy. In the models without our proxy, increasing micro-environment population is posited to increase the number of offenders, targets, and guardians (the first two will increase the crime rate, whereas the last will reduce it). To the extent that our guardian proxy actually captures the level of guardians, the micro-environment population measure in these models mostly captures just the increased number of offenders and targets, which should demonstrate a purer positive effect on crime.

As expected, the strength of the relationship between micro-environment population and crime was stronger in the models including this proxy for guardians than in the models without it. Although the strength of this relationship was only modestly stronger for robberies (and not at all for homicides), it was much larger for the other crime types. Given the nonlinearity of our models, we assessed the strength of this relationship by computing the range of predicted values for each of the macro-environments plotted in figures 2-7, and compared them to the ranges when excluding the guardians proxy variable. For the robbery models, the predicted effect for the micro-environment population was 16% larger when including this guardians proxy; furthermore this predicted effect was about 70% larger for motor vehicle theft and larceny models, 315% larger for the burglary models, and 60 times larger for the aggravated assault models. The fact that these ancillary results conform to expectations is encouraging, and implies that future work using more sophisticated measures of offender, target, and guardianship presence may further unpack the strong relationships we detected between micro and macro population.

Conclusion

In this study, we theoretically and empirically explored the relationship between the population of the micro- and macro-environment, and various types of crime. We emphasize the importance of distinguishing between population density and population size, and reconceptualizing these notions more precisely as the number of persons in the micro-environment and the macro-environment. We measured the micro environment through *population density exposure*, which accounted for the population density experienced within each block group in the place, and measured population size based on a 20 mile radius around the place. We argue that these are more conceptually appropriate measures of these constructs as theorized by Louis Wirth and other scholars and produce stronger empirical support than traditional measures. Where these novel measures exhibit robust relationships with crime rates, researchers should extend these results by exploring the efficacy of these measures through other urban sociological phenomena, such as social networks, anomie, and cohesion.

Our theoretical contribution is to emphasize the inherent nonlinearity in the relationship between population density and crime implied by routine activities theory along the urban dimensions specified by Wirth. Combining the Chicago School's urban sociology with routine activities theory suggests that these nonlinearities can be further conditioned by macro-environmental context. Prior research has neglected these possibilities, yet our investigation shows that they hold implications for crime. These relationships are complex, but important and robust. We demonstrate that Wirth's theories regarding urbanity and spatial concentration—not just heterogeneity, but also population size, and population density—have been too quickly dismissed. They ultimately remain pivotal and should be considered in future research on structural crime correlates to sort out their mechanisms. We have proposed routine activities theory as but one potential mechanism through which they exert influence. Indeed, these relationships may hold for other social outcomes as well and should be investigated in future research. Further, our findings were demonstrated on national level data—another avenue of research will be to investigate these relationships for subnational geographies.

We found two broad patterns of results for the effect of population size of the macro-environment on crime rates that conform generally to the relationships outlined by Wirth. First, the strongest effects occurred for two types of crime characterized as generally occurring between strangers. Population of the macro-environment had a positive effect for robberies and motor vehicle thefts, although it is notable that this effect was only detected in relatively low density areas. The innominance of these crime types makes them more likely to occur in larger areas where individuals are unlikely to encounter acquaintances. However, the fact that this effect faded or even reversed in higher density environments argues for the potential role of more guardians in such settings, consistent with routine activities theory.

Second, consistent with the corollary of anonymity, macro-environment population demonstrated no effect for homicide and even a negative effect for aggravated assault. Given that most homicides and aggravated assaults occur between acquaintances and intimates, there is no reason to expect increased macro-environment population to increase the homicide rate. These findings for homicide are especially important given their disproportionate representation in crime studies, which may contribute to potentially overbroad conclusions about the general nature of crime. In fact, with respect to population correlates, our results suggest that homicide may be strongly unrepresentative of general crime patterns. And although many prior studies argue for a positive relationship between population size and homicide rates, we demonstrate that such a relationship is entirely erased by accounting for micro-environment population, micro-environment nonlinearity, and interaction effects.

We also detected three patterns regarding the effects of density in micro-environments on crime rates: 1) strong curvilinear effects for the three types of property crime; 2) diminishing positive effects for robbery and homicide; and 3) a strikingly different pattern for aggravated assault. First, the three types of property crime showed a sharp curvilinear pattern, peaking at a much lower level for burglaries and larcenies than for motor vehicle thefts. The burglary and larceny findings raise the question: What about average density levels is criminogenic for these property crimes? One explanation is that potential guardians increase with density more than the other routine activity factors and that at these fairly low densities a lack of guardians (e.g., neighbors) may enhance property crimes. A similar dynamic has been found for methamphetamine in more isolated areas (Roussell, Holmes, and Anderson-Sprecher 2009). *Fear* of crime may also be lower in these places due to a misplaced perception that danger is limited to highly urban areas, which may diminish the use of preventative measures such as door locking and alarm systems. These are important directions for future research. Motor vehicle theft rates showed a stronger positive relationship with micro-environment population, exhibiting a curvilinear effect that levels off at higher density levels, suggesting a very different social process. The fact that vehicle thefts begin decreasing at very high levels of density may not be that surprising: New York, for example, as a quintessentially “dense place,” maintains one of the world’s most effective public transport systems, largely obviating the need for personal vehicles. We controlled for the total number of vehicles, and yet this effect was still observed.

Second, robbery and homicide showed generally positive relationships with micro-environment population, slowing only at the highest density levels. These violent crimes loosely demonstrate Wirth’s social friction argument as increased proximity between people, to a point, increases the chances of violence. These findings are also consistent with psychological findings suggesting aggression as a “fight” response to cope with psychological arousal (c.f., Regoeczi 2003). The fact that these crimes increase at slower rates at higher levels of density suggest that the presence of more potential guardians may counteract the greater number of targets and offenders. Future studies would need to explore this question directly to assess whether this is indeed the case.

Third, aggravated assault shows a unique pattern, displaying an increasing nonlinear relationship with the micro-environment population and a surprising negative relationship with macro-environment population. Small and mid-sized areas exhibit the strongest positive relationship between density and assaults. However, larger areas have flatter relationships with micro-environment population in which assault rates only start increasing at the highest density levels. Nonetheless, when comparing cities with a similar population size in the macro-environment, aggravated assault rates are consistently higher with higher levels of micro-environment population.

Our measures of personal space density and vacancy rates generally showed robust effects. Greater crowding within the housing unit showed a positive effect on four of the crime types. This is consistent with psychological theories that close proximity in such small quarters can lead to greater levels of frustration and aggression. The fact that it most strongly affected violent crimes as opposed to property crimes is consistent with this explanation. Most importantly, crowding affects crime *in addition to* the effect of general density, a finding unique in the literature which bears further investigation. We also found that the presence of more vacant units leads to more crime, beyond that captured by measuring area population density, for all of these crime types. This positive relationship may reflect an increase in offender gathering spots as Stark (1987) suggests or it could reflect fewer potential guardians nearby. More research in this area must tease out which effects may be at work.

Our results have highlighted the importance of simultaneously taking into account both the population of the micro- and macro-environment. One major implication of these findings is the potential importance of the effect of *change* in micro- and macro- population on changing crime rates. Change includes both growth and decline, and an obvious research question is whether these effects would be truly symmetric: Does increasing population have the opposite effect as decreasing population on crime rates? Given that a city with increasing population typically represents an economically vibrant area, whereas a city with decreasing population represents an economically struggling area, it may be important to operationalize and disentangle these differing economic contexts when attempting to understand the pure effect of micro- and macro-environment population. These are interesting directions for researchers to consider in extending our conceptualization and measures.

An additional issue that arises when considering the dynamic nature of micro- and macro population change is that crime may also help drive such changes. Such possibilities were outside the scope of the present study, but are worth exploring given that research has found that residents respond to crime with residential mobility (Hipp 2010; Hipp, Tita, and Greenbaum 2009; South and Crowder 1997; Xie and McDowall 2008). To the extent that crime leads to population outflow from cities, this would be important to account for in longitudinal analyses. Our cross-sectional analyses simply revealed a complex system at equilibrium, and longitudinal analyses would help to tease apart these processes. In a classic example, high levels of crime may cause residents to move from the denser core of the city and to the fringe (e.g., the suburbs or burgeoning edge cities). This would lower the micro-population level in the city core, but have no impact on the overall macro-population, since residents would remain in the metropolitan area. On the other hand, if residents actually leave the city and move to the ex-urban fringe then one could say that crime caused a reduction in both the micro- and macro-population. It would be useful for future research to explore how these processes play out.

Although our study addresses a host of neglected theoretical and methodological issues, we acknowledge some limitations. Whereas an ideal approach would utilize precise locational information on all persons and all crime events across the entire U.S. to precisely estimate the density/crime relationship, no such data exist. We were forced to assume relative density homogeneity in our units of analysis, although by computing a population density exposure measure based on the average block group density we increased the plausibility of this assumption over traditional calculations. Nonetheless, our reliance on this assumption is important when interpreting the results. Second, we were limited to using official crime reports. The limitations of such data due to underreporting are well-known and raise the possibility that population density and size are in fact related to the probability of reporting crimes. Nonetheless, the bulk of the large body of prior research testing (and dismissing) the effect of population size and density on crime rates also relies on these data. Furthermore, such underreporting would only bias the results if it is systematically related to the characteristics of the community (Lott and Whitley 2003), and evidence suggests that such bias is minimal (Baumer 2002). Third, we did not test possible causal mechanisms explaining these robust nonlinear effects. Although theory guided us to these results, other theoretical explanations may be consistent with the observed relationships. Further research must tease out these processes.

In conclusion, we emphasize that the nonlinear relationship between population density, population size, and crime is indeed quite robust, and should be accounted for in models exploring structural processes and crime. This nonlinearity is unsurprising given the insights of routine activities theory. Furthermore, this nonlinear relationship differs somewhat for places with differing sized macro-populations, suggesting that the insights of Wirth interact with routine activities theory in ways important to crime—and potentially other social outcomes as well. Our findings highlight that scholars cannot test population and crime based on subsamples of particular geographic units within one part of the density spectrum and assume the generalizability of their findings. Taken together, these findings suggest that prior scholarship implying the inaccuracy of Wirth's insights are premature, and that appropriately measuring micro-environment and macro-environment population, as well as taking into account the multiplicative relationship among them, yields robust, nuanced results. Simultaneously, our results with respect to vacancy and personal crowding further reveal the extent to which different accumulations of people in places have a strong effect on crime, and the paucity of theory which accounts for these variations among and between measures. Micro- and macro-environment provide important insights to scholars of structural criminogenesis, and the notion that they can be safely ignored by studies focusing on more meso-level processes is clearly premature. Exploring *why* this is the case, and to what other social pathologies they may apply, should be a focus of future research.

References

Aiken, Leona S. and Stephen G. West. 1991. *Multiple Regression: Testing and Interpreting Interactions*. Newbury Park, CA: Sage.

Bailey, William C. 1984. "Poverty, Inequality, and City Homicide Rates." *Criminology* 22:531-550.

Baller, Robert D., Luc Anselin, Steven F. Messner, Glenn Deane, and Darnell F. Hawkins. 2001. "Structural Covariates of US County Homicide Rates: Incorporating Spatial Effects." *Criminology* 39:561-590.

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

Calhoun, John C. 1962. "Population Density and Social Pathology." *Scientific American* 206:139-148.

Chilton, Roland J. 1964. "Continuity in Delinquency Area Research: A Comparison of Studies for Baltimore, Detroit, and Indianapolis." *American Sociological Review* 29:71-83.

Choldin, Harvey M. 1978. "Urban Density and Pathology." *Annual Review of Sociology* 4:91-113.

Cohen, Lawrence E. and Marcus Felson. 1979. "Social Change and Crime Rate Trends: A Routine Activity Approach." *American Sociological Review* 44:588-608.

Cohen, Lawrence E. and Kenneth C. Land. 1987. "Age Structure and Crime: Symmetry versus Asymmetry and the Projection of Crime Rates through the 1990s." *American Sociological Review* 52:170-183.

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

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

Fischer, Claude S. 1981. "The Public and Private Worlds of City Life." *American Sociological Review* 46:306-316.

Gans, Herbert J. 1962. *The Urban Villagers*. New York: Free Press.

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

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

—. 2010. "Violent crime, mobility decisions, and neighborhood racial/ethnic transition." *Social Problems* 58:410-432.

Hipp, John R., Daniel J. Bauer, Patrick J. Curran, and Kenneth A. Bollen. 2004. "Crimes of Opportunity or Crimes of Emotion: Testing Two Explanations of Seasonal Change in Crime." *Social Forces* 82:1333-1372.

Hipp, John R., George E. Tita, and Robert T. Greenbaum. 2009. "Drive-bys and Trade-ups: The Impact of Crime on Residential Mobility Patterns in Los Angeles." *Social Forces* 87:1777-1812.

Jacobs, Jane. 1995. "The Uses of Sidewalks." Pp. 111-129 in *Metropolis: Center and Symbol of Our Times*, edited by P. Kasinitz. New York: New York University.

Kovandzic, Tomislav V., Lynne M. Vieratis, and Mark R. Yeisley. 1998. "The Structural Covariates of Urban Homicide: Reassessing the Impact of Income Inequality and Poverty in the Post-Reagan Era." *Criminology* 36:569-599.

Kposowa, Augustine J., Kevin D. Breault, and Beatrice M. Harrison. 1995. "Reassessing the Structural Covariates of Violent and Property Crimes in the USA: A County Level Analysis." *British Journal of Sociology* 46:79-105.

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

Land, Kenneth C., Patricia L. McCall, and Lawrence E. Cohen. 1990. "Structural Covariates of Homicide Rates: Are There Any Invariances across Time and Social Space?" *American Journal of Sociology* 95:922-963.

Liska, Allen E., John R. Logan, and Paul E. Bellair. 1998. "Race and Violent Crime in the Suburbs." *American Sociological Review* 63:27-38.

Lott, John R. Jr. and John Whitley. 2003. "Measurement Error in County-Level UCR Data." *Journal of Quantitative Criminology* 19:185-198.

Mayhew, Bruce H. and Roger L. Levinger. 1977. "Size and the Density of Interaction in Human Aggregates." *American Journal of Sociology* 82:86-110.

McNulty, Thomas L. and Steven R. Holloway. 2000. "Race, Crime, and Public Housing in Atlanta: Testing a Conditional Effect Hypothesis." *Social Forces* 79:707-729.

Messner, Steven F. 1983. "Regional and Racial Effects on the Urban Homicide Rate: The Subculture of Violence Revisited." *American Journal of Sociology* 88:997-1007.

Messner, Steven F. and Robert J. Sampson. 1991. "The Sex Ratio, Family Disruption, and Rates of Violent Crime: The Paradox of Demographic Structure." *Social Forces* 69:693-713.

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

Osgood, D. Wayne and Jeff M. Chambers. 2000. "Social Disorganization Outside the Metropolis: An Analysis of Rural Youth Violence." *Criminology* 38:81-116.

Ousey, Graham C. 1999. "Homicide, Structural Factors, and the Racial Invariance Assumption." *Criminology* 37:405-426.

Regoeczi, Wendy C. 2003. "When Context Matters: A Multilevel Analysis of Household and Neighbourhood Crowding on Aggression and Withdrawal." *Journal of Environmental Psychology* 23:457-470.

Roncek, Dennis W. 1981. "Dangerous Places: Crime and Residential Environment." *Social Forces* 60:74-96.

Roncek, Dennis W. and Pamela A. Maier. 1991. "Bars, Blocks, and Crimes Revisited: Linking the Theory of Routine Activities to the Empiricism of 'Hot Spots'." *Criminology* 29:725-753.

Roussell, Aaron, Malcolm D. Holmes, and Richard Anderson-Sprecher. 2009. "Community Characteristics and Methamphetamine Use in a Rural State: An Analysis of Preincarceration Usage by Prison Inmates." *Crime & Delinquency* Prepublished July 1, 2009.

Sampson, Robert J. 1987. "Urban Black Violence: The Effect of Male Joblessness and Family Disruption." *American Journal of Sociology* 93:348-382.

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

Shihadeh, Edward S. and Graham C. Ousey. 1996. "Metropolitan Expansion and Black Social Dislocation: The Link Between Suburbanization and Center-City Crime." *Social Forces* 75:649-666.

Skogan, Wesley G. 1999. "Measuring What Matters: Crime, Disorder, and Fear." Pp. 37-88 in *Measuring What Matters: Proceedings from the Policing Research Institute Meetings*, edited by R. Langworthy. Washington, D.C.: National Institute of Justice.

South, Scott J. and Kyle D. Crowder. 1997. "Residential Mobility Between Cities and Suburbs: Race, Suburbanization, and Back-to-the-City Moves." *Demography* 34:525-538.

Stark, Rodney. 1987. "Deviant Places: A Theory of the Ecology of Crime." *Criminology* 25:893-909.

Williams, Kirk R. 1984. "Economic Sources of Homicide: Reestimating the Effects of Poverty and Inequality." *American Sociological Review* 49:283-289.

Wirth, Louis. 1938. "Urbanism as a Way of Life." *American Journal of Sociology* 44:1-24.

Xie, Min and David McDowall. 2008. "Escaping Crime: The Effects of Direct and Indirect Victimization on Moving." *Criminology* 46:809-840.

Endnotes

1. Although SMSA's attempt to solve this problem, they 1) include the population from a much larger area than a person would ever encounter, and 2) still have an arbitrary and inconsistent areal size.

2. Some studies measure structural density: the number of buildings in some prescribed area (such as structural units with 5 or more housing units). These have generally found weak results (Sampson 1987; Shihadeh and Ousey 1996) We therefore focus explicitly on Wirth's hypotheses regarding density.

3. We do not include a measure of the rape rate given that there are serious concerns about the reporting of this crime across different police jurisdictions (Skogan 1999).

4. Our density exposure variable is correlated r = .90 with a traditional population density measure of the persons per square mile. Nonetheless, there is a conceptual distinction between the two, and we suggest that our measure is a more refined measure of the theoretical construct of interest.

5. This decision was also empirically justified. Models including this log-transformed measure showed a stronger relationship with the various types of crime than models including the untransformed measure. We point out that this measure was only correlated .2 with the logged population size of the city as defined by political boundaries, highlighting the improvement of this conceptualization of population size.

6. We include the 11 core ex-Confederate states (Messner 1983) as well as the historically borderline Oklahoma and Kentucky.

7. We also estimated models adopting the more traditional approach of using the population of the city as the offset. The results were very similar in both specifications. Nonetheless, we use the number of vehicles as the exposure measure given that it is more conceptually appropriate.

8. There might be concern that including several polynomials will lead to multicollinearity. Although polynomial variance inflation factor values (VIF) are larger, multicollinearity is not necessarily a problem as standard errors are the main concern and they are affected by four characteristics: 1) sample size (which is very large in our case), 2) the variance explained in the equation, 3) the shared correlation (VIF's), and 4) the actual variance of the variable of interest (for an in-depth discussion, see O'Brien

(2007)). On this last point, higher order polynomials have much larger variance than linear variables which therefore reduces the standard errors and offsets the larger VIF's. If there is too much collinearity, the standard errors will be too large to make meaningful interpretations, which is not the case here. To demonstrate that such Type I error is not a concern here, we simulated ten datasets from a model which is actually linear and found no significant higher order polynomials in nine of the ten datasets (regardless of centering to reduce collinearity); one dataset yielded a single significant parameter, but plotting the results showed that it was not capturing a substantive nonlinear effect. We then simulated ten datasets for a model with polynomials raised to the sixth power. In all ten models we retrieved the proper solution: despite extremely high multicollinearity for the uncentered data (and VIF's around 30 for the centered data), the plotted results were always identical between the centered and uncentered data and very similar to the population model, consistent with the insights of Aiken and West (1991). Thus, there is virtually no evidence that the substantive nonlinearities that we detect in this paper are the result of an "artifact" of collinearity.

9. When computing the difference between the models including measures of population in the micro- and macro-environment as well as their interaction (with no polynomials), to our final models that included the various polynomials for the micro-environment population variable, the models adding the polynomials showed strong improvement in model fit. The chi square difference tests for each crime type were all significant at $p < .0000001$: $\chi2 = 73.9$, df = 3 for aggravated assault, $\chi2 = 521.9$, df = 8 for robbery, $\chi2 = 115.6$, df = 7 for homicide, $\chi2 = 144.1$, df = 9 for burglary, $\chi2 = 124.1$, df = 6 for motor vehicle theft, and $\chi2 = 294.0$, df = 10 for larceny.

10. We also estimated nonlinear interaction models using the traditional measures of population size and density, and the results were considerably different from those using our proposed measures. These differences across the two sets of measures parallel the findings from Table 2 when specifying these as linear relationships.

Tables and Figures

Table 1. Summary statistics of variables used in analyses.

	Mean	Std Dev.
Outcome variables		
Aggravated assaults	75.41	746.33
Robberies	40.45	527.83
Homicides	1.47	22.40
Burglaries	160.26	929.30
Motor vehicle thefts	106.05	917.75
Larcenies	585.75	3116.18
Predictor variables		
Population density exposure	2368.21	3462.62
Proportion crowded households	0.038	0.053
Proportion vacant units	0.092	0.100
Logged population size (25 miles)	14.10	1.76
Proportion aged 16 to 29	0.19	0.06
Ratio 30-64 to 16-29 year olds	2.518	1.030
Racial/ethnic heterogeneity	0.253	0.190
Proportion black	0.083	0.157
Proportion Latino	0.078	0.148
Proportion Native American	0.009	0.034
Proportion Asian	0.018	0.039
Proportion other race	0.024	0.041
Proportion immigrants	0.060	0.080
Concentrated disadvantage index	0.000	0.906
Residential stability index	0.000	0.931
South	0.285	0.451
N = 8,000		

Table 2. Models predicting various types of crime in cities in 2000. using traditional measures of population size and density, and this study's measures of population density exposure and logged 20 mile population size

	Aggravated assault		Robbery		Homicide		Burglary		Motor vehicle theft		Larceny	
Panel 1: Traditional measures of population size and density												
Population density (traditional)	0.0605		0.7480	**	0.0699		-0.0908	**	0.3552	**	-0.2025	**
	(1.25)		(12.75)		(1.05)		-(2.94)		(6.96)		-(5.33)	
Logged city population size	-0.0048		0.2268	**	0.2488	**	0.0273	**	-0.0228	*	-0.0185	**
	-(0.56)		(22.64)		(17.82)		(4.76)		-(2.32)		-(3.04)	
Panel 2: Our measures of population size and density												
Population density exposure	0.1244	**	0.8004	**	0.2946	**	0.0029		0.3714	**	-0.1133	**
	(3.60)		(17.50)		(7.02)		(0.13)		(9.79)		-(4.35)	
Logged population size (20 miles)	-0.0267	**	0.0804	**	-0.0031		0.0059		0.0414	**	0.0371	**
	-(4.39)		(10.02)		-(0.19)		(1.42)		(7.13)		(8.01)	
Panel 3: Traditional measures of population size and density, including interaction												
Population density (traditional)	-1.1351	**	2.9027	**	0.4682		-1.1912	**	-1.2786	**	-1.4978	**
	-(3.85)		(10.44)		(1.62)		-(5.69)		-(3.91)		-(6.65)	
Logged city population size	-0.0064		0.2390	**	0.2554	**	0.0275	**	-0.0148		-0.0147	*
	-(0.76)		(23.63)		(17.32)		(4.79)		-(1.51)		-(2.41)	
Size X density	0.1204	**	-0.2133	**	-0.0330		0.1103	**	0.1675	**	0.1314	**
	(4.06)		-(8.12)		-(1.43)		(5.25)		(5.00)		(5.74)	
Panel 4: Our measures of population size and density, including interaction												
Population density exposure	0.2000	**	1.1800	**	0.4125	**	0.0702	*	0.5714	**	0.0512	
	(4.83)		(20.04)		(7.12)		(2.35)		(12.64)		(1.38)	
Logged population size (20 miles)	-0.0301	**	0.0750	**	0.0149		0.0020		0.0305	**	0.0262	**
	-(4.85)		(8.96)		(0.85)		(0.46)		(5.01)		(5.25)	
Size X density	-0.0564	**	-0.2949	**	-0.0637	**	-0.0414	**	-0.1594	**	-0.0967	**
	-(3.41)		-(11.24)		-(2.89)		-(3.43)		-(8.69)		-(6.29)	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. Negative binomial regression models, including population size as offset variable. N = 8,000*

Note: All models include all control variables shown in Table 3

Table 3. Models predicting various types of crime in cities in 2000

	Aggravated assault		Robbery		Homicide		Burglary		Motor vehicle theft		Larceny	
Population density exposure	0.1253	*	2.1326	**	1.5516	**	0.2171	**	0.8311	**	0.2119	**
	(2.11)		(27.13)		(10.23)		(4.81)		(13.41)		(4.33)	
Population density (^2)	0.0933	†	-2.4326	**	-1.4780	**	-0.6384	**	-0.4352	**	-1.2204	**
	(1.95)		-(11.65)		-(6.20)		-(5.96)		-(5.27)		-(8.89)	
Population density (^3)	-0.0121	*	1.0969	**	0.5935	**	0.3571	**	0.0972	**	0.6602	**
	-(2.00)		(7.17)		(4.60)		(4.96)		(3.08)		(6.25)	
Population density (^4)			-0.1803	**	-0.0967	**	-0.0687	**	-0.0077	**	-0.0945	**
			-(5.46)		-(3.82)		-(4.37)		-(2.75)		-(4.66)	
Population density (^5)			0.0067	**	0.0054	**	0.0042	**				
			(3.46)		(3.33)		(3.88)					
Logged population size (20 miles)	-0.0297	**	0.0359	**	-0.0280		-0.0048		0.0176	**	-0.0191	**
	-(4.76)		(3.74)		-(1.53)		-(0.99)		(2.62)		-(2.88)	
Size X density	-0.0632	**	-0.2194	**	0.0289		-0.0554	**	-0.1283	**	-0.1952	**
	-(3.36)		-(5.09)		(1.09)		-(2.82)		-(4.60)		-(7.96)	
Size X density (^2)			0.3283	**			0.0254	*	0.0290	†	0.4652	**
			(3.38)				(2.05)		(1.66)		(8.07)	
Size X density (^3)			-0.1628	**							-0.2491	**
			-(2.67)								-(5.78)	
Size X density (^4)			0.0255	*							0.0365	**
			(2.40)								(4.44)	

Proportion crowded households	2.7477	**	-5.7689	**	1.0804		1.3221	**	-1.8046	**	-3.5044	**
	(7.37)		-(7.36)		(0.98)		(5.09)		-(2.67)		-(6.94)	
Proportion crowded households squared			16.1139	**	4.5804	**			8.6147	**	5.8003	**
			(10.57)		(2.89)				(6.19)		(5.47)	
Proportion vacant units	3.7263	**	-0.7657	†	8.8361	**	2.9721	**	-1.3333	**	-1.2681	**
	(6.71)		-(1.92)		(5.41)		(8.08)		-(4.48)		-(6.01)	
Proportion vacant units squared	-10.3035	**	3.3905	**	-26.5431	**	-6.0740	**	3.3381	**	4.3241	**
	-(5.19)		(5.51)		-(3.58)		-(4.80)		(7.22)		(13.99)	
Proportion vacant units cubed	9.9377	**			22.9412	**	6.7290	**				
	(5.45)				(3.07)		(6.00)					
Proportion aged 16 to 29	-128.1511	**	-397.2071	**	-587.5371	**	-151.7585	**	-269.1125	**	-47.2572	*
	-(5.00)		-(11.46)		-(7.46)		-(8.54)		-(9.05)		-(2.46)	
Ratio 30-64 to 16-29 year olds	-0.0152		-0.3001	**	-0.6286	**	-0.0373	**	-0.2662	**	-0.0286	**
	-(1.16)		-(9.68)		-(7.25)		-(3.29)		-(11.61)		-(3.51)	
Racial/ethnic heterogeneity	0.9703	**	2.0963	**	1.7906	**	0.5636	**	-0.2785	**	0.4503	**
	(9.56)		(18.85)		(10.72)		(8.14)		-(2.75)		(5.50)	
Proportion black	0.4457	**	2.1514	**	1.8801	**	0.6523	**	2.3450	**	0.4710	**
	(4.14)		(18.39)		(11.46)		(8.79)		(23.41)		(5.83)	
Proportion Latino	0.1952		0.2524		0.0717		0.4888	**	2.1935	**	1.1607	**
	(1.44)		(1.63)		(0.29)		(5.25)		(17.27)		(12.50)	
Proportion Native American	-5.5590	**	-3.9019	**	2.9492		-5.5517	**	-15.4675	**	-4.0126	**
	-(5.12)		-(3.15)		(1.37)		-(7.56)		-(18.27)		-(4.91)	
Proportion Asian	-0.2342		-0.6455	†	-0.1277		0.1730		1.4599	**	0.9271	**
	-(0.69)		-(1.96)		-(0.26)		(0.74)		(4.22)		(3.39)	
Proportion other race	5.6477	**	4.2342	**	-2.3372		5.6643	**	16.9983	**	4.0441	**
	(6.00)		(3.95)		-(1.34)		(8.83)		(23.24)		(5.75)	

Proportion immigrants	-2.0028	**	0.4305		-2.1411	**	-1.2618	**	-0.8116	**	-1.3997	**
	-(7.30)		(1.50)		-(4.37)		-(6.77)		-(3.12)		-(6.71)	
Concentrated disadvantage index	0.3876	**	0.1589	**	0.1476	**	0.1948	**	0.0637	**	0.1656	**
	(19.28)		(6.65)		(3.41)		(14.28)		(3.39)		(12.61)	
Residential stability index	0.0010		-0.0862	**	-0.0551	†	-0.1231	**	-0.1480	**	-0.2108	**
	(0.07)		-(5.36)		-(1.73)		-(13.50)		-(11.30)		-(21.03)	
South	0.0753	**	0.1587	**	0.0421		0.1742	**	-0.0250		-0.0322	
	(2.83)		(5.25)		(0.82)		(9.70)		-(0.97)		-(1.60)	
Intercept	-6.4607	**	-6.8411	**	-9.1705	**	-5.2945	**	-4.9726	**	-3.5656	**
	-(77.85)		-(48.42)		-(24.55)		-(84.24)		-(44.74)		-(61.39)	
Pseudo R-square	0.055		0.152		0.156		0.054		0.074		0.031	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). T-values in parentheses. Negative binomial regression models, including population size as offset variable. N = 8,000*

Figure 1. Moderating effect on robbery rate of macro-environment population on micro-environment population for linear model specification

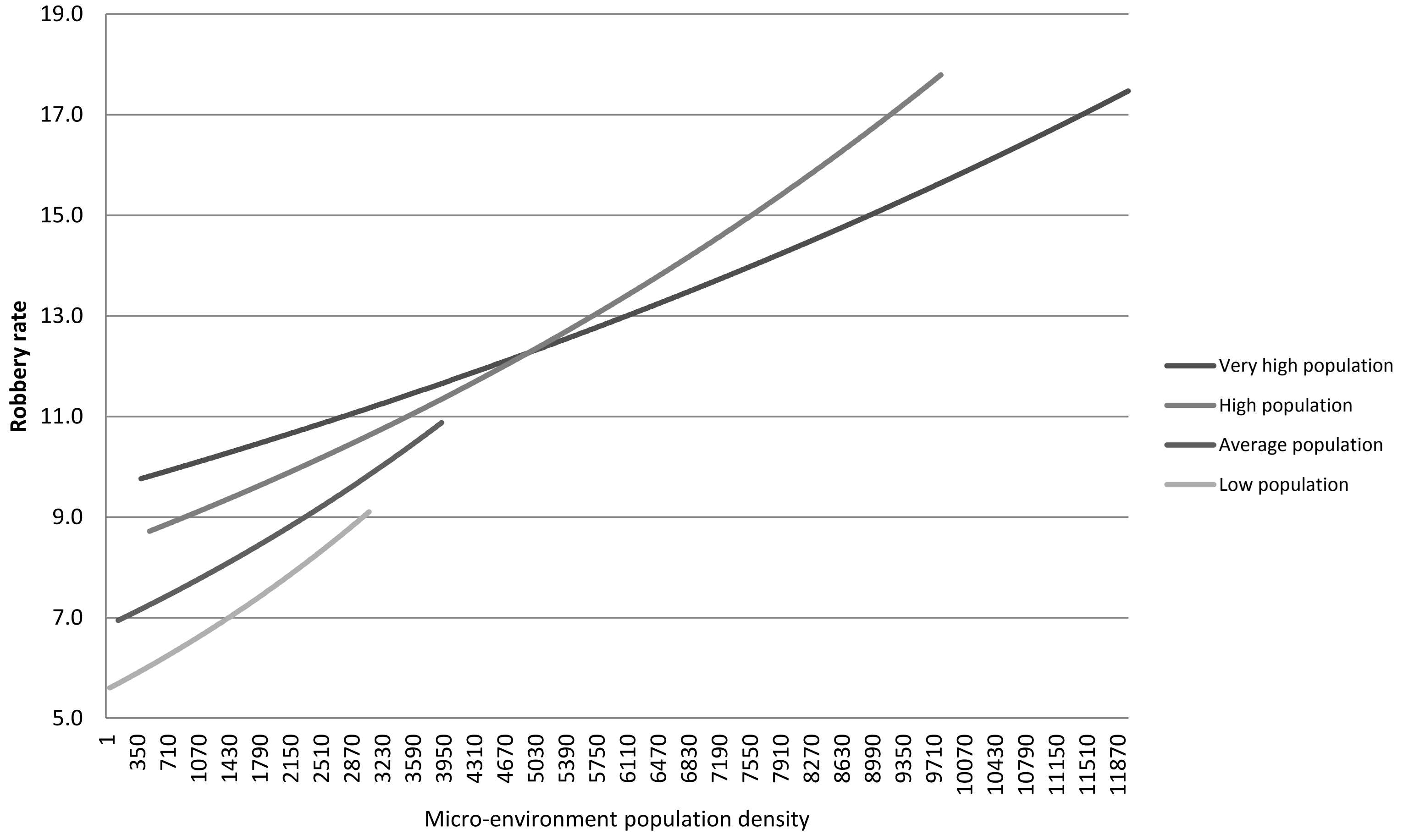


Figure 2. Moderating effect on robbery rate of macro-environment population on micro-environment population for nonlinear model specification

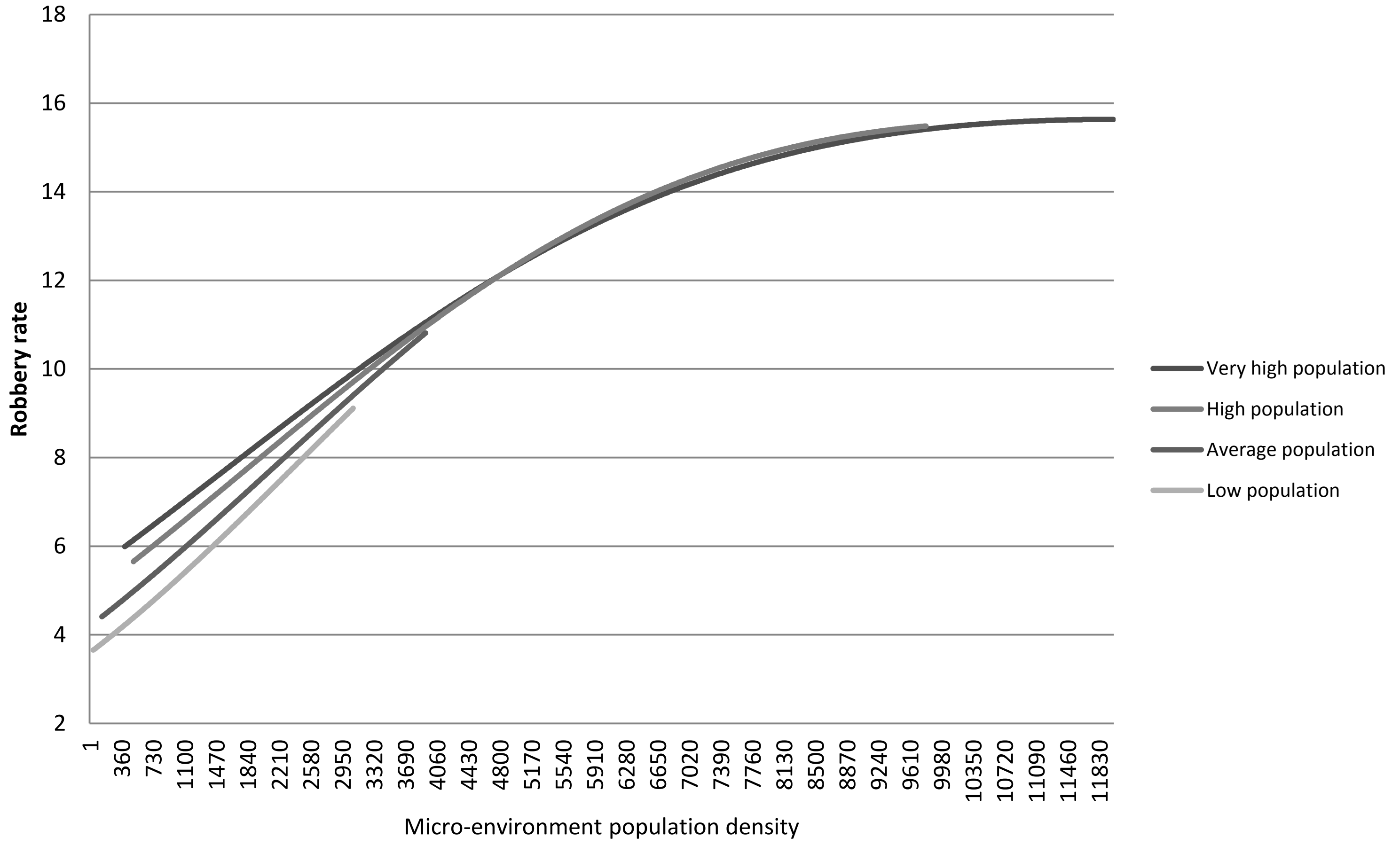


Figure 3. Moderating effect on aggravated assault rate of macro-environment population on micro-environment population for nonlinear model specification

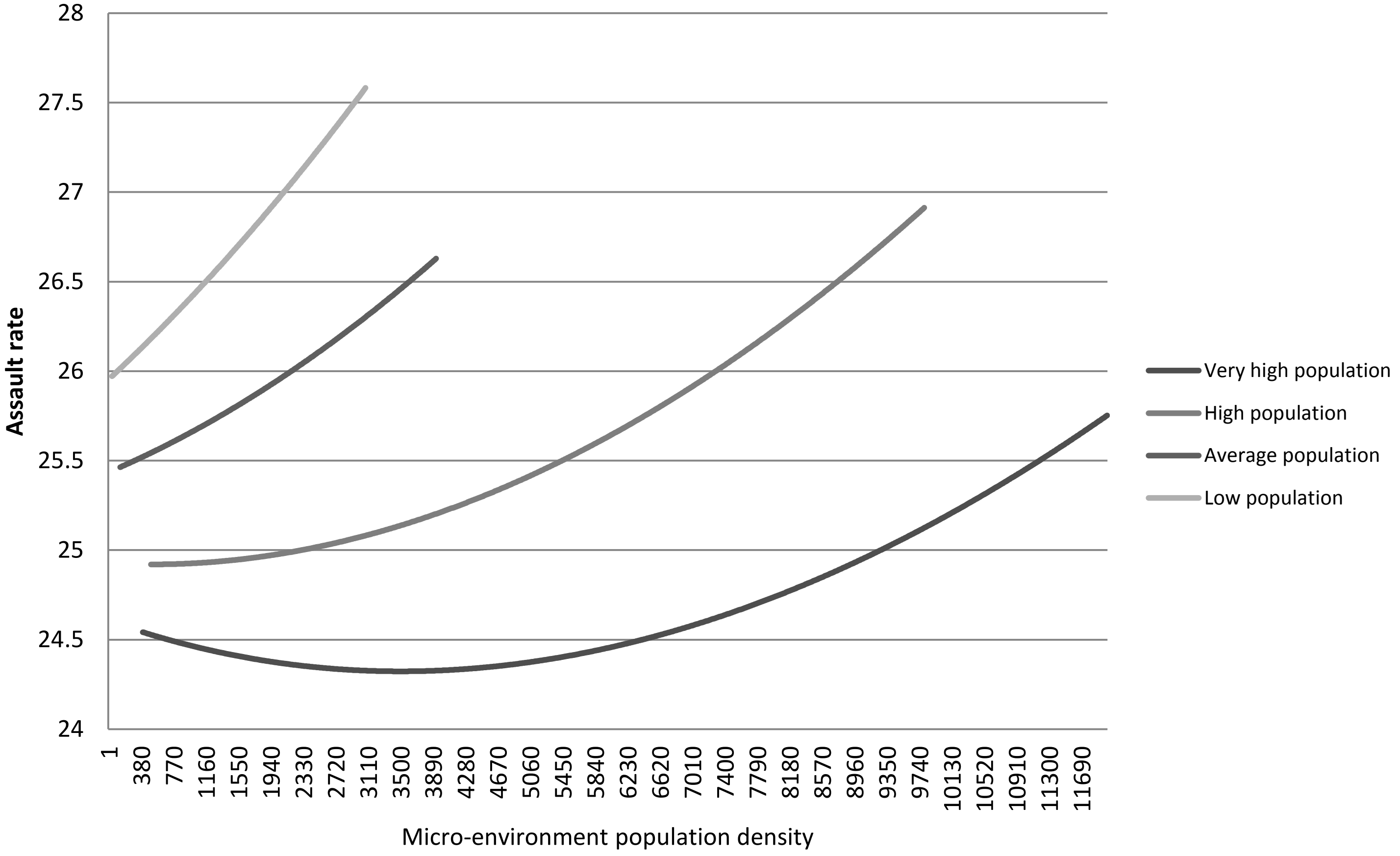
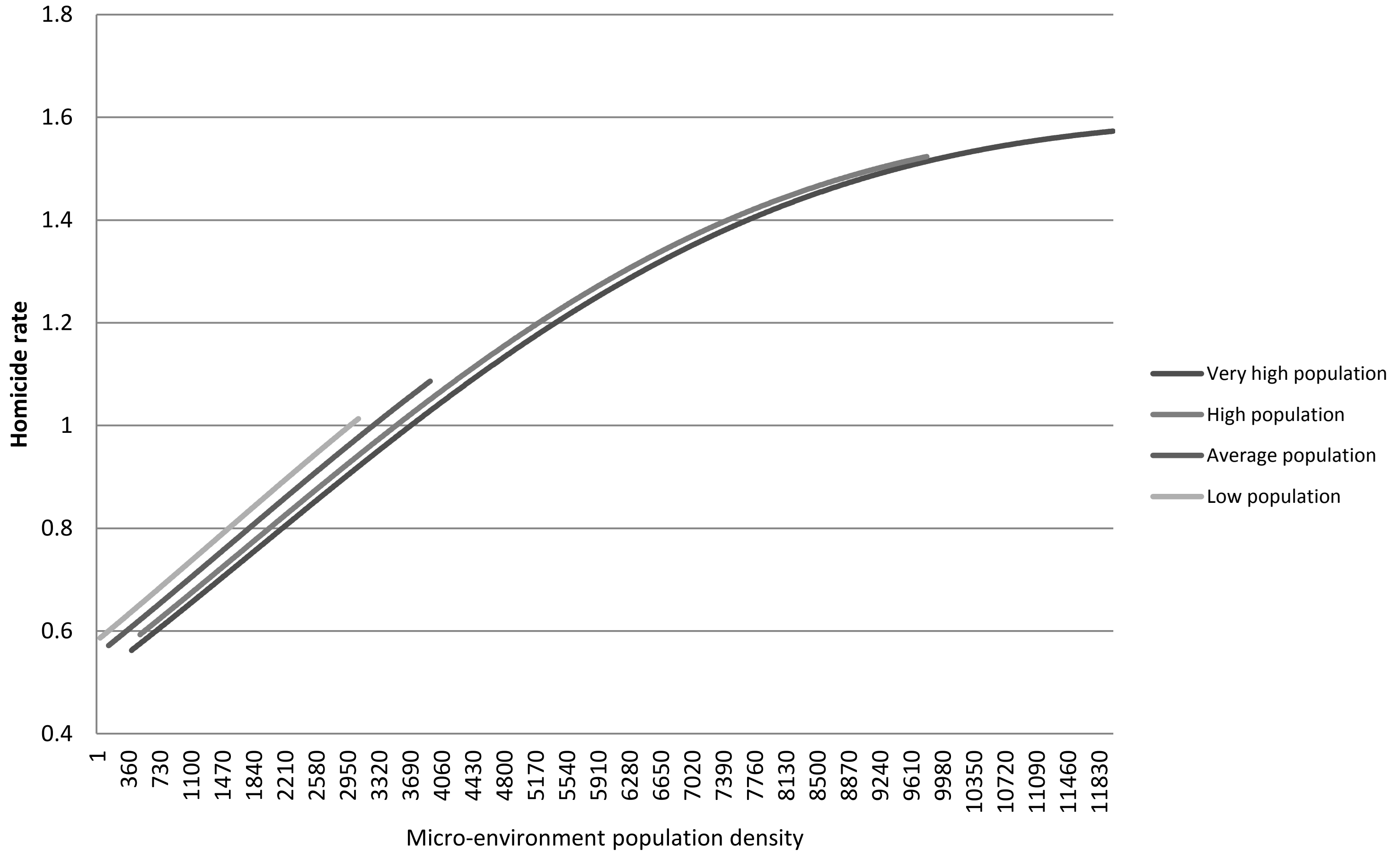


Figure 4. Moderating effect on homicide rate of macro-environment population on micro-environment population for nonlinear model specification



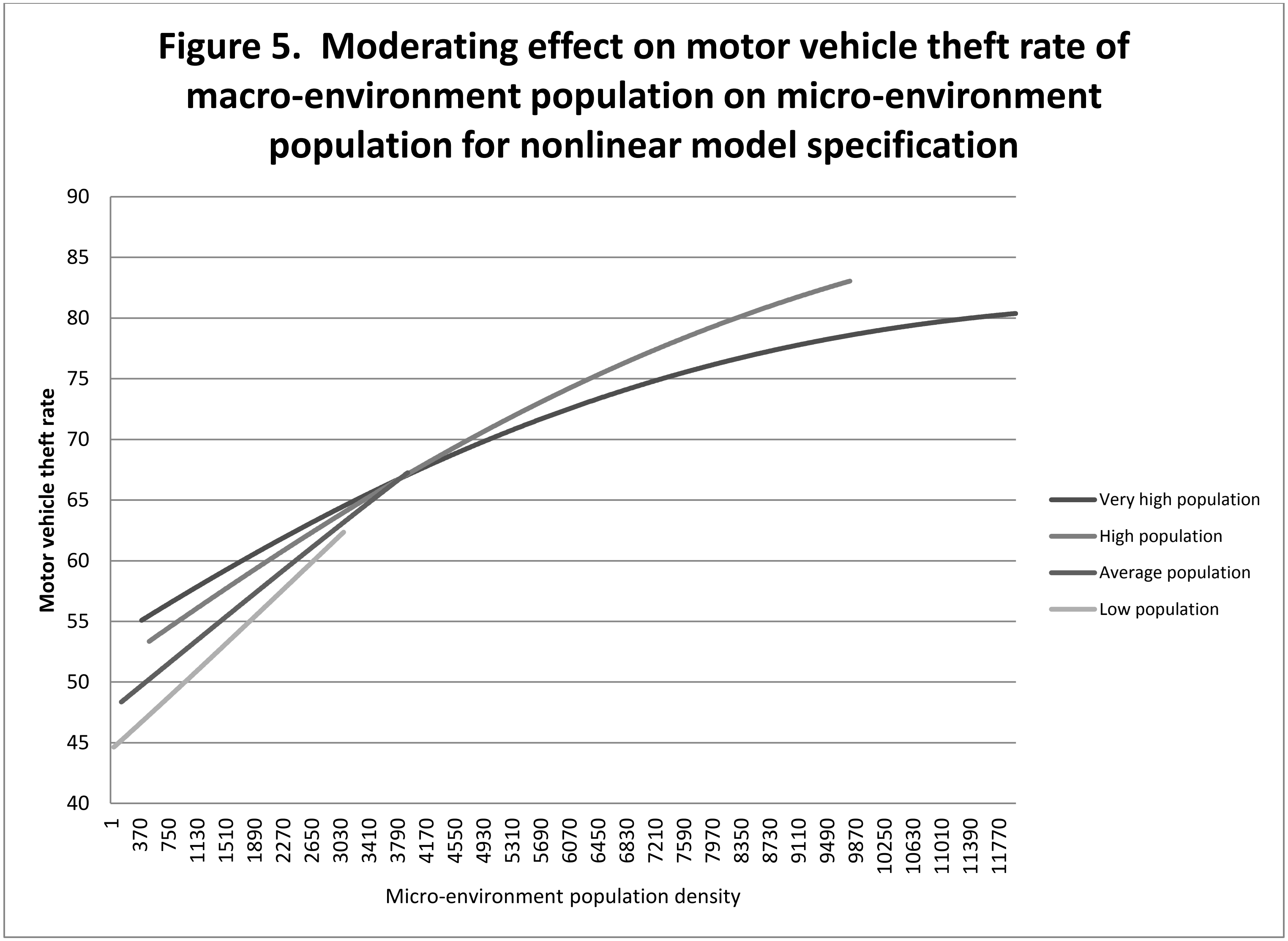


Figure 5. Moderating effect on motor vehicle theft rate of macro-environment population on micro-environment population for nonlinear model specification

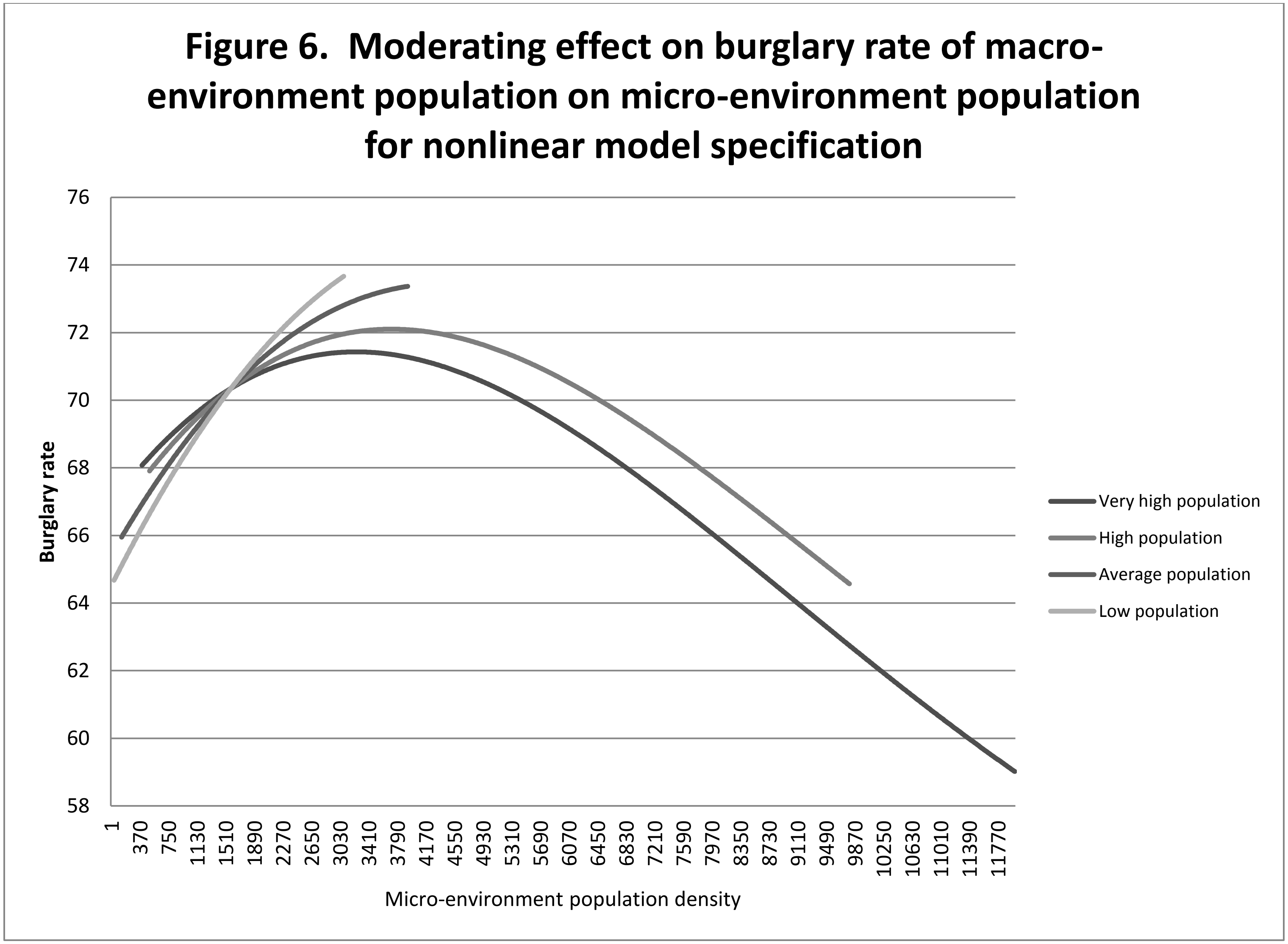


Figure 6. Moderating effect on burglary rate of macro-environment population on micro-environment population for nonlinear model specification
Burglary rate
76
74
72
70
68
66
64
62
60
58
1
370
750
1130
1510
1890
2270
2650
3030
3410
3790
4170
4550
4930
5310
5690
6070
6450
6830
7210
7590
7970
8350
8730
9110
9490
9870
10250
10630
11010
11390
11770
Micro-environment population density
Very high population
High population
Average population
Low population

Figure 7. Moderating effect on larceny rate of macro-environment population on micro-environment population for nonlinear model specification