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# Income Inequality, Race, and Place: Does the distribution of race and class within neighborhoods affect crime rates?


## Abstract

This study tests the effects of neighborhood inequality and heterogeneity on crime rates. Using a large sample of census tracts in 19 cities in 2000, the results provide strong evidence of the importance of racial/ethnic heterogeneity for the amount of all types of crime generally committed by strangers, even controlling for the effects of income inequality. Consistent with the predictions of several theories, greater overall inequality in the tract was associated with higher crime rates, particularly for violent types of crime. There was also strong evidence that *within racial/ethnic group* inequality increases crime rates: only the relative deprivation model predicted this association. An illuminating finding is that the effect of tract poverty on robbery and murder becomes non-significant when taking into account the level of income inequality, suggesting that past studies failing to take into account income inequality may have inappropriately attributed causal importance to poverty. This large sample also provides evidence that it is the presence of homeowners, rather than residential stability (as measured by the average length of residence), that significantly reduces the level of crime in neighborhoods.


***Keywords***: neighborhoods, crime, income inequality, racial/ethnic heterogeneity, fixed effects model, spatial effects

***Bio***

**John R. Hipp** is an Assistant Professor in the department of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *Social Forces*, *Social Problems*, *Mobilization, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

**Income Inequality, Race, and Place: Does the distribution of race and class within neighborhoods affect crime rates?**

A long line of theorizing in sociology and criminology has suggested that race and class play important roles in neighborhood crime rates: both in how race and class are distributed *across* neighborhoods as well as *within* neighborhoods. One consequence is considerable research testing whether the distribution of race and class *across* neighborhoods affects crime rates. Specifically, studies have tested how the distribution of economic resources across neighborhoods, as measured by income or poverty, or the distribution of racial/ethnic minority members across neighborhoods, as measured by the percent nonwhite, etc., affects neighborhood crime rates. There is less research, however, on the effect of the distribution of racial/ethnic groups *within* neighborhoods on crime, and almost no research testing whether the distribution of economic resources in neighborhoods affects crime.

The distribution of race and class *within* neighborhoods suggests focusing on the racial/ethnic heterogeneity and income inequality of neighborhoods, and how they affect the amount of crime. The lack of neighborhood-level research simultaneously considering both of these characteristics is surprising given that there is no shortage of theoretical reasons why we should expect such relationships. At least six key theories propose various relationships between ethnic heterogeneity or inequality and crime: relative deprivation (or strain) theory, social disorganization theory, social distance theory, consolidated inequality theory, group threat theory, and routine activities theory. Despite this plethora of theories, there are few empirical tests of them using neighborhood-level data. In part, this is due to the difficulty of obtaining such data.

As a result, the wave of research testing the importance of inequality and its interaction with racial/ethnic composition in the 1980's and early 1990's used data aggregated to units much larger than neighborhoods: generally, counties, large cities (often greater than 100,000 population), or even SMSA's. Perhaps because of the use of such large units of analysis, the findings were mixed for inequality and crime (Blau and Blau 1982; Chamlin and Cochran 1997; Kposowa, Breault, and Harrison 1995; Land, McCall, and Cohen 1990; Simpson 1985) and for inequality between races and crime (Blau and Blau 1982; Blau and Golden 1986; Golden and Messner 1987; Simpson 1985). Scholars thus proposed an alternative strategy of focusing on race-disaggregated crime rates—though still using large units of analysis—and found that inequality *within* race was a stronger predictor of crime types (Harer and Steffensmeier 1992; Shihadeh and Ousey 1996). However, given that the mechanisms explaining the relationship between race and class distributions and crime rates require interaction among residents, measuring the distribution of race and class for such a large unit of analysis arguably does not capture the construct of interest. For instance, two *cities* with equal amounts of ethnic heterogeneity can have *neighborhoods* that look considerably different depending on the distribution of the population in the community: the community with a high degree of ethnic segregation will have neighborhoods that are very homogeneous with one racial/ethnic group dominating (and thus the ethnic heterogeneity occurs *across* neighborhoods), while the community with minimal segregation will have a high degree of ethnic heterogeneity *within* the neighborhoods (and little difference in ethnic heterogeneity *across* neighborhoods). I therefore suggest that a more appropriate solution to the problem utilizes smaller units of analysis more closely approximating neighborhoods to test these theories.

While the paucity of empirical tests of these theories using neighborhood-level data is in part due to the difficulty of collecting neighborhood-level crime data, testing these theories present additional challenges: 1) some of these theories make similar predictions about expected empirical relationships (e.g., both social distance and relative deprivation theory predict a positive relationship between general inequality and crime rates), and 2) some also make predictions regarding interactions of ethnic heterogeneity and inequality (e.g., consolidated inequality predicts that inequality *across* racial/ethnic groups will increase crime, whereas relative deprivation predicts that inequality *within* racial/ethnic groups will increase crime). Thus, studies only testing racial/ethnic heterogeneity or one form of inequality may be missing important pieces of the puzzle. This points out a need to either explicitly test the mechanisms, or to simultaneously consider various theories.

Regarding the second challenge, given the conceptual and statistical interdependence between ethnic heterogeneity, general inequality, inequality *within* racial/ethnic groups, and inequality *across* racial/ethnic groups, testing only one of these relationships without taking into account the others raises the possibility of obtaining spurious results. For instance, I am aware of only two studies that have tested the relationship between neighborhood income inequality and crime rates: one study using 100 Seattle census tracts in 1980 found a positive relationship between income inequality and murder, but failed to find significant relationships with violent crime, assault, robbery, or rape (Crutchfield 1989). A second study using just 26 New York neighborhoods in 1981 failed to find a significant relationship with homicide (Messner and Tardiff 1986). However, given that neither of these studies simultaneously tested the effects of ethnic heterogeneity, the low statistical power of these tests due to sample size, and the limited ability to generalize the results due to focusing on just a single city at a single point in time leaves this question unanswered. And while numerous studies have tested the relationship between ethnic heterogeneity and neighborhood crime rates using cross-sectional data (Bellair 1997; Roncek and Maier 1991; Rountree and Warner 1999; Sampson and Groves 1989; Warner and Pierce 1993; Warner and Rountree 1997) their failure to take into account possible effects of inequality may have produced confounded results. Importantly, I am aware of *no* studies that have tested for inequality *within* racial/ethnic groups or inequality *across* racial/ethnic groups using data for small units of analysis.

In the next section I first introduce the competing theories being considered here and their posited mechanisms for each of the inequality and ethnic heterogeneity constructs. Following that I describe the data I will use in the tests. I then present results using data for census tracts in 19 different cities. I conclude by summarizing the results and pointing out implications.

## Theories of the relationship between inequality, ethnic heterogeneity and crime rates

I begin by considering the posited mechanisms of inequality and ethnic heterogeneity for six key theoretical models. Table 1 lists the theories, showing which constructs they are hypothesized to affect, and the geographic level at which they should work.

<<<Table 1 about here>>>

### *Routine activities theory*

The routine activities theory posits that a combination of potential targets (the wealthy), motivated offenders (the poor) and the absence of guardians combine to increase the amount of crime in a neighborhood (Cohen and Felson 1979). Thus, inequality will increase potential targets and motivated offenders, leading to higher rates of crime. The geographical location of inequality in this model is intermediate: while it need not be limited to the local neighborhood, it should be within the distance offenders are willing to travel and thus relatively contiguous neighborhoods.  Studies have suggested that a distance decay function explains how far perpetrators will travel (Rengert, Piquero, and Jones 1999), and one study found an average distance between 1 and 2.5 miles, depending on the crime type (Pyle 1974).  Given that the median census tract in 2000 was about 1.4 miles across (1.95 square miles), this suggests that the census tract should largely account for such effects.

*Relative deprivation theory*

The relative deprivation model, sometimes referred to as reference group theory (Jasso 1980; Merton 1968), or as strain theory (Agnew 1985; Agnew 1999) posits that perceived inequality gives rise to deviant behavior on the part of individuals.  That is, individuals compare themselves to others in their "reference group" and respond with deviant behavior if they feel they have an inequitable economic share.  A challenge to the relative deprivation literature in general is determining what constitutes an appropriate reference group.  If the appropriate reference group is co-residents of one's neighborhood, given that some work suggests that reference groups are limited to those with whom one comes into contact (Alwin 1987; Crutchfield 1989; Homans 1974), then greater inequality in the neighborhood should lead to more crime.  This criminal response might either be through property crimes aimed at "equalizing" the perceived injustice, or through violent crimes enacted through frustration.

A key feature of the reference group model is that individuals will only compare themselves with others to whom they feel similar (Merton 1968: 296).  While residents may compare themselves with all other members of their neighborhood, it is certainly plausible that individuals are more likely to compare themselves with others of *their own* racial/ethnic group when determining the appropriateness of their economic rewards.  This implies that large income disparities *within* a racial/ethnic group will increase the crime rate. If individuals are more likely to compare themselves to others who are similar to themselves and with whom they come into frequent contact (Lau 1989), inequality *within an ethnicity* within the neighborhood will increase the crime rate. Studies testing for the effects of within-race inequality using large units of analysis such as SMSA's are unable to test for such possible neighborhood effects (Harer and Steffensmeier 1992; LaFree and Drass 1996; Shihadeh and Ousey 1996). This prediction for the effect of within racial/ethnic group inequality on crime is unique to the relative deprivation theory, distinguishing it from the other theories considered here.

*Social distance and social disorganization theories*

The social distance and social disorganization models are tightly intertwined: the social distance model (Blau 1977; Blau 1987; McPherson and Ranger-Moore 1991; McPherson and Smith-Lovin 1987; Simmel 1955) focuses on explaining social interactions among individuals. In this model, the social statuses of individuals create social distance between them that then affects interactions. Thus, it focuses on explaining *who* interacts, whereas the social disorganization model focuses on the *consequences* of those interactions for neighborhood crime rates. The social disorganization model refers to the ability of a neighborhood to have common values that enable maintaining effective social control (Janowitz 1975; Reiss 1951: 196; Sampson and Groves 1989: 777). In this model, social networks, voluntary organizations, and institutions within the community help maintain the social order (Sampson and Groves 1989; Shaw and McKay 1942). Thus, social distance reduces interaction, which then impacts neighborhood crime rates.

Although the social disorganization model posits that anything reducing relations between neighbors will increase the crime rate, studies in this tradition have rarely considered the effect of relative inequality.  While the model suggests three key structural characteristics of neighborhoods lead to more crime—ethnic heterogeneity, residential instability, and poverty—only the first two are posited to affect crime by reducing interaction.  The social disorganization model posits that high poverty neighborhoods will have more crime due to their inability to obtain resources from the city to combat crime (Shaw and McKay 1942; Taylor 1996). However, high poverty in a neighborhood implies *less* social distance (in the extreme case, everyone has equally few economic resources).  Nonetheless, if the social distance model is correct in positing that inequality will reduce interaction (Blau 1977; Blau 1987), this should increase crime.  Despite this fact, the few social disorganization scholars who have taken into account income inequality frequently collapsed it into an index of "general economic distress" along with other measures including poverty.  But given that these two measures posit different mechanisms for increasing crime, it is incumbent upon researchers to test whether both indeed increase crime rates.

The social distance model also posits that higher levels of racial/ethnic heterogeneity limit the amount of interaction between residents, and the social disorganization model posits that the resulting lack of ties will lead to higher crime rates (Bellair 1997; Sampson and Groves 1989; Shaw and McKay 1942; Veysey and Messner 1999; Warner and Pierce 1993; Warner and Rountree 1997).  Indeed, numerous cross-sectional studies have found that areas with higher levels of ethnic heterogeneity have higher crime rates (Bellair 1997; Dahlback 1998; Krivo and Peterson 1996; Miethe, Hughes, and McDowall 1991; Rountree and Warner 1999; Sampson 1985; Sampson and Groves 1989; Sampson and Wilson; Skogan 1990; Smith and Jarjoura 1988; Veysey and Messner 1999; Warner and Rountree 1997).  However, it should be highlighted that these studies have failed to simultaneously take into account the level of inequality in these neighborhoods.

Besides making an explicit prediction regarding the effect of overall inequality, the social distance model also differs from the social disorganization model in that it predicts that the "intersecting parameters" of inequality and ethnic heterogeneity will increase the social distance between members of these groups (Blau 1977; Blau 1987). This suggests that inequality *between* racial/ethnic groups will reduce interaction and lead to higher rates of crime. Note that the social disorganization model does not explicitly propose such a hypothesis—and studies have thus not tested it—though it naturally follows if this social distance affects interaction in the neighborhood.

*Consolidated inequality theory*

The consolidated inequality theory (Blau and Blau 1982), is a variant of the relative deprivation model in that the combination of economic inequality and the ascribed status of race gives rise to particularly strong feelings of injustice and hence a violent deviant response. Thus, it focuses on inequality *between* races. Members of the minority group view this disadvantage as illegitimate and respond with diffuse forms of aggression such as criminal violence given their limited ability for political action (Golden and Messner 1987). Note that this model does not require that the inequality across racial/ethnic groups be spatially located in the neighborhood; however, for the response to be toward members of the dominant group it does require that such members at least be located in spatially contiguous neighborhoods. It is posited that this will lead to a *violent* response.

*Group threat theory*

The group threat model also focuses on inequality across races; however, it posits that when the economic differences between two groups *narrow* members of the *dominant* group will respond through violent behavior (Blumer 1958; Bobo and Hutchings 1996; Quillian 1995). The dominant group perceives the narrowing of the economic gap between the two groups as threatening, provoking a violent response. While this model does not necessarily imply that these economically improving minority members live in the same neighborhood as members of the dominant ethnic group, they clearly need to have at least a degree of spatial contiguity to allow for this hypothesized violent response. That is, members of a dominant group may not be aware or concerned about minority group members in distant neighborhoods with similar levels of income; however, an increasing number of minority members nearby at a similar level of income will be perceived as threatening.

*Summary*

In summary, we see that the considerable overlap in the predictions of these theories provides a challenge for disentangling these processes. To test the proposed mechanisms of the theories outlined here requires data for the neighborhoods within communities. While past neighborhood studies often use data only for a single city for such tests, I address this by using data from 19 cities. As well, studies rarely test these various hypothesized relationships simultaneously; I address this limitation here. I directly test the effects of the various forms of income inequality and heterogeneity within neighborhoods on local crime rates.

## Data and Methods

### *Data*

This study utilizes crime data for census tracts in 19 cities in year 2000, as listed in Table A1 in the appendix. These cities were not selected randomly, but rather are a convenience sample of cities with available crime data. Therefore, I am not generalizing to this population of cities, but rather I am viewing the differences in tracts within particular cities by conditioning out the differences across cities, as described in the methods section. An advantage of using census tracts is that past studies have frequently used them to proxy for neighborhoods, they contain a mean of about 4,300 residents in 2000 (with 95% of the tracts containing between about 1,400 and 8,000 persons), and they were initially constructed by the Census Bureau to be relatively homogeneous neighborhoods (Green and Truesdell 1937; Lander 1954). However, not all of my data are available for tracts. For instance, some of the crime data are only available for police beats, which on occasion may partially overlap more than one census tract. Likewise, some of my predictor variables are not aggregated to census tracts, also necessitating re-collapsing these data to census tracts. I assumed homogeneity across physical areas in apportioning these data to census tracts.[1]

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[1] To place a per capita measure into common units, I take into account the proportion of the tract's population contained within each zip code:

(2) $$X_i = \frac{1}{J}\sum_{j=1}^{J} X_j (P_{ji} / P_i)$$

where $X_i$ represents the per capita measure of the variable of interest in the tract which we are estimating, $X_j$ represents the per capita measure of the variable of interest in the j=1 to J zip codes the tract overlaps, $P_{ji}$ represents the population of zip code *j* contained within tract *i*, and $P_i$ represents the population of tract *i*. To calculate the proportion of a tract's population in a zip code I used the MABLE/GEOCORR website at the University of Missouri that places zip codes into tracts based on population (http://mcdc2.missouri.edu/websas/geocorr2k.html). Since the majority of the tracts contained crime data in 1990 tracts (rather than 2000 tracts), I placed all of the data in 1990 tracts. Since most tracts split over time (as populations increase) placing the data into 1990 tracts simply requires collapsing the demographic characteristics of two tracts in year 2000 together. This approach accurately represents the year 2000 demographic characteristics and crime rate of the tract boundaries in 1990; while this may muddy some relationships by yielding larger, possibly more heterogeneous tracts, I suggest this approach is more desirable

*Dependent Variables*

The dependent variables in the analyses are based on the crime reports officially coded and reported by the police departments in the cities of the study, aggregated to census tracts. I estimated models using five types of crime separately: aggravated assault, murder, robbery, burglary, and motor vehicle theft. These five vary along the dimensions of property/violent crime and personal/public (depending whether the crime generally occurs between people who know each other or between strangers). Aggravated assault is a violent crime that generally occurs between strangers; murder is a violent crime that often occurs between people who know each other; robbery is a combination of both violent and property crime (since it involves the threat or use of force, and the goal of obtaining something of value) that occurs between strangers (Cohen, Felson, and Land 1980); while burglary and motor vehicle theft are property crimes that generally occur between strangers. This strategy allows testing whether these income inequality and ethnic heterogeneity measures behave differently for these different forms of crime. For each of these crime measures I calculated the number of crime events that occurred per 100,000 population and natural log transformed these variables to reduce the skew and minimize the possibility of outliers.

*Independent Variables: income inequality and heterogeneity*

My key predictor variables are the various constructs of income inequality and heterogeneity discussed above. These data are available from the U.S. census for 2000. I

than placing the data into year 2000 tracts. The latter approach requires the additional assumption that the crime rate is uniform across both 2000 tracts: although the uniformity assumption is not a strong one (and, indeed, I am compelled to employ it when collapsing areas such as zip codes into tracts), I prefer to avoid it when possible. Additionally, I estimated the models placing the data into 2000 tracts and the results were broadly similar to those presented here.

constructed a measure of the racial/ethnic heterogeneity in the tract by using a Herfindahl index (Gibbs and Martin 1962: 670) of five racial/ethnic groupings,[2] which takes the following form:

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

where G represents the proportion of the population of ethnic group *j* out of *J* ethnic groups. Subtracting from 1 makes this a measure of heterogeneity.

I constructed three types of income inequality measures: within-group income inequality, between-group income inequality, and overall income inequality. Note that the first two approximately sum to the third measure, precluding simultaneously estimating these three effects.

To measure overall income inequality, I utilized the Gini coefficient here, given the arguments of Yitzhaki (1979) and Pedersen (2004) that the Gini coefficient contains the desirable property of capturing relative deprivation when measured on a population in which such relative comparison is appropriate. The Gini coefficient is defined as:

(2) $$G = \frac{2}{\mu n^2} \sum_{i=1}^{n} i x_i - \frac{n+1}{n}$$

where $x_i$ is the household's income for 1999 as reported in the 2000 census, $\mu$ is the mean income value, the households are arranged in ascending values indexed by *i*, up to *n* households in the sample. Since the data are binned (as income is coded into various ranges of values), I take this into account by utilizing the Pareto-linear procedure (Aigner and Goldberger 1970;

[2] These groups are white, African-American, Latino, Asian, and other races.

Kakwani and Podder 1976), which Nielsen and Alderson (1997) adapted from the U.S. Census Bureau strategy (for further details of this algorithm, see Nielsen and Alderson 1997).[3]

Second, I included a measure of the income inequality *between* racial/ethnic groups. I first calculated the average family income of each racial/ethnic group and then calculated the ratio of: 1) white to African-American income, log transformed, and 2) white to Latino income, log transformed. Log transforming after calculating this proportion reduces the possibility of outliers. Higher values indicate tracts in which white income is much higher than that of minority members, thus likely increasing perceived injustice.

Third, I included a measure of within-group income inequality. I constructed this as the average income inequality of the racial/ethnic groups (weighted by the population size of each group). That is, I: 1) calculated the Gini coefficient for family income for each group, 2) multiplied each of these values by the proportion of the tract comprised by the group, 3) summed these values.

*Independent variables: Tract Clustering of Race and Class*

I also included measures of the composition of race and class in these tracts. Since the social disorganization theory posits that neighborhoods with high levels of poverty will lack the resources to combat crime when it appears in the neighborhood, I measured the economic resources of a neighborhood by including: 1) the average family income in the tract, and 2) the percent of the population at or below 125% of the poverty rate. To capture effects of racial composition (beyond the effect of ethnic heterogeneity), I included the percent African-

[3] I use the prln04.exe program provided by Francois Nielsen at the following website: http://www.unc.edu/~nielsen/data/data.htm.

American, percent Latino, percent Asian, and percent other races (with percent white as the reference category).

*Independent variables: additional controls*

I included several additional measures to minimize the possibility of spurious results. Since homeowners have a greater investment in the neighborhood and hence likely engage in more crime-reducing behavior, I calculated the percentage of tract households who own their residence. To account for residential stability, I included the average length of residence in the tract. Since broken families are posited to reduce crime-inhibiting activities I calculated the proportion of divorced families in the tract. To capture increased crime possibilities by abandoned buildings (Krivo and Peterson 1996; Roncek 1981; Roncek and Maier 1991), I included the percentage of residential units that are occupied. While there are conflicting views whether higher unemployment increases crime by providing more potential offenders or decreases it by providing more guardians (since these individuals are at home), I test this effect here by including the percent unemployed in the tract.

Finally since certain types of retail outlets may affect crime rates, I included two measures to capture this. Both of these measures come from the 1997 Economic census. Numerous recent cross-sectional studies have found a positive relationship between the crime rate in a neighborhood and the presence of bars and liquor stores nearby (Alaniz, Cartmill, and Parker 1998; Gorman, Speer, Gruenewald, and Labouvie 2001; Gyimah-Brempong 2001; Lipton and Gruenewald 2002; Nielsen and Martinez 2003; Ouimet 2000; Peterson, Krivo, and Harris 2000; Roncek and Maier 1991; Smith, Frazee, and Davison 2000). I thus included a measure of the number of employees of bars and liquor stores per 10,000 population in the tract.[4] I also included a measure of the number of retail employees per 10,000 population in the tract, as the presence of retail establishments being patronized should increase criminal opportunities; indeed, cross-sectional studies have found such an effect (Ouimet 2000; Smith, Frazee, and Davison 2000). The summary statistics for the variables used in the analyses are presented in Table 2.

<<<Table 2 about here>>>

**Methodology**

If there were no spatial effects to take into account, these cross-sectional models could be estimated using ordinary least squares regression and fixed effects for cities. However, a complication for analyses of neighborhoods in cities is that neighborhoods are adjacent to one another, raising the possibility of spatial autocorrelation or spatial lag. To assess possible spatial effects requires determining what constitutes "close" neighborhoods. Given that past studies have suggested a distance decay function for offenders (Rengert, Piquero, and Jones 1999), with an average distance traveled between 1 to 2.5 miles (Pyle 1974), and that the median census tract in 2000 was about 1.4 miles across (1.95 square miles), I adopted a distance decay function with a cutoff at two miles (beyond which the neighborhoods have a value of zero in the W matrix) in measuring the distance of surrounding neighborhoods from the focal neighborhood. This resulting weight matrix (W) was then row-standardized.

[4] I used the number of employees rather than the number of establishments since this measure likely provides a more accurate depiction of the impact of such businesses on the neighborhood. That is, it is not the simple presence of these establishments that is posited to increase crime, but rather the number of people they attract (both patrons, and possible perpetrators). Since establishments with more business will have a greater number of employees, the number of employees thus better captures this effect than a simple count of the number of establishments. An alternative approach suggested by a reviewer would not adjust this measure of employees for the population size of the tract. I prefer the per capita measure since the increase in crime possibly caused by such activity should be in proportion to the relative size of the neighborhood. Nonetheless, it is reassuring to note that when estimating parallel models in which I substituted a measure of employees instead of employees per capita, the results were very similar to those presented here. Most importantly, there were no substantive differences for the inequality and heterogeneity measures.

I tested for spatial autocorrelation and spatial lag effects using Lagrange Multiplier (LM) tests devised by Anselin et. al. (1996) that are "robust" to testing each of these possible spatial effects independently of the other, and found overwhelming evidence pointing to a spatial lag effect.[5] Given a spatial lag effect, the model estimated is:

$$Y = \rho WY + \beta_1 IE + \beta_2 EH + \Gamma X + \beta_3 C + \zeta \quad (3)$$

where Y is crime in the tract of interest, $\rho$ represents the spatial autoregressive parameter, W is the chosen spatial contiguity matrix, WY represents the spatially lagged dependent variable, $\beta_1$ is the effect of income inequality (IE) on the crime rate, $\beta_2$ is the effect of ethnic heterogeneity (EH) on the crime rate, $\Gamma$ is a vector of parameters showing the effects of various measures in the X matrix, C is a vector of $J$-1 indicator variables for $J$ cities in the sample which have a $\beta_3$ effect on the crime rate, and $\zeta$ is a vector of disturbances. Since I only have 19 cities, and they are not randomly sampled, I do not estimate a multilevel model, but instead account for this clustering with the dummy variables for the cities. Thus, I am estimating a fixed effects model conditioning on cities.

Because a maximum likelihood (ML) estimator (Anselin 1988) for a spatial lag model is computationally intensive for a sample of this size given the size of the W matrix, I used a two-stage least squares (2SLS) estimator suggested by Anselin (1988) and modified by Land and Deane (1992).[6] I used as instruments WX variables that are created by multiplying the matrix of

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[5] All analyses were performed using Stata 8.0. To test for possible spatial effects, I used the set of ado files written by Maurizio Pisati at the University of Milano Bicocca, Italy. I performed these tests on each of the cities separately, since the spatial weights matrix grows exponentially as the sample size increases. With a sample of over 3,000 tracts, this implies a matrix with over 9 million rows and columns. Testing each of the cities separately is an appropriate strategy given that there is no reason to suspect spatial effects *across* cities. For the various crime types, nearly all of the cities showed significant evidence of spatial lag effects, while there was little evidence of spatial autocorrelation.

[6] Land and Deane (1992: 221) suggested that the 2SLS strategy is "much more computationally efficient than the ML estimator and yields numerical estimates of comparable statistical efficiency." They argued that their approach

X variables by the weight matrix (W). This approach was suggested by Anselin (1995), and employed by Morenoff (2003) in a study of Chicago neighborhoods.[7] In all models presented, I assessed possible multicollinearity with variance inflation values and detected no problems.

**Results**

*Models not including the income inequality measures*

I begin by viewing the results of the baseline models (not including the measures of income inequality) for these crime types. The results for the economic and racial/ethnic composition of the neighborhood are generally consistent with past studies viewing cross-sectional effects of neighborhoods, as seen in Table 3. Tracts with a higher proportion of residents at or below 125 percent of the poverty level have higher rates of the violent types of crime (assault, robbery and murder), but are not significantly different for the two types of property crime (burglary and motor vehicle theft). These effects for tract poverty should be kept in mind when we turn next to the models including income inequality.

<<<Table 3 about here>>>

The results for the racial/ethnic composition and distribution are generally as expected: consistent with past research, neighborhoods with a higher percentage of African-Americans

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will perform relatively well in large samples when good exogenous identifying variables are available, and illustrated a particular example in which the estimates obtained both through 2SLS and ML were very similar.

[7] The two-stage least squares estimator was generally well-behaved: for instance, in the violent crime model the R-square for the first stage regression ranged from .56 in the burglary models to .83 in the robbery models, suggesting that I am getting a rather reasonable estimate of the $\hat{y}^*$ that I am including in the structural model. Also important is that these instruments help to uniquely explain this $\hat{y}^*$ from the X variables in the structural equation: I tested for collinearity by regressing this $\hat{y}^*$ on the X variables in the structural equation. While I found relatively high R-squares near the suggested cutoff value of .90, the fact that the pattern of coefficients in the 2SLS structural model was generally similar to those from an OLS model failing to take into account spatial effects, as well as the lack of inflated standard errors compared to the OLS model, suggests that these instruments are doing a reasonable job of creating an independent estimate of the spatial effects.

have higher rates of violent types of crime (controlling for the other measures in the model). And neighborhoods with a higher percentage of Latinos have similarly higher rates of the violent crime types. Consistent with the social distance model, we see that neighborhoods with higher levels of racial/ethnic heterogeneity have higher levels of both violent and property crime types, even controlling for the racial composition of the neighborhood and these other predictors of neighborhood crime. A one standard deviation increase in the amount of racial/ethnic heterogeneity in the tract is associated with between 12 and 15 percent increase in four of these crime types. The lone exception is for murder rates: we see no effect of racial/ethnic heterogeneity for this violent crime that often occurs between individuals who know each other. Instead, murder is largely driven by a greater composition of racial/ethnic minority members in the neighborhood.

To get an idea of the magnitude of these effects, I plotted the marginal effect on the various types of crime for different racial/ethnic combinations in tracts. In this exercise, I simulated the effect on crime types for seven hypothetical racial/ethnic compositions in neighborhoods: 1) 100% white, 2) 100% Latino, 3) 100% African-American, 4) half white and half Latino, 5) half white and half African-American, 6) half Latino and half African-American, 7) 1/3 each of these groups (high heterogeneity). All other variables are held to their mean values. Figure 1A illustrates that the presence of minority members is not enough to explain aggravated assault rates: while a neighborhood that is all white has the lowest assault rate, a neighborhood with a mix of racial/ethnic groups actually has a slightly higher assault rate than does an all-Latino or all-African-American tract. The pattern of racial composition effects is similar for motor vehicle theft (results not shown). This effect of mixing groups is even more dramatic for robbery rates, as seen in Figure 1B. Again, neighborhoods with a mixture of racial/ethnic groups—in this instance, those with the highest level of heterogeneity—have the highest robbery rates. The pattern is similar for the property crime of burglary, though the presence of Latinos has a much smaller effect (results not shown).[8]

<<<Figures 1A and 1B about here>>>

I briefly note that the control variables generally work as expected. Consistent with past research, neighborhoods with more bar and liquor store employees have higher rates of all the types of crime measured here. There is also evidence consistent with the hypothesis that retail shops will increase the rate of crime in neighborhoods by increasing criminal opportunities. And the presence of more broken families leads to higher rates of all of these crime types, though the weakest effect is for murder. Neighborhoods with a higher proportion of occupied units or a higher proportion of homeowners generally have lower rates of crime. The presence of homeowners have their weakest effect for murder rates, suggesting that homeowners have less ability to engage in activities that reduce this type of crime often occurring between individuals who know one another. It is notable that neighborhoods with higher residential stability actually have *higher* rates of crime, inconsistent with the social disorganization view that such neighborhoods will have less crime. While there is a bivariate negative relationship between residential stability and crime rates, this disappears when accounting for the percentage of homeowners. These findings, along with the exit, voice, loyalty literature (Lyons and Lowery 1986; Lyons and Lowery 1989) and community of limited liability literature (Janowitz 1952) arguing that homeowners have a particularly strong motivation to get involved in crime fighting behavior beyond their effect on residential stability, suggest the inappropriateness of combining these two variables into a single construct of residential stability.

[8] The Figures for the effect of racial composition for the other crime types are available at www.XXX (suppressed).

*Models including income inequality measures*

I next explore whether neighborhoods characterized by higher rates of income inequality—either total, within racial/ethnic groups, or between racial/ethnic groups—have higher rates of crime by adding these measures to the previous models. One key finding to highlight is that across all of these crime outcomes (in Tables 4 and 5), the effect of racial/ethnic heterogeneity is largely unaffected by the inclusion of measures of income inequality. This suggests that the social distance created by racial/ethnic heterogeneity is consistently related to higher levels of crime in neighborhoods, even controlling for the level of income inequality.

Focusing first on the models with the violent crime types as outcomes, model 1 of Table 4 suggests that overall income inequality is positively associated with aggravated assault rates, even controlling for the economic resources of neighborhoods and their racial/ethnic composition and distribution. Model 2 substitutes the measure of income inequality *within* racial/ethnic groups for this overall measure of income inequality and comes to a similar conclusion: neighborhoods with higher rates of income inequality within racial/ethnic groups have higher rates of aggravated assault. On the other hand, these cross-sectional models show little effect for income inequality *across* racial/ethnic groups in model 3. And the story is similar for robbery and murder: higher levels of overall inequality in the tract increase the robbery rate (model 4) and the murder rate (model 7). Likewise, higher levels of income inequality *within* racial/ethnic groups also increase the robbery rate (model 5) and the murder rate (model 8). . Again, income inequality *across* racial/ethnic groups shows no relationship with either robbery or murder rates.

>>>Table 4 about here>>>

The models for the two property crimes show weaker effects for the income inequality measures. While overall income inequality and within-race income inequality are significantly positively related to burglary rates in models 1 and 2 in Table 6, these effects are weaker than the violent crime types. And the effects are even weaker for motor vehicle theft—while the direction of the effects is still positive, they are not significant in models 4 and 5. These findings suggest that income inequality has its strongest effect on violent crimes, rather than property crimes.

>>>Table 5 about here>>>

While the findings consistently show that overall inequality and within group inequality increase the amount of crime in tracts—particularly violent crime—which has a stronger effect? While including both measures in the model might help adjudicate between these two constructs, this is not feasible in this sample given the high correlation (.91) between these two measures. Including both simultaneously in the model resulted in unacceptably high variance inflation values: the values approached 10, suggesting a higher degree of multiple correlation between the inequality measures and the other predictors compared to the overall variance explained of the model (Maddala 1977: 185). Thus, we do not have enough information in this sample to definitively adjudicate between these two forms of inequality. Nonetheless, it is notable that for each of these crime types in Tables 4 and 5, increasing the amount of within racial group inequality has a slightly stronger effect than overall inequality. For instance, whereas a one standard deviation increase in within racial group inequality increases the aggravated assault rate 8.7%, the robbery rate 10.3%, the murder rate 12.3%, and the burglary rate 6%, the similar values for a one standard deviation increase in overall inequality are 7.3%, 9.3%, 10.3%, and 5.1%. Given that these values are consistently larger for within racial group inequality suggest that it may be particularly important for fostering these types of violent crime, though additional samples will be necessary for a more definitive conclusion.

*Alternative specifications*

While no effect was found for the inequality across racial/ethnic groups in this cross-sectional analysis, Balkwell (1990) argued that a limitation of such measures is their inability to take into account the relative sizes of the two racial/ethnic groups and therefore created a measure multiplicatively combining the racial composition and relative income. I instead prefer a strategy that includes measures of both ethnic heterogeneity and income inequality between racial/ethnic groups, as well as a term measuring their interaction. This strategy avoids conflating racial/ethnic heterogeneity and racial/ethnic inequality. When I included such an interaction for all these analyses, I still found no significant effects for the main effects of inequality across race/ethnicity, and for the interaction term (results available upon request). This emphasizes that racial/ethnic heterogeneity alone explained the higher crime rates in these neighborhoods.

A key point to highlight in these models is that when taking into account income inequality, the effect of poverty is greatly reduced and frequently falls to non-significance. For instance, the significant effect of poverty on robbery and murder is reduced to non-significance when taking into account tract income inequality. This suggests that the causal effect explaining these relationships may be income inequality (either overall or within race income inequality) rather than the level of poverty in the neighborhood. Only in the aggravated assault model does tract poverty remain a significant predictor when taking into account income inequality. And this pattern of results is not simply an artifact of including two measures of economic resources in the model (average household income and percent in poverty): similar effects were found for the poverty measure when estimating ancillary models that did not include the average household income measure (results available upon request).

While the results here consistently suggested that residential stability is associated with *higher* rates of crime (with the exception of the nonsignificant finding for the murder model), an alternative possibility is that the hypothesized protective effect of residential stability may not exist in high poverty neighborhoods (Warner and Pierce 1993; Warner and Rountree 1997). To test this possibility, I re-estimated these models along with an interaction between residential stability and the poverty rate since Warner and Rountree (1997) found that residential stability had essentially no effect on burglary or aggravated assault rates in high poverty neighborhoods but had a negative effect in low poverty neighborhoods. The findings with this large dataset are illuminating: whereas there was no significant effect found for the interaction between residential stability and poverty in the two property crime models, there was a positive effect of this interaction for the three violent crime types in models that *did not take into account income inequality* (results available upon request). In these models, I found that whereas increasing residential stability is associated with higher robbery and aggravated assault rates even in low poverty tracts, this relationship is even stronger in high poverty tracts. However, including a measure of total income inequality or within race income inequality reduced this interaction to nonsignificance in these two models. Only in the model with murder as an outcome did the results parallel those found in Warner and Rountree (1997). These findings reinforce the notion that inequality may be a more important causal mechanism than is poverty.

**Conclusion**

Several theories suggest that the distribution of race and class in neighborhoods will affect crime rates. Although numerous studies have looked at the relationship between race and class compositions and neighborhood crime rates, almost no studies have tested whether the distribution of economic resources *within* neighborhoods affects the crime rate. Studies instead have generally been limited to large units of analysis—such as SMSA's or large cities—to test the relationship between various types of income inequality and crime rates. But given that most theoretical mechanisms posit that this inequality should work through the social interaction of residents, testing it at the neighborhood-level is arguably most appropriate. The results of this study thus fill an important lacuna.

Another important contribution of this study is testing these hypothesized relationships on a large sample of census tracts located in 19 different cities, rather than focusing on neighborhoods within a single city as is common in much neighborhood research. As a result, the results of this study generalize considerably more than studies focusing on a single city. The large sample size of this study also provided enough statistical power to test these relationships. Note that studies of a single city run the risk of type 2 errors: it is unclear whether a null finding in such studies represents the absence of a relationship or simply a lack of statistical power to detect the relationship.

Given that at least six different theories propose that income inequality, ethnic heterogeneity, or some combination of these, will increase neighborhood crime rates it is incumbent upon researchers to simultaneously consider these inter-related constructs in tests. So what have we discovered regarding the six theories tested here?

First, we saw strong support for the relative deprivation theory. As is well known, a key task when operationalizing this theory is accurately defining the reference group used by the individual in such injustice determinations. One approach defines the reference group as all other members of the neighborhood: we saw evidence that the overall income inequality was positively associated with various crime types. A second approach defines the reference group as consisting of members of the neighborhood of *the same racial/ethnic group* as the individual. The findings here were even stronger for this specification, as income inequality *within* racial/ethnic groups was associated with higher rates of violent crime types. This is an important finding, as the relative deprivation theory is the only one of the theories considered here positing that income inequality within racial/ethnic groups will be associated with higher crime rates.

The social distance model saw fairly strong support. We saw strong support for the hypothesis that the social distance created by ethnic heterogeneity will reduce interaction and lead to higher levels of crime: ethnic heterogeneity consistently showed a positive relationship for crimes generally committed by strangers. We also saw evidence that overall income inequality increases crime rates. But while the social distance model predicts that income inequality across racial ethnic groups will affect crime rates by reducing social interaction that would otherwise allow the neighborhood to engage in crime prevention activities, we saw no support for this proposition in these cross-sectional models.

Although the social disorganization theory is an important mechanism for explaining how the social distance model works—as it argues that the social interactions among residents that are impacted by racial/ethnic heterogeneity can help foster a watchful environment that will reduce crime—other predictions of the social disorganization model did not fare particularly well. For instance, there was virtually no evidence in this sample that higher residential stability leads to lower crime rates, a key prediction of the social disorganization theory. Instead, it appears that it is the presence of homeowners—and their greater investment in the neighborhood leading to more involvement in crime-fighting behaviors—that results in lower rates of crimes between strangers. And while the social disorganization theory predicts that neighborhoods with higher levels of poverty will have more crime, the evidence for this was not particularly strong. Higher poverty levels in tracts were only associated with higher aggravated assault rates. There was no evidence in this particularly large sample that higher levels of poverty are associated with higher levels of the two property crime types—burglary and motor vehicle theft. Additionally, the positive association between poverty and both robbery and murder rates was reduced to nonsignificance when including the income inequality measures. This is an important finding suggesting that the causal mechanism sometimes specified for why higher poverty rates lead to more crime—that such neighborhoods are less able to obtain resources from the larger community—may not be accurate. Instead, the level of income inequality in the neighborhood—particularly income inequality among members of the same racial/ethnic group—may be more important. Nonetheless, future research will need to determine precisely *why* within racial/ethnic group income inequality leads to such higher violent crime rates.

There was little support for the consolidated inequality and group threat theories in this cross-sectional study. There was no support for the consolidated inequality hypothesis that increasing income inequality *across* racial/ethnic groups will increase crime rates. Likewise, the group threat literature's prediction of a *negative* association between income inequality across races and violent crime was not borne out. The finding that the economic threat to the dominant group is less important mirrors the findings of a study that the simple influx of other racial groups into the neighborhood was more important than economic inequality between races for explaining racially motivated crime (Green, Strolovitch, and Wong 1998). It should be highlighted that the authors' suggestion that the causal mechanism between increasing ethnic heterogeneity and hate crimes is a defense of territory strategy differs from the explanation given by the social distance model used in this study. How do we adjudicate between these two explanations? One notable feature is that while both of these mechanisms posit a relationship between ethnic heterogeneity and violent crime, only the social distance model predicts the relationship between ethnic heterogeneity and property crime observed in this sample, lending greater credence to this explanation. Nonetheless, this emphasizes the need for future research to directly test these posited mechanisms.

Finally, there was support for the routine activities theory's prediction that general inequality would increase crime by bringing into close proximity both motivated offenders (those with less) and suitable targets (those with more). There was a positive relationship between general income inequality and various violent crime types. Note also that this theory is somewhat ambivalent on the degree of physical contiguity of motivated offenders and potential targets. That is, they need not reside in the same tract as long as they are within the typical range traveled by offenders. One possible avenue for future research would test whether the presence of motivated offenders and suitable targets in adjacent neighborhoods is important for fostering crime. A second possible avenue of future research would be to test whether the presence of guardians in neighborhoods is altering this proposed relationship (Wilcox, Land, and Hunt 2003).

While this study has shown the importance of measuring income inequality and ethnic heterogeneity within neighborhoods for explaining crime rates, certain limitations should be acknowledged. First, this study has not been able to measure the mechanisms posited by the various theories. I attempted to address this by carefully considering the predictions of the various theories and simultaneously measuring them. Nonetheless, as I have highlighted above, there is a clear need for future research to explicitly explore these mechanisms. For instance, one possible explanation for why income inequality within race/ethnicity is particularly important for crime is that this inhibits the ability of the neighborhood to band together to petition for such resources. Thus, it would not be poverty per se that reduces the collective efficacy of the neighborhood, but rather the economic inequality among same-race individuals that would otherwise band together. While clearly speculative, this is an important avenue for future research. Another limitation of this study is that while using 19 cities in a single study is a large advance over past research, it is still the case that the generalizability of the findings requires the assumption that these cities are at least fairly representative. Studies using additional cities will be necessary to assess this.

Despite these caveats, this study has provided an important test of the predictions of these six theories regarding possible relationships between income inequality, ethnic heterogeneity, and neighborhood crime rates. This study has shown that not only is the composition of race and class in neighborhoods important for explaining crime rates, but that the distribution of race and class *within* neighborhoods also has important effects. Regardless of the theoretical mechanisms present, two robust effects were found. First, racial/ethnic heterogeneity was consistently positively associated with all crime types primarily committed by strangers. If racial/ethnic heterogeneity indeed increases crime by reducing interaction among residents, which then leads to more crime, this suggests that policy interventions might focus on providing organizations and institutions that can bridge the effects this distance might otherwise have on social interactions. Second, both overall inequality and *within* racial/ethnic group income inequality were consistently positively associated with violent crime types. While this suggests a general policy implication of minimizing economic differences between neighbors, it also implies that this income inequality may be even more acutely felt when residents perceive it is others of their own racial/ethnic reference group who have more economic resources than themselves.

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**Tables and Figures**

**Table 1.**

| | **Geographic level of hypothesized construct** | | | |
|---|---|---|---|---|
| **Theory** | **General inequality** | **Ethnic heterogeneity** | **Inequality between races** | **Inequality within race** |
| Relative Deprivation | Unspecified | | | Unspecified |
| Social Disorganization | Neighborhood | Neighborhood | | |
| Social Distance | Neighborhood | Neighborhood | Neighborhood | |
| Consolidated Inequality | | | Nearby[1] | |
| Group Threat | | | Nearby[1] | |
| Routine Activities | Nearby | | | |

[1] This only is posited to affect violent crime.

**Table 2. Summary statistics of variables used in analyses**

| | Mean | SD |
|---|---|---|
| Aggravated assault rate per 100,000 persons | 5.5691 | 1.9889 |
| Robbery rate per 100,000 persons | 4.8481 | 2.1369 |
| Murder rate per 100,000 persons | 0.9445 | 1.2607 |
| Burglary rate per 100,000 persons | 6.4624 | 1.6970 |
| Motor vehicle theft rate per 100,000 persons | 5.9779 | 1.8958 |
| | | |
| Ethnic heterogeneity | 0.4084 | 0.1935 |
| Inequality | 0.4223 | 0.0717 |
| Inequality within race | 0.4061 | 0.0773 |
| Inequality between blacks/whites | 0.1954 | 0.2667 |
| Inequality between Latinos/whites | 0.0166 | 0.0502 |
| Owners | 0.5002 | 0.2449 |
| Occupied units | 0.9226 | 0.0756 |
| Divorced | 0.3589 | 0.1771 |
| At/below 125% of poverty | 0.2556 | 0.1694 |
| Average household income (in $10,000's) | 5.8221 | 3.6581 |
| Unemployment rate | 0.0909 | 0.0754 |
| White | 0.4583 | 32.0044 |
| African-American | 0.2181 | 0.2992 |
| Asian | 0.0551 | 0.0824 |
| Latino | 0.2381 | 0.2679 |
| Other race | 0.0292 | 0.0262 |
| Average length of residence | 0.1028 | 0.0360 |
| Bars and liquor store employees per capita | 4.0142 | 1.6976 |
| Retail employees per capita | 6.0065 | 0.8725 |

*Sample sizes of outcomes: aggravated assault = 3,319; robbery = 3,218; murder = 2,884; burglary = 3,426; motor vehicle theft = 3,249*

**Table 3. Fixed effects models clustering by city, using two-stage least squares (2sls) estimation to handle spatial lag, predicting various types of crime**

| | Individual types of crime | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Aggravated assault** | | **Robbery** | | **Murder** | | **Burglary** | | **Motor vehicle theft** | |
| ***Economic resources*** | | | | | | | | | | |
| At/below 125% of poverty | 1.076 | ** | 0.563 | † | 0.560 | * | 0.438 | | 0.006 | |
| | (0.315) | | (0.313) | | (0.263) | | (0.314) | | (0.300) | |
| Average household income | -0.020 | * | 0.000 | | 0.006 | | 0.007 | | -0.020 | * |
| | (0.009) | | (0.009) | | (0.008) | | (0.010) | | (0.009) | |
| ***Racial/ethnic composition and distribution*** | | | | | | | | | | |
| Ethnic heterogeneity | 0.773 | ** | 0.791 | ** | -0.202 | | 0.604 | ** | 0.624 | ** |
| | (0.155) | | (0.163) | | (0.137) | | (0.167) | | (0.154) | |
| African-American | 0.586 | ** | 0.627 | ** | 1.281 | ** | -0.016 | | 0.035 | |
| | (0.142) | | (0.172) | | (0.153) | | (0.132) | | (0.136) | |
| Latino | 0.678 | ** | 1.021 | ** | 1.273 | ** | 0.095 | | 0.282 | † |
| | (0.160) | | (0.177) | | (0.157) | | (0.151) | | (0.154) | |
| Asian | -0.080 | | 0.418 | | -0.510 | † | -0.014 | | 0.129 | |
| | (0.333) | | (0.331) | | (0.281) | | (0.354) | | (0.319) | |
| Other race | -0.299 | | 1.754 | | -0.584 | | -0.334 | | -0.935 | |
| | (0.977) | | (1.222) | | (0.882) | | (1.029) | | (0.991) | |
| ***Control variables*** | | | | | | | | | | |
| Owners | -0.798 | ** | -1.249 | ** | -0.040 | | -0.355 | † | -0.913 | ** |
| | (0.179) | | (0.193) | | (0.156) | | (0.201) | | (0.175) | |
| Occupied units | -1.841 | ** | -1.275 | ** | -0.984 | ** | -1.603 | ** | -0.923 | * |
| | (0.381) | | (0.405) | | (0.348) | | (0.367) | | (0.368) | |
| Divorced | 1.677 | ** | 1.547 | ** | 0.334 | | 1.294 | ** | 1.275 | ** |
| | (0.280) | | (0.319) | | (0.260) | | (0.305) | | (0.288) | |
| Unemployment rate | -0.621 | | -0.535 | | 0.051 | | -1.234 | * | -0.781 | † |
| | (0.471) | | (0.437) | | (0.371) | | (0.492) | | (0.444) | |
| Average length of residence | 4.220 | ** | 4.550 | ** | -1.435 | | 2.517 | * | 2.961 | ** |
| | (1.076) | | (1.059) | | (0.925) | | (1.075) | | (1.021) | |
| Bars/liquor stores per capita | 0.077 | ** | 0.081 | ** | 0.051 | ** | 0.070 | ** | 0.075 | ** |
| | (0.017) | | (0.018) | | (0.015) | | (0.018) | | (0.019) | |
| Retail establishments per capita | 0.091 | ** | 0.233 | ** | -0.034 | | 0.123 | ** | 0.141 | ** |
| | (0.031) | | (0.032) | | (0.030) | | (0.029) | | (0.031) | |
| *R-square* | 0.65 | | 0.70 | | 0.43 | | 0.57 | | 0.65 | |
| *N* | 3,319 | | 3,218 | | 2,884 | | 3,436 | | 3,249 | |

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. Intercept, and indicators for all but one cities, estimated for all models but not shown*

**Table 4. Fixed effects models clustering by city, using two-stage least squares (2sls) estimation to handle spatial lag, predicting aggravated assault and robbery**

| | Aggravated Assault | | | Robbery | | | Murder | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| ***Economic resources and distribution*** | | | | | | | | | |
| Inequality | 1.021 * | | | 1.292 ** | | | 1.431 ** | | |
| | (0.411) | | | (0.396) | | | (0.409) | | |
| Inequality within race | | 1.132 ** | | | 1.330 ** | | | 1.593 ** | |
| | | (0.371) | | | (0.336) | | | (0.362) | |
| Inequality between blacks/whites | | | -0.022 | | | -0.101 | | | -0.350 * |
| | | | (0.190) | | | (0.211) | | | (0.171) |
| Inequality between Latinos/whites | | | -0.283 | | | 0.002 | | | 0.505 |
| | | | (0.497) | | | (0.496) | | | (0.458) |
| At/below 125% of poverty | 0.840 ** | 0.884 ** | 1.084 ** | 0.272 | 0.355 | 0.569 † | 0.254 | 0.336 | 0.582 * |
| | (0.325) | (0.314) | (0.319) | (0.322) | (0.311) | (0.315) | (0.276) | (0.262) | (0.264) |
| Average household income | -0.026 ** | -0.025 ** | -0.019 * | -0.007 | -0.006 | 0.001 | -0.002 | -0.001 | 0.007 |
| | (0.010) | (0.010) | (0.009) | (0.009) | (0.009) | (0.010) | (0.008) | (0.008) | (0.008) |
| ***Racial/ethnic composition and distribution*** | | | | | | | | | |
| Ethnic heterogeneity | 0.789 ** | 0.830 ** | 0.774 ** | 0.809 ** | 0.858 ** | 0.779 ** | -0.196 | -0.136 | -0.277 * |
| | (0.156) | (0.158) | (0.157) | (0.162) | (0.163) | (0.166) | (0.136) | (0.136) | (0.139) |
| African-American | 0.573 ** | 0.562 ** | 0.569 ** | 0.614 ** | 0.602 ** | 0.549 * | 1.271 ** | 1.244 ** | 1.025 ** |
| | (0.143) | (0.143) | (0.203) | (0.172) | (0.171) | (0.228) | (0.152) | (0.152) | (0.198) |
| Latino | 0.699 ** | 0.692 ** | 0.672 ** | 1.048 ** | 1.032 ** | 1.014 ** | 1.319 ** | 1.302 ** | 1.251 ** |
| | (0.159) | (0.158) | (0.162) | (0.177) | (0.177) | (0.176) | (0.158) | (0.156) | (0.157) |
| Asian | -0.098 | -0.108 | -0.084 | 0.393 | 0.377 | 0.408 | -0.540 † | -0.554 † | -0.558 * |
| | (0.333) | (0.333) | (0.334) | (0.331) | (0.331) | (0.332) | (0.282) | (0.284) | (0.281) |
| Other race | -0.349 | -0.420 | -0.302 | 1.711 | 1.577 | 1.751 | -0.578 | -0.651 | -0.513 |
| | (0.975) | (0.973) | (0.978) | (1.221) | (1.218) | (1.227) | (0.874) | (0.870) | (0.883) |
| N | 3,319 | 3,319 | 3,319 | 3,218 | 3,218 | 3,218 | 2,884 | 2,884 | 2,884 |

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. All models control for percent owners, percent occupied units, percent divorced, unemployment rate, average length of residence, bars/liquor stores per capita, retail establishments per capita, intercept, and indicator variables for each city.*

**Table 5. Fixed effects models clustering by city, using two-stage least squares (2sls) estimation to handle spatial lag, predicting burglary and motor vehicle theft**

| | Burglary | | | Motor vehicle theft | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Economic resources and distribution*** | | | | | | |
| Inequality | 0.707 † | | | 0.169 | | |
| | (0.390) | | | (0.393) | | |
| Inequality within race | | 0.782 * | | | 0.433 | |
| | | (0.383) | | | 0.327 | |
| Inequality between blacks/whites | | | -0.125 | | | -0.091 |
| | | | (0.198) | | | (0.248) |
| Inequality between Latinos/whites | | | 0.161 | | | -0.170 |
| | | | (0.441) | | | (0.448) |
| At/below 125% of poverty | 0.270 | 0.308 | 0.444 | -0.034 | -0.065 | 0.018 |
| | (0.328) | (0.330) | (0.317) | (0.324) | (0.309) | (0.300) |
| Average household income | 0.003 | 0.003 | 0.007 | -0.021 * | -0.022 * | -0.019 * |
| | (0.010) | (0.010) | (0.010) | (0.009) | (0.009) | (0.009) |
| ***Racial/ethnic composition and distribution*** | | | | | | |
| Ethnic heterogeneity | 0.623 ** | 0.655 ** | 0.587 ** | 0.627 ** | 0.647 ** | 0.616 ** |
| | (0.166) | (0.162) | (0.170) | (0.154) | (0.155) | (0.158) |
| African-American | -0.030 | -0.036 | -0.114 | 0.032 | 0.023 | -0.035 |
| | (0.132) | (0.133) | (0.205) | (0.136) | (0.136) | (0.211) |
| Latino | 0.109 | 0.102 | 0.084 | 0.285 † | 0.285 † | 0.270 † |
| | (0.151) | (0.152) | (0.156) | (0.154) | (0.154) | (0.153) |
| Asian | -0.028 | -0.038 | -0.027 | 0.124 | 0.111 | 0.117 |
| | (0.354) | (0.353) | (0.360) | (0.320) | (0.320) | (0.318) |
| Other race | -0.404 | -0.459 | -0.340 | -0.949 | -0.995 | -0.935 |
| | (1.034) | (1.036) | (1.025) | (0.991) | (0.992) | (0.993) |
| N | 3,436 | 3,436 | 3,436 | 3,249 | 3,249 | 3,249 |

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. All models control for percent owners, percent occupied units, percent divorced, unemployment rate, average length of residence, bars/liquor stores per capita, retail establishments per capita, intercept, and indicator variables for each city.*

**Figure 1a. Marginal effect of simulated racial/ethnic compositions of tracts on aggravated assault rates**

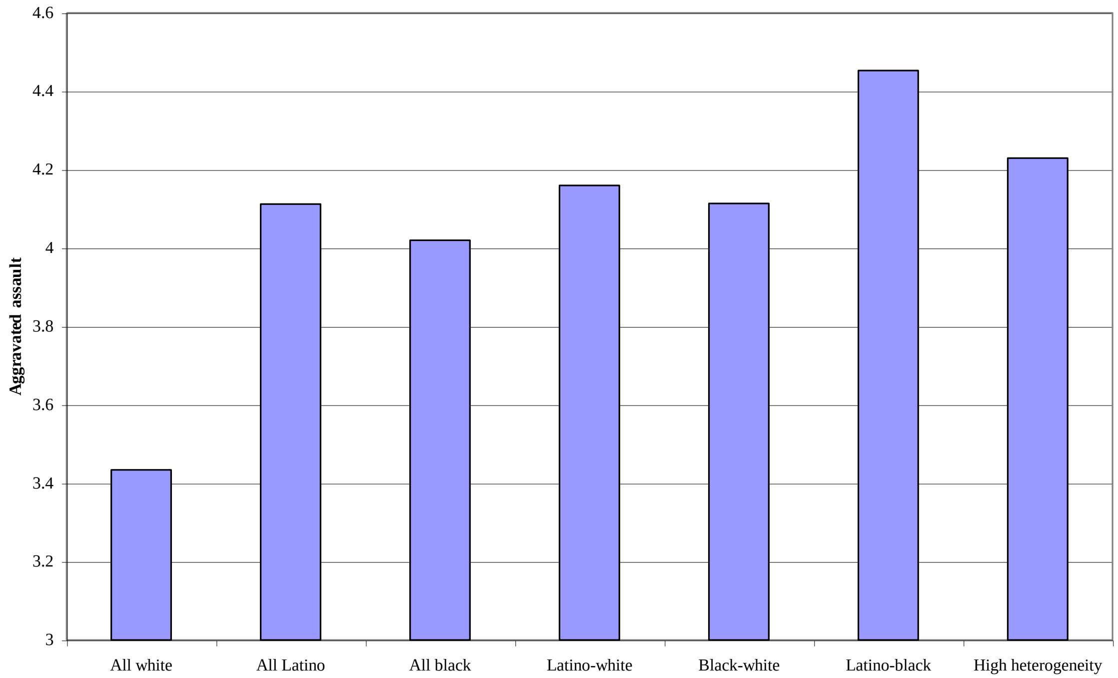
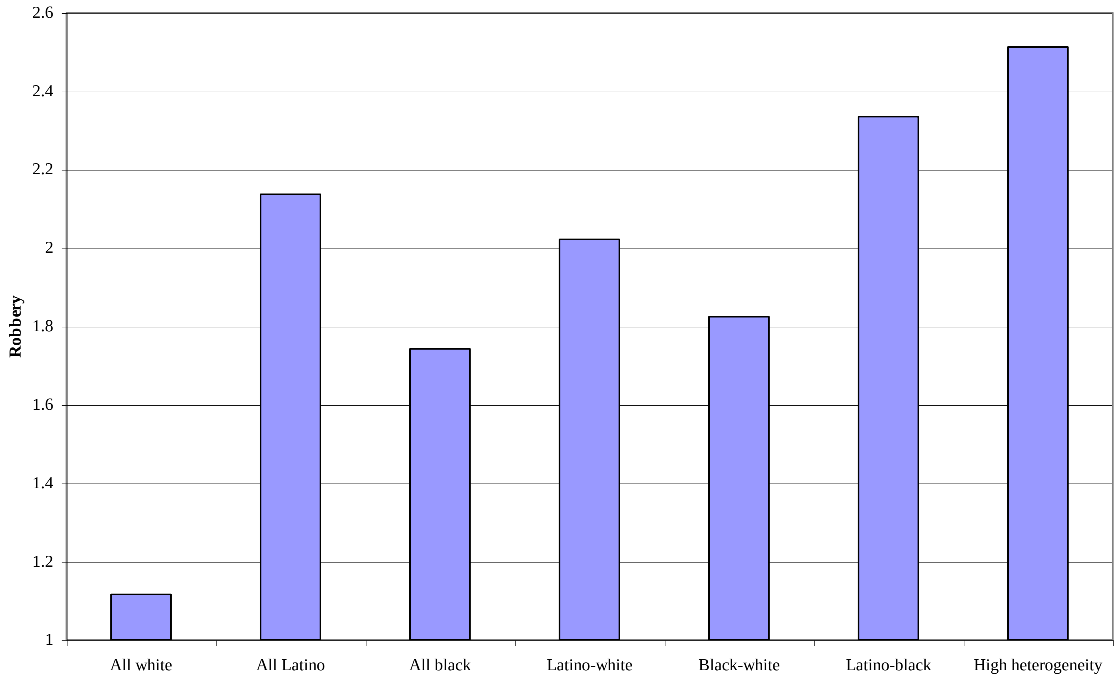


**Figure 1B. Marginal effect of simulated racial/ethnic compositions of tracts on robbery rates**



## Appendix

**Table A1. Cities, years, and crime types in analyses**

| City | Tracts | Crime types* |
|---|---|---|
| Austin | 165 | All |
| Buffalo | 93 | All |
| Cincinnati | 154 | All |
| Cleveland | 225 | All |
| Denver | 187 | Just burglary |
| Indianapolis | 146 | All |
| Los Angeles | 713 | All |
| Miami | 70 | Just assault and robbery |
| Milwaukee | 235 | All |
| Philadelphia | 365 | All except murder |
| Sacramento | 145 | All |
| Salinas | 27 | All |
| San Antonio | 219 | All |
| San Diego | 233 | All |
| San Diego county | 134 | All |
| Seattle | 126 | All |
| St. Petersburg | 66 | All |
| Tampa | 98 | All |
| Tucson | 101 | All except robbery |
| Total tract years | 3337 | |

** Unless otherwise noted, crime types are: aggravated assault, robbery, murder, burglary, and motor vehicle theft*