INCOME INEQUALITY, RACE, AND PLACE: DOES THE DISTRIBUTION OF RACE AND CLASS WITHIN NEIGHBORHOODS AFFECT CRIME RATES?*

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This study tests the effects of neighborhood inequality and heterogeneity on crime rates. The results of this study, which were obtained by using a large sample of census tracts in 19 cities in 2000, 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 predictions of several theories, greater overall inequality in the tract was associated with higher crime rates, particularly for violent types of crime. Strong evidence revealed 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 nonsignificant when the level of income inequality is taken into account; this finding suggests that past studies that failed to take income inequality into account 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.

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

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within neighborhoods. One consequence of this theorizing is that considerable research has been performed to test 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, affects neighborhood crime rates or the how the distribution of racial/ethnic minority members across neighborhoods, as measured by the percent nonwhite, and so on, affects neighborhood crime rates. Less research exists, however, on the effect of the distribution of racial/ethnic groups *within* neighborhoods on crime, and almost no research exists that tests 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 on how they affect the amount of crime. The lack of neighborhood-level research simultaneously considering both of these characteristics is surprising given that no shortage of theoretical reasons exists about 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, few empirical tests use neighborhood-level data. In part, this shortage is from the difficulty of obtaining such data.

As a result, the wave of research that tested the importance of inequality and its interaction with racial/ethnic composition in the 1980s and early 1990s used data aggregated to units much larger than neighborhoods: generally, counties, large cities (often greater than 100,000 population), or even Standard Metropolitan Statistical Areas (SMSAs). 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—although 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), whereas 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 would use smaller units of analysis that more closely approximate neighborhoods in order to test these theories.

The paucity of empirical tests of these theories using neighborhood-level data is in part because of the difficulty of collecting neighborhood-level crime data. Yet, testing these theories presents 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 theories also make predictions regarding interactions of ethnic heterogeneity and inequality (e.g., consolidated inequality theory predicts that inequality *across* racial/ethnic groups will increase crime, whereas relative deprivation theory predicts that inequality *within* racial/ethnic groups will increase crime). Thus, studies that only test racial/ethnic heterogeneity or one form of inequality may be missing important pieces of the puzzle. Thus, a need exists either to explicitly test the mechanisms or to simultaneously consider various theories.

Regarding the second challenge, given the conceptual and statistical interdependence among 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 that used 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 that used just 26 New York neighborhoods in 1981 failed to find a significant relationship between income inequality and homicide (Messner and Tardiff, 1986). However, because neither of these studies simultaneously tested the effects of ethnic heterogeneity, they have low statistical power due to sample size, and the results cannot be generalized due to the focus on just a single city at a single point in time, the relationship between inequality and crime remains uncertain. Although 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 the 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 inequality and ethnic heterogeneity construct. Then I describe the data I will use in the tests. I 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 AMONG 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, shows which constructs they are hypothesized to affect, and identifies the geographic level at which they should work.

Table 1. Six Theories Specifying a Relationship between Ethnic Heterogeneity or Inequality and Crime

	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[a]	
Group threat			Nearby[a]	
Routine activities	Nearby			

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

ROUTINE ACTIVITIES THEORY

The routine activities theory posits that 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 the number of potential targets and motivated offenders, which leads to higher rates of crime. The geographical location of inequality in this model is intermediate. It need not be limited to the local neighborhood, but it should be within the distance that offenders are willing to travel: thus, relatively contiguous neighborhoods. Studies have suggested that a distance decay function explains how far perpetrators will travel (Rengert, Piquero, and Jones, 1999). One study found that they will travel an average distance of between 1 and 2.5 miles, depending on the crime type (Pyle, 1974). The median census tract in 2000 was about 1.4 miles across (1.95 square miles); therefore, the census tract should largely account for such effects.

RELATIVE DEPRIVATION THEORY

The relative deprivation model, which is sometimes referred to as reference group theory (Jasso, 1980; Merton, 1968) or as strain theory (Agnew, 1985, 1999), posits that perceived inequality gives rise to deviant behavior on the part of individuals. That is, individuals compare themselves with others in their "reference group" and respond with deviant behavior if they feel that they have an inequitable economic share. A challenge to the relative deprivation literature in general is to determine what constitutes an appropriate reference group. If the appropriate reference group is co-residents in a 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 be either through property crimes aimed at "equalizing" the perceived injustice or through violent crimes enacted out of 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). Although 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 with others who are similar to themselves and with whom they come into frequent contact (Lau, 1989), then inequality *within an ethnicity* within the neighborhood will increase the crime rate. Studies that test for the effects of within-race inequality by using large units of analysis such as SMSAs cannot 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 and distinguishes 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, 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 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 that reduces relations between neighbors will increase the crime rate, studies in this tradition have rarely considered the effect of relative inequality. Even though the model suggests that 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 suggests that high-poverty neighborhoods will have more crime because of 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, 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. Given that these two measures posit different mechanisms for increasing crime, however, it is incumbent on 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; 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, 1995; 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.

In addition to 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, 1987). This prediction 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—although 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, to 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, in order for the response to be toward members of the dominant group, it does require that the members be located in spatially contiguous neighborhoods at least. It is posited that this model will lead to a *violent* response.

GROUP THREAT THEORY

The group threat model also focuses on inequality across races; however, it posits that when 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, and this perception provokes a violent response. Although 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 of or be 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, data for the neighborhoods within communities are required. Past neighborhood studies often used data only for a single city for such tests, but I address this by using data from 19 cities. Similarly, studies rarely test various hypothesized relationships simultaneously, but I address this limitation here. I directly test the effects of the various forms of income inequality as well as heterogeneity within neighborhoods on local crime rates.

DATA AND METHODS

DATA

This study uses crime data for census tracts in 19 cities in 2000, as listed in appendix A. These cities were not selected randomly but are a convenience sample of cities with available crime data. Therefore, I am not generalizing to this population of cities, but I am viewing the differences in tracts within particular cities by conditioning out the differences across cities, as described in the Methods section. Some advantages of using census tracts are that past studies have frequently used them to proxy for neighborhoods, they contain a mean of about 4,300 residents in 2000 (with 95 percent of the tracts containing between about 1,400 and 8,000 persons), and they were initially constructed by the U.S. 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 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; this also requires recollapsing these data to census tracts. I assumed homogeneity across physical areas in apportioning these data to census tracts.[1]

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

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 types vary along the dimensions of property/violent crime and personal/public crime (depending on 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 (because it involves the threat or use of force as well as the goal of obtaining something of value) that occurs between strangers (Cohen, Felson, and Land, 1980); and burglary and motor vehicle theft are property crimes that generally occur between strangers. This strategy allows for 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 in order to reduce the skew and to minimize the possibility of outliers.

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

where X_i represents the per capita measure of the variable of interest in the tract that 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 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). Because most cities contained crime data in 1990 tracts (rather than 2000 tracts), I placed all data in 1990 tracts. Placing the data into 1990 tracts simply requires collapsing the demographic characteristics of two tracts in year 2000 together because most tracts split over time (as populations increase). This approach accurately represents the year 2000 demographic characteristics and crime rate of the tract boundaries in 1990; although this may muddy some relationships by yielding larger, possibly more heterogeneous tracts, I suggest that this approach is more desirable 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 by placing the data into 2000 tracts, and the results were broadly similar to those presented here.

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 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] that takes the following form:

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

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 types approximately sum to the third measure, precluding simultaneously estimating these three effects.

To measure overall income inequality, I used 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:

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

where x_i is the household income for 1999 as reported in the 2000 census, μ is the mean income value, and the households are arranged in ascending values indexed by i up to n households in the sample. The data are binned (as income is coded into various ranges of values), so I take this into account by using the Pareto-linear procedure (Aigner and Goldberger, 1970; Kakwani and Podder, 1976) that Nielsen and Alderson (1997) adapted from the U.S. Census Bureau strategy (for more 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

2. These groups are white, African American, Latino, Asian, and other races.
3. I use the prln04.exe program provided by Francois Nielsen at the following website: http://www.unc.edu/~nielsen/data/data.htm.

possibility of outliers. Higher values indicate tracts in which white income is much higher than that of minority members, which thus likely increases perceived injustice.

Third, I included a measure of within-group income inequality. I constructed this measure 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, and 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. Because 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 percent of the poverty rate. To capture the effects of racial composition (beyond the effect of ethnic heterogeneity), I included the percent African 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. I calculated the percentage of tract households who own their residence because homeowners have a greater investment in the neighborhood and hence are likely to engage in more crime-reducing behavior. To account for residential stability, I included the average length of residence in the tract. I calculated the proportion of divorced families in the tract because broken families are posited to reduce crime-inhibiting activities. Because abandoned buildings may increase crime possibilities (Krivo and Peterson, 1996; Roncek, 1981; Roncek and Maier, 1991), I included the percentage of residential units that are occupied. Although conflicting views exist about whether higher unemployment increases crime by providing more potential offenders or decreases crime by providing more guardians (because these individuals are at home), I test this effect here by including the percent unemployed in the tract.

Finally because 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 et al., 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.

METHODOLOGY

If no spatial effects were taken 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, which raises the possibility of spatial autocorrelation or spatial lag. Assessing 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 and 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 2 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.

I tested for spatial autocorrelation and spatial lag effects using Lagrange

4. I used the number of employees rather than the number of establishments because 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). Because 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 because 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, no substantive differences existed for the inequality and heterogeneity measures.

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	.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	.4084	.1935
Inequality	.4223	.0717
Inequality within race	.4061	.0773
Inequality between blacks/whites	.1954	.2667
Inequality between Latinos/whites	.0166	.0502
Owners	.5002	.2449
Occupied units	.9226	.0756
Divorced	.3589	.1771
At/below 125% of poverty	.2556	.1694
Average household income (in $10,000s)	5.8221	3.6581
Unemployment rate	.0909	.0754
White	.4583	.3200
African American	.2181	.2992
Asian	.0551	.0824
Latino	.2381	.2679
Other race	.0292	.0262
Average length of residence	.1028	.0360
Bars and liquor store employees per capita	4.0142	1.6976
Retail employees per capita	6.0065	.8725

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

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

$$Y = \rho WY + \beta_1 IE + \beta_2 EH + \Gamma X + \mathrm{B}_3\mathrm{C} + \zeta \qquad (3)$$

where Y is crime in the tract of interest, ρ represents the spatial autoregressive parameter, W is the chosen spatial contiguity matrix, WY represents the spatially lagged dependent variable, β_1 is the effect of

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, because 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 no reason exists to suspect spatial effects *across* cities. For the various crime types, nearly all of the cities showed significant evidence of spatial lag effects, and little evidence existed of spatial autocorrelation.

income inequality (IE) on the crime rate, β_2 is the effect of ethnic heterogeneity (EH) on the crime rate, Γ is a vector of parameters showing the effects of various measures in the X vector, C is a vector of J-1 indicator variables for J cities in the sample and B_3 is a vector of their effects on the crime rate, and ζ is a disturbance. Because I only have 19 cities and they are not randomly sampled, I do not estimate a multilevel model, but instead I 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 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

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 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, which suggests that I am getting a 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. Although 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 ordinary least-squares (OLS) model failing to take into account spatial effects, as well as the lack of inflated standard errors compared with the OLS model, suggests that these instruments are doing a reasonable job of creating an independent estimate of the spatial effects.

consistent with past studies viewing cross-sectional effects of neighborhoods, as observed in table 3. Tracts with a higher proportion of residents at or below 125 percent of the poverty level have higher rates of 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.

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 have higher rates of violent types of crime (controlling for the other measures in the model). Also neighborhoods with a higher percentage of Latinos have similarly higher rates of the violent crime types. Consistent with the social distance model, we observe 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 1 standard deviation increase in the amount of racial/ethnic heterogeneity in the tract is associated with an increase of between 12 and 15 percent in four of these crime types. The lone exception is for murder rates: We observe 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 percent white, 2) 100 percent Latino, 3) 100 percent African American, 4) half white and half Latino, 5) half white and half African American, 6) half Latino and half African American, and 7) one third 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: Although a neighborhood that is all white has the lowest assault rate, a neighborhood with a mixture 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 observed 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, although the presence of Latinos has a much smaller effect (results

Table 3. Fixed Effects Models Clustering by City, using 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**	.563†	.560*	.438	.006
	(.315)	(.313)	(.263)	(.314)	(.300)
Average household income	–.020*	.000	.006	.007	–.020*
	(.009)	(.009)	(.008)	(.010)	(.009)
Racial/Ethnic Composition and Distribution					
Ethnic heterogeneity	.773**	.791**	–.202	.604**	.624**
	(.155)	(.163)	(.137)	(.167)	(.154)
African American	.586**	.627**	1.281**	–.016	.035
	(.142)	(.172)	(.153)	(.132)	(.136)
Latino	.678**	1.021**	1.273**	.095	.282†
	(.160)	(.177)	(.157)	(.151)	(.154)
Asian	–.080	.418	–.510†	–.014	.129
	(.333)	(.331)	(.281)	(.354)	(.319)
Other race	–.299	1.754	–.584	–.334	–.935
	(.977)	(1.222)	(.882)	(1.029)	(.991)
Control Variables					
Owners	–.798**	–1.249**	–.040	–.355†	–.913**
	(.179)	(.193)	(.156)	(.201)	(.175)
Occupied units	–1.841**	–1.275**	–.984**	–1.603**	–.923*
	(.381)	(.405)	(.348)	(.367)	(.368)
Divorced	1.677**	1.547**	.334	1.294**	1.275**
	(.280)	(.319)	(.260)	(.305)	(.288)
Unemployment rate	–.621	–.535	.051	–1.234*	–.781†
	(.471)	(.437)	(.371)	(.492)	(.444)
Average length of residence	4.220**	4.550**	–1.435	2.517*	2.961**
	(1.076)	(1.059)	(.925)	(1.075)	(1.021)
Bars/liquor store employees per capita	.077**	.081**	.051**	.070**	.075**
	(.017)	(.018)	(.015)	(.018)	(.019)
Retail employees per capita	.091**	.233**	–.034	.123**	.141**
	(.031)	(.032)	(.030)	(.029)	(.031)
R-square	.65	.70	.43	.57	.65
N	3,319	3,218	2,884	3,436	3,249

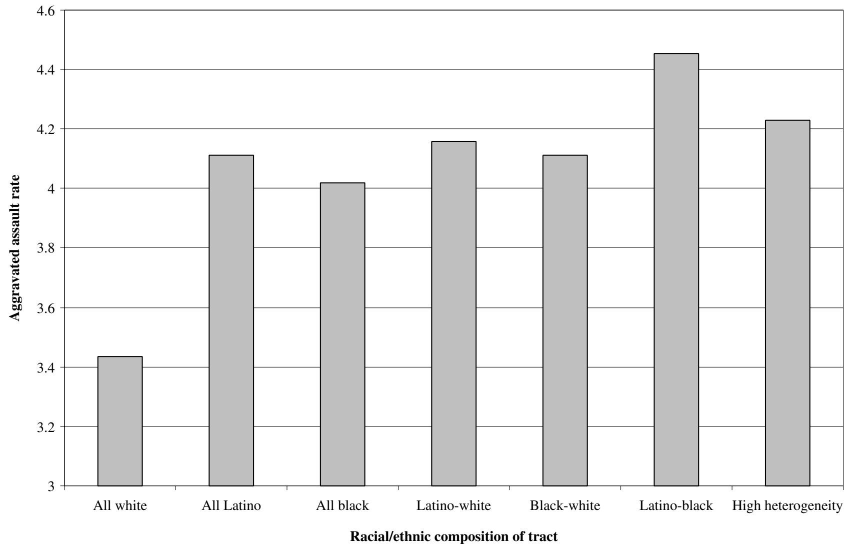
*p < .05 (two-tail test); **p < .01(two-tail test); †p < .05 (one-tail test). Standard errors in parentheses. Intercept and indicators for all but one city were estimated for all models but not shown.

not shown).[8]

I briefly note that the control variables generally work as expected. Consistent with past research, neighborhoods with more bar and liquor

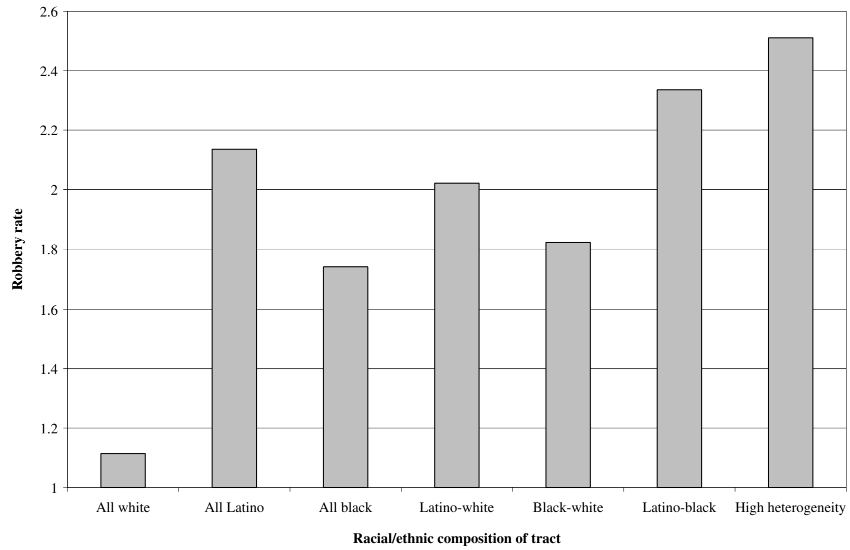
8. The figures for the effect of racial composition for the other crime types are available at http://webfiles.uci.edu/hippj/johnhipp/ineq_cross.htm.

Figure 1A. Marginal Effect of Simulated Racial/Ethnic Compositions of Tracts on Aggravated Assult Rates



store employees have higher rates of all types of crime measured here. Evidence also exists that is consistent with the hypothesis that retail shops will increase the rate of crime in neighborhoods by increasing criminal opportunities. The presence of more broken families leads to higher rates of all of these crime types, although 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 has its weakest effect for murder rates, which suggests 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, which is inconsistent with the social disorganization view that such neighborhoods will have less crime. Although a bivariate negative relationship exists 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, 1989) and community of limited liability literature (Janowitz, 1952), which argue 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.

Figure 1B. Marginal Effect of Simulated Racial/Ethnic Compositions of Tracts on Robbery Rates



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.

The models for the two property crimes show weaker effects for the income inequality measures. Although overall income inequality and within-race income inequality are positively related to burglary rates in models 1 and 2 in table 5, 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 on property crimes.

Although 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? Although 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, which suggests a higher degree of multiple correlation between the inequality measures and the other predictors compared with 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 an increase of 1 standard deviation in within racial group inequality increases the aggravated assault rate 8.7 percent, the robbery rate 10.3 percent, the murder rate 12.3 percent, and the burglary rate 6 percent, the similar values for an increase of 1 standard deviation in overall inequality are 7.3 percent, 9.3 percent, 10.3 percent, and 5.1 percent, respectively. Given that these values are consistently larger for within racial group inequality suggests that it may be particularly important for fostering these types of violent crime, although additional samples will be necessary for a more definitive conclusion.

ALTERNATIVE SPECIFICATIONS

Although 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, Balkwell created a measure multiplicatively combining the racial composition and relative

Table 4. Fixed Effects Models Clustering by City, Using 2SLS Estimation to Handle Spatial Lag, Predicting Aggravated Assault, Robbery, and Murder

	Aggravated Assault			Robbery			Murder		
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Economic Resources and Distribution									
Inequality	1.021*			1.292**			1.431**		
	(.411)			(.396)			(.409)		
Inequality within race		1.132**			1.330**			1.593**	
		(.371)			(.336)			(.362)	
Inequality between blacks/whites			–.022			–.101			–.350*
			(.190)			(.211)			(.171)
Inequality between Latinos/whites			–.283			.002			.505
			(.497)			(.496)			(.458)
At/below 125% of poverty	.840**	.884**	1.084**	.272	.355	.569†	.254	.336	.582*
	(.325)	(.314)	(.319)	(.322)	(.311)	(.315)	(.276)	(.262)	(.264)
Average household income	–.026**	–.025**	–.019*	–.007	–.006	.001	–.002	–.001	.007
	(.010)	(.010)	(.009)	(.009)	(.009)	(.010)	(.008)	(.008)	(.008)
Racial/Ethnic Composition and Distribution									
Ethnic heterogeneity	.789**	.830**	.774**	.809**	.858**	.779**	–.196	–.136	–.277*
	(.156)	(.158)	(.157)	(.162)	(.163)	(.166)	(.136)	(.136)	(.139)
African American	.573**	.562**	.569**	.614**	.602**	.549*	1.271**	1.244**	1.025**
	(.143)	(.143)	(.203)	(.172)	(.171)	(.228)	(.152)	(.152)	(.198)
Latino	.699**	.692**	.672**	1.048**	1.032**	1.014**	1.319**	1.302**	1.251**
	(.159)	(.158)	(.162)	(.177)	(.177)	(.176)	(.158)	(.156)	(.157)
Asian	–.098	–.108	–.084	.393	.377	.408	–.540†	–.554†	–.558*
	(.333)	(.333)	(.334)	(.331)	(.331)	(.332)	(.282)	(.284)	(.281)
Other race	–.349	–.420	–.302	1.711	1.577	1.751	–.578	–.651	–.513
	(.975)	(.973)	(.978)	(1.221)	(1.218)	(1.227)	(.874)	(.870)	(.883)
N	3,319	3,319	3,319	3,218	3,218	3,218	2,884	2,884	2,884

*$p < .05$ (two-tail test); **$p < .01$(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 store employees per capita, retail establishment employees per capita, intercept, and indicator variables for each city.

Table 5. Fixed Effects Models Clustering by City, Using 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	.707†			.169		
	(.390)			(.393)		
Inequality within race		.782*			.433	
		(.383)			.327	
Inequality between blacks/whites			–.125			–.091
			(.198)			(.248)
Inequality between Latinos/ whites			.161			–.170
			(.441)			(.448)
At/below 125% of poverty	.270	.308	.444	–.034	–.065	.018
	(.328)	(.330)	(.317)	(.324)	(.309)	(.300)
Average household income	.003	.003	.007	–.021*	–.022*	–.019*
	(.010)	(.010)	(.010)	(.009)	(.009)	(.009)
Racial/Ethnic Composition and Distribution						
Ethnic heterogeneity	.623**	.655**	.587**	.627**	.647**	.616**
	(.166)	(.162)	(.170)	(.154)	(.155)	(.158)
African American	–.030	–.036	–.114	.032	.023	–.035
	(.132)	(.133)	(.205)	(.136)	(.136)	(.211)
Latino	.109	.102	.084	.285†	.285†	.270†
	(.151)	(.152)	(.156)	(.154)	(.154)	(.153)
Asian	–.028	–.038	–.027	.124	.111	.117
	(.354)	(.353)	(.360)	(.320)	(.320)	(.318)
Other race	–.404	–.459	–.340	–.949	–.995	–.935
	(1.034)	(1.036)	(1.025)	(.991)	(.992)	(.993)
N	3,436	3,436	3,436	3,249	3,249	3,249

$*p < .05$ (two-tail test); $**p < .01$(two-tail test); $\dagger p < .05$ (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 store employees per capita, retail establishment employees per capita, intercept, and indicator variables for each city.

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 on request). This finding 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 nonsignificance. For instance, the significant effect of poverty on robbery and murder is reduced to nonsignificance when taking into account tract income inequality. This finding 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 on request).

Although 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 reestimated 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 data set are illuminating: Whereas no significant effect was found for the interaction between residential stability and poverty in the two property crime models, a positive effect of this interaction was found for the three violent crime types in models that *did not take into account income inequality* (results available on 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 SMSAs 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 consequence, 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 on researchers to simultaneously consider these interrelated constructs in tests. So what have we discovered regarding the six theories tested here?

First, we saw strong support for 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 finding is important, 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 although 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 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, virtually no evidence was found in this sample that higher residential stability leads to lower crime rates, which is a key prediction of social disorganization theory. Instead, it seems 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 although 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. No evidence was found 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 important finding suggests 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.

Little support was found for the consolidated inequality and group threat theories in this cross-sectional study. No support was found for the consolidated inequality hypothesis that increasing income inequality *across* racial/ethnic groups will increase crime rates. Likewise, the prediction of the group threat literature 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 those of a study that found 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 suggestion by Green, Strolovitch, and Wong 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 although 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, which lends greater credence to this explanation. Nonetheless, this outcome emphasizes the need for future research to directly test these posited mechanisms.

Finally, support was found for the prediction of the routine activities theory that general inequality would increase crime by bringing into close proximity both motivated offenders (those with less) and suitable targets (those with more). A positive relationship existed 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).

Although 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 limitation by carefully considering the predictions of the various theories and simultaneously measuring them. Nonetheless, as I have highlighted above, a clear need exists 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 it 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 the economic inequality among same-race individuals that would otherwise band together. Although clearly speculative, this avenue is important for future research. Another limitation of this study is that although 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 generalizability.

Despite these caveats, this study has provided an important test of the predictions of these six theories regarding possible relationships among 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 also that the distribution of race and class *within* neighborhoods 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 positively associated with violent crime types. Although this association 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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Appendix A. Cities, Number of Census Tracts, and Crime Types in Analyses

City	Tracts	Crime types*
Buffalo	93	All
Cincinnati	154	All
Denver	187	Just burglary
Milwaukee	235	All
Sacramento	145	All
San Diego	233	All
San Diego county	134	All
Cleveland	225	All
Seattle	126	All
Austin	165	All
Indianapolis	146	All
Miami	70	Just assault and robbery
Philadelphia	365	All except murder
Salinas	27	All
San Antonio	219	All
St. Petersburg	66	All
Tucson	101	All except robbery
Tampa	98	All
Los Angeles	713	All
Total tracts	3,409	

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