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Racial Socioeconomic Inequality, Structural Disadvantage, and Neighborhood Crime: Testing the Relative and Absolute Deprivation Perspectives

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by

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DEDICATION

You may tell that German College that their honor comes too late,

But they must not waste repentance on the grizzly savant's fate.

Though my soul may set in darkness, it will rise in perfect light;

I have loved the stars too fondly to be fearful of the night.

-Sarah Williams, “The Old Astronomer to His Pupil” (1936)

This work is dedicated to my loving family and supportive friends, peers, teachers, and mentors—that is, to everyone who encouraged me to follow the evidence where it leads, pushed me to pursue my intellectual curiosity about human societies, and helped me understand what Kawachi, Kennedy, and Wilkinson (1999:719) meant when they noted that “crime is a social mirror.”

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ABSTRACT

Few studies of urban crime patterns have explored whether indicators of relative deprivation (e.g., income inequality) significantly associate with crime at the most theoretically appropriate level of analysis, the neighborhood; whether they do so net of controls for measures of absolute deprivation (e.g., structural disadvantage); and whether their effects vary by race/ethnicity. Drawing on data from the 2000 National Neighborhood Crime Study (NNCS) and census data extracted from the National Historical Geographic Information System (NHGIS), I explore these questions for overall, intraracial, and interracial inequality in income and educational attainment with respect to neighborhood homicide, burglary, and robbery rates. Their effects are compared across majority White, Black, and Latino census tracts embedded in a nationally representative sample of large U.S. cities. Consistent with prior research, I find that overall and intraracial inequality are more reliable predictors of neighborhood crime rates than interracial inequality, net of disadvantage; that the overall and intraracial inequality measures exert racially invariant effects only for homicide rates; and that for robbery and burglary rates, the most severe effects of these predictors are found in majority White neighborhoods. Although interracial inequality is never a significant covariate of homicide, it evinces an interesting pattern for the other two crime types: the largest effects are consistently found when the disadvantaged racial group in the comparison resides in neighborhoods where the more advantaged group is in the majority. Theoretical implications and directions for future research are discussed.

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INTRODUCTION

Does inequality make unique impacts on crime beyond poverty? If so, are its effects greater if it manifests between members of different ethno-racial groups or among members of the same group? And how does the ethno-racial composition of a place condition this relationship—might its effects be more severe for some groups than others, for example? While sociological criminologists have been interested in the general relationship between crime and economic conditions for at least a century (Bonger, 1916), recent decades have witnessed these specific questions become salient in the wake of Blau and Blau's (1982) seminal investigation of them. Due in large part to advancements in the operationalization of the concept of inequality, model specification, and the use of race-specific explanatory and dependent variables (Golden & Messner, 1987; Harer & Steffensmeier, 1992), contemporary research has established a sizable body of evidence suggesting that intraracial and overall inequality are more robust predictors of offending than interracial inequality (Harer & Steffensmeier, 1992; Hipp, 2007; LaFree & Drass, 1996; Martinez, 1996; Messner, Raffalovich, & McMillan, 2001; Phillips, 1997; Shihadeh & Steffensmeier, 1994). In contrast, findings regarding differential effects by ethno-racial group have remained more equivocal (Harer & Steffensmeier, 1992; Messner & Golden, 1992; Messner, Raffalovich, & McMillan, 2001; Parker & McCall, 1997). Yet the Blaus' original thesis concerning the link between interracial socioeconomic inequality and violent crime has retained its intuitive appeal and has occasionally found support even in more recent investigations (Hipp, Tita, & Boggess, 2009; Stolzenberg, Eitle, & D'Alessio, 2006).

Several limitations undermine the conclusions that can be drawn from this body of work, however. One important oversight involves the distinction between two different perspectives on poverty: *absolute deprivation*, or the inability to acquire the resources necessary for one's subsistence, and *relative deprivation*, or the inability to live in a manner comparable to others in one's community (Messner, 1982; Miller & Roby, 1970; Townsend, 1974). Introduced by Stouffer and colleagues (Stouffer, Lumsdaine, et al., 1949; Stouffer, Suchman, et al., 1949) and Merton (1968), the relative deprivation perspective contends that indicators of absolute deprivation are insufficient to explain a person's level of satisfaction with his or her socioeconomic conditions. Instead, it maintains that satisfaction is dependent upon salient referents available to serve as bases for self-appraisal (Pettigrew, 2015); thus, how content we are with our socioeconomic circumstances varies relative to whom we compare ourselves. Unfortunately, prior studies have not always distinguished between absolute and relative poverty (Bernard, Snipes, & Gerould, 2016:22), and when they have made this distinction they have typically utilized federal poverty threshold measures to indicate absolute deprivation and income inequality measures to indicate relative deprivation (Hipp, 2007; Kawachi, Kennedy, & Wilkinson, 1999). Yet because the extent to which these measures capture absolute and relative deprivation is arguably limited, even these studies have not tested the two conceptions of poverty against each other in a manner that would provide a clear empirical portrait of the criminogenic effects of one vis-à-vis the other.

A second limitation of extant research on the racial inequality-crime link concerns the units of analysis for which this evidence has been accumulated. Blau and Blau (1982) investigated their thesis using data aggregated at the Standard Metropolitan Statistical

Area (SMSA) level, and virtually every study that attempted to replicate or extend their analysis between the late 1980's and the early 2000's used data for this level or for a sample of large American cities (for reviews see Peterson & Krivo, 2005; McCall & Parker, 2005; or Stolzenberg, Eitle, & D'Alessio, 2006; for an exception see Messner & Tardiff, 1986). However, as Hipp (2007) cogently argues and as I will emphasize, all the mechanisms theorized to link racial socioeconomic inequality with variation in crime rates assume interactions between local residents which indicators at the SMSA or city level are too broad to capture adequately. Only rarely have researchers employed data on race and inequality at more local levels, such as the census tract (Hipp, 2007; Hipp, Tita, & Boggess, 2009; Messner & Tardiff, 1986).

Beyond these conceptual and methodological limitations, the vast majority of researchers have assumed that the effect of racial socioeconomic inequality on crime rates is monolithic across the units in their sample, instead of entertaining the possibility that it may depend on the ethno-racial composition of the place in which its association with crime is estimated. Put differently, instead of asking, "Does the socioeconomic disparity between (or within) group *X* and group *Y* affect total or group-specific crime rates?" the question becomes, "Is the effect of socioeconomic disparity between (or within) group *X* and group *Y* different in a locale where members of *X* are the majority compared with one where members of *Y* are the majority?" Only two studies have explored this kind of question, each with different methods and findings (Balkwell, 1990; Hipp, 2007).

First, Balkwell (1990) devised a new measure of ethnic inequality that accounted for the number of different ethnic groups sharing a single living area and the proportion of that area which each constituted. He argued that the more a single ethnic group held a disproportionately large share of the aggregate income of a metropolitan area, the more acute would be perceptions of unjust deprivation among other ethnic groups in the same area. These feelings would be further aggravated by the size of the wealthiest ethnic group: the smaller the proportion of the total area it constituted, the more unfair its relative advantage would appear to be. Using data on a sample of 150 SMSAs for 1980, he found his measure to be a strong and consistent predictor of homicide rates. Second, in a study of over 3,000 census tracts in a convenience sample of 19 cities for 2000, Hipp (2007) estimated an interaction term between his measures of racial heterogeneity and income inequality to retest Balkwell's assertions, but the product term and its income inequality component failed to attain statistical significance in fixed effects regression models. While promising, these studies had their own limitations: Balkwell's analysis considered units that may be too large for precise estimates of ethno-racial inequality effects, and although Hipp utilized data for neighborhood-level areas within cities, the non-probability nature of his sample constrained the external validity of his findings.

In the present study, I extend the work of Hipp (2007) and others by offering a more comprehensive analysis of the relationships between race/ethnicity, socioeconomic inequality, and crime among neighborhood residents in major urban locations in the United States. I specifically explore how overall, intraracial, and interracial inequality, as measures of relative deprivation, associate with variation in neighborhood crime rates net of indicators of absolute deprivation. I investigate these relationships (1) along multiple dimensions of inequality, (2) across neighborhoods that vary in their ethno-racial compositions, and (3) for both violent and property crimes, using the first dataset to contain sociodemographic and crime information for census tracts within a nationally representative sample of U.S. cities: the National Neighborhood Crime Study (NNCS) (Peterson & Krivo, 2010b). I also explore whether racial socioeconomic inequality exhibits racially uniform or differential effects on crime across neighborhood areas that vary in their ethno-racial compositions.[1] The large sample of neighborhoods from multiple cities in the NNCS permits appropriate comparisons of similarly situated neighborhoods that differ in their ethno-racial makeup.

Beyond contributing to unresolved debates in the criminological literature, the findings from this analysis may hold important policy implications as well. According to multiple accounts, income inequality alone has been on the rise since the 1960's in the United States and has grown continually through 2012 (Congressional Budget Office, 2011; Fisher, Johnson, & Smeeding, 2015; Pinketty & Saez, 2003), and disparity in educational attainment may mirror this trend (Rich, Cox, & Bloch, 2016). Given that neighborhood ethno-racial composition has tended toward greater stability than neighborhood socioeconomic status (Gay, 2004), such that "the racial composition of one's neighborhood depends much more on one's race than on one's income" (Reardon, Fox, & Townsend, 2015:85), national increases in income and educational disparity may be shaping neighborhood outcomes for different ethno-racial groups in unequal ways. Criminologists, therefore, shoulder the responsibility of rigorously determining how and where racial inequality shapes criminal offending outcomes so that law enforcement and social welfare resources can be allocated effectively.

This paper is divided into five parts. In the first part I review the pertinent literature that informs the hypotheses I develop later, beginning with contrasting explanations for the racial socioeconomic inequality-crime relationship and the empirical research that supports them. For the most part these explanations and their respective studies can be categorized as aligning with either the relative or absolute deprivation perspectives, but there are several alternative explanations as well. I then proceed to the evidence on the extent to which structural predictors of criminal involvement operate in racially uniform ways, noting that racial socioeconomic inequality has generally been neglected in the otherwise comprehensive body of research on the racial invariance thesis. In Part II, I describe my own study tasks more fully and formulate my specific empirical expectations for the present investigation. Part III contains a discussion of the data, variables, and methods I will use to test my hypotheses. In Part IV I present and narrate the results of my analysis, and in Part V I discuss the implications of my findings and conclude.

PART I. LITERATURE REVIEW

Relative Deprivation and Reference Group Theory

The origins of relative deprivation can be traced to the work of Samuel Stouffer, who utilized the perspective in his study of satisfaction levels among servicemen in World War II (Stouffer, Lumsdaine, et al., 1949; Stouffer, Suchman, et al., 1949). According to Stouffer and his colleagues, persons experience relative deprivation when they (1) make cognitive comparisons with some referent group, (2) make cognitive appraisals that they are disadvantaged, and (3) perceive this disadvantage as unfair, which arouses anger and resentment (Pettigrew, 2015). Stouffer et al. proposed these processes to make sense of their unexpected findings that WWII military police were more highly satisfied than their air corpsmen counterparts even though the latter enjoyed swifter promotions, and that African American soldiers in Southern camps exhibited higher satisfaction levels than their Northern counterparts despite the reduced segregation levels to which the latter were subjected. In each case, the more absolutely disadvantaged group had greater satisfaction levels because they compared themselves only with each other, rather than with members of the more advantaged groups whom they infrequently encountered.

The relative deprivation perspective was originally only intended as an ad hoc explanation of these findings, however, and thus was not part of any theoretical framework until Merton and his colleagues incorporated it into their reference group theory (Merton, 1968; Merton & Kitt, 1950). Merton (1938, 1968) is widely known for his argument that in cultures with universally accepted symbols of success, a greater emphasis placed on acquiring these symbols than on the institutionalized means for obtaining them could exert a definite pressure on individuals to employ the most expedient methods of achieving success as possible. Resource-poor persons experienced this strain most severely because they had the most restricted access to legitimatized means, so they were expected to be the most likely group of individuals to innovate deviant means for acquiring success symbols. But Merton (1968) also asserted that deviant behavior in such contexts was likely when people based their self-appraisals on reference groups that they believed were comparable to themselves, and perceived their socioeconomic circumstances to be inequitable. Blau and Blau (1982) drew explicitly from Merton to construct a theory of how race interacted with the inequality-deviance relationship (Peterson & Krivo, 2005:332).

Blau and Blau (1982) argued that in formally democratic societies like the United States, a high degree of association (or “consolidation”) between achieved statuses and ascribed statuses is perceived as illegitimate, because in such societies it is universally expected that status distinctions that one can earn ought to be independent of those into which one is born. When this consolidation of status distinctions involves one’s racial identity and socioeconomic status, especially intense feelings of alienation, frustration, and despair manifest among members of the racial group who are disadvantaged. These feelings, in turn, result in expressions of diffuse aggression, which can be observed in rates of violent crime:

> The hypothesis inferred is that socioeconomic inequalities that are associated with ascribed positions, thereby consolidating and reinforcing ethnic and class differences, engender pervasive conflict in a democracy. Great economic

> inequalities generally foster conflict and violence, but ascriptive inequalities do so particularly. (Blau & Blau, 1982:119)

Analyzing sociodemographic and Uniform Crime Reports (UCR) offending data for the 125 largest SMSAs in the United States in 1970, the Blaus found that (1) both white-black interracial and intraracial inequality were significant predictors of violent crime rates, and (2) the independent effects of poverty, Southern region, and percent black were greatly attenuated (in the cases of poverty and Southern region, fully mediated) once measures of inequality were controlled. Despite these confirmatory results, studies attempting to replicate the Blaus' work in the mid-1980's turned up mixed findings (Balkwell, 1983; Blau & Golden, 1986; Blau & Schwartz, 1984; Messner & Golden, 1985; Sampson, 1985; Williams, 1984). In assessing this body of research, Golden and Messner (1987) noted that inequality operationalization (e.g., income vs. socioeconomic) and model specification (e.g., types of controls included) could dramatically alter the results of a racial inequality-crime analysis. They concluded that the link between the two is either not very robust, or else more subtle than the Blaus assumed (Golden and Messner, 1987:539).

Research utilizing a relative deprivation framework to analyze the racial inequality-crime link in the 1990's and 2000's employed race-specific explanatory and dependent variables, shifted analytical focus toward intraracial inequality, explored antecedents of particular racial offender-victim dyads, and considered Latinos as well as whites and blacks (Harer & Steffensmeier, 1992; Hipp, 2007; LaFree & Drass, 1996; Martinez, 1996; Messner & Golden, 1992; Messner, Raffalovich, & McMillan, 2001; Phillips, 1997; Stolzenberg, Eitle, & D'Alessio, 2006). Using official homicide data disaggregated by race of offender as well as victim for a sample of cities, Messner and Golden (1992) found that white-black socioeconomic inequality significantly predicted total, white, and black offending. However, they interpreted these findings as more consistent with a social disorganization perspective than a relative deprivation one since their index of inequality did not predict interracial offending. Yet two authors publishing in the same year argued that the search for an interracial inequality-crime association was misguided. Harer and Steffensmeier (1992) maintained that the proper "reference group" for blacks was in fact not whites, but rather other blacks, since "the conclusion of a number of researchers [is] that blacks do not use whites as referents for feelings about themselves" (1992:1036). Thus, they asserted that *intraracial*, rather than *interracial*, socioeconomic inequality should be the stronger and more robust predictor for offending among both blacks and whites, although their analysis in fact only found this to be the case for whites. Nevertheless, within-group inequality has been found in later studies to significantly predict crime rates net of controls for both blacks (LaFree & Drass, 1996; Messner, Raffalovich, & McMillan, 2001; Phillips, 1997) and Latinos (Martinez, 1996).

The findings from two more studies merit attention in this section. First, and in contrast to the patterns noted above, Stolzenberg, Eitle, and D'Alessio (2006) found white-black interracial income inequality to be the superior predictor of crime rates for multiple violent offense types compared with overall and intraracial income inequality. Using data from the National Incident-Based Reporting System (NIBRS) and census data for 91 cities for the year 2000, their analysis revealed that while overall and intraracial inequality had no significant association with the total or any offender-victim dyad crime rates, white-black interracial income inequality significantly predicted both the total crime rate and the black-on-black crime rate. Second, Hipp (2007) found that white-black and white-Latino interracial income inequality were weaker and less consistent predictors of crime than were overall and intraracial inequality. Between the latter two covariates, intraracial inequality appeared to exhibit stronger effects on crime than overall inequality. Only Merton's (1968) reference group theory, he argued, could have predicted the observed significant impact of intraracial income inequality on crime. Similar to Blau and Blau (1982), Hipp also found that including income inequality in the same model as poverty caused the latter's relationship with robbery and murder to become insignificant.

Absolute Deprivation and Social Disorganization Theory

The accumulation of findings in the prior section notwithstanding, two major critiques can be raised against the relative deprivation perspective concerning its application to community crime, and both involve its theoretical counterpart, absolute deprivation. The first is that relative deprivation has more limited utility for predicting serious violent offenses than absolute deprivation. This criticism is exemplified by the interchange between Steven Messner and William Bailey in the early 1980's (Bailey, 1984; Messner, 1982). Seeking to determine whether poverty or income inequality exhibited greater effects on homicide rates in 204 SMSAs for 1970, Messner (1982) was surprised to discover that income inequality had *no* statistically significant relationship with homicide rates whereas poverty evinced a significant *negative* relationship with the outcome. He thus concluded with a call for a comprehensive reconsideration of the relationships between these variables.

However, Bailey (1984) argued that the source of Messner's anomalous findings was simply his use of SMSAs, which were too large and heterogeneous to allow for reasonable comparison. His own analysis using data on a sample of cities for 1950, 1960, and 1970 revealed the expected positive and significant association between poverty and homicide, but replicated Messner's finding of a non-statistically significant relationship between income inequality and homicide. Yet this finding was *not* unexpected for Bailey because, as he asserted, the theoretical underpinnings of economic inequality anchor it more firmly to property offenses and other instrumental crimes (e.g., Bonger 1916; Engels 1968; Merton 1938, 1968). More recent studies support Messner's (1982) initial hypothesis that overall income inequality is an important determinant of homicide, at least for members of some ethno-racial groups (Harer & Steffensmeier, 1992; Hipp, 2007; Messner, Raffalovich, & McMillan, 2001; but see Messner & Tardiff, 1986). Even so, this interchange is important because it begs the question of exactly which offenses different types of racial socioeconomic inequality can be expected to predict, a question which many studies have not considered (Stolzenberg, Eitle, & D'Alessio, 2006).

One can raise a more fundamental objection the relative deprivation perspective. Perhaps measures of relative deprivation are simply capturing the *absolute deprivation* of the more disadvantaged group in an unequal comparison; in other words, *destitution*, not *disparity*, may be the true driver of crime rate variation. Thus, communities with different levels of socioeconomic disparity among their residents may still have comparable crime rates as long as their average levels of socioeconomic resources are the same. This idea is not new in the relative deprivation and crime literature—indeed, the inability of absolute deprivation to sufficiently account for observed crime patterns prompted calls for reconceptualizing poverty along relative deprivation lines in the first place (Messner, 1982). But measures of absolute deprivation have undergone their own development over the last several decades, and one such measure has received recognition as being among the strongest and most consistent predictors of aggregate criminal involvement: structural disadvantage (Peterson & Krivo, 2005; Pratt & Cullen, 2005). Mounting evidence concerning the importance of disadvantage as a determinant of community crime rates provides indirect support for this second critique of the relative deprivation perspective (Krivo & Peterson, 1996; Peterson and Krivo, 2010a; Wilson, 1987).

For example, in his seminal book *The Truly Disadvantaged*, Wilson (1987) traced how deindustrialization, migration to Northern and Midwestern cities, and a drop in the average age of residents resulted in an unprecedented high concentration of low-skill African Americans living in impoverished inner-city neighborhoods in the 1970's United States. Combining with their social isolation from mainstream individuals and institutions via residential segregation, this concentrated poverty had an especially destabilizing effect on local institutions like churches, schools, and families through its removal of "social buffers"—that is, economically stable individuals and families who would otherwise support these institutions and their social control functions. Wilson argued that this disadvantaged context, in turn, results in especially high rates of social dislocations like joblessness, female-headed families, welfare dependency, and crime. To directly test this thesis, Krivo and Peterson (1996) analyzed data on a sample of 177 census tracts in Columbus, Ohio for 1990. They found that several indicators of structural disadvantage (e.g. poverty, % employed in managerial or professional occupations) exhibited nonlinear effects on crime at their highest values. Specifically, increasing community disadvantage from high to extreme levels resulted in particularly acute crime rate increases. Furthermore, these relationships operated similarly in both predominantly white and black census tracts. Peterson and Krivo (2010a) assert that this helps account for why rates of crime are so much higher in neighborhoods that are predominantly black compared with other ethno-racial neighborhood types: blacks are subject to the most severe levels of disadvantage, whereas white neighborhoods experience the lowest levels and Latino and other neighborhood types fall between these extremes.

Peterson and Krivo (1996; 2010a) maintain that extreme levels of structural disadvantage lead to abnormally high community crime rates because the conditions that promote engagement in crime in such areas are especially prevalent (i.e. delinquent peer influence via role modeling, adaptation to crime as an ordinary part of everyday life), and the mechanisms that would ordinarily discourage criminal involvement are especially absent (i.e. familial or neighborly supervision of property or youth activities, socialization by mainstream institutions, deterrence by police activity, or prevention by internal peacekeeping activities like neighborhood watch meetings). This explanation is consistent with the primary theoretical framework used to account for community crime rate variation: social disorganization (Shaw & McKay, 1942). This theory originates with Clifford Shaw and his colleagues (Shaw et al., 1929; Shaw & McKay, 1942, 1949) who observed that delinquency rates in Chicago in the early 1900's clustered in areas characterized by high rates of poverty, ethno-racial heterogeneity, and residential mobility and that this geographical concentration tended to remain fixed despite complete population changes over several decades. Contemporary formulations of the theory are rooted in Kasarda and Janowitz's (1974) 'systemic model' of community attachment—which views the local community as "a complex system of friendship and kinship networks and formal and informal associational ties rooted in family life and on-going socialization processes" (1974:329)—and define social disorganization as the inability of community residents to realize common values and maintain effective social controls (Bursik, 1988; Kornhauser, 1978; Sampson & Groves, 1989; Sampson, Raudenbush, & Earls, 1997). Recent research highlights the importance of structural disadvantage as a major determinant of this condition (Peterson & Krivo, 2010a), but whether any indicator of relative deprivation retains independent effects on crime in neighborhoods of varying ethno-racial compositions net of disadvantage remains unknown.

Alternative Explanations: Social Distance, Group Competition, and Routine Activity Theories

In addition to the reference group and social disorganization theories, there are a number of alternative theoretical explanations for the relationship between racial socioeconomic inequality and crime. Adjudicating between these is beyond the scope of this paper, but it should be noted that (1) each explanation is consistent with the relative deprivation perspective in its prediction that racial socioeconomic inequality will significantly predict crime rates net of absolute deprivation indicators (Hipp, 2007; Stolzenberg, Eitle, & D'Alessio, 2006; Wang & Arnold, 2008), yet (2) they diverge in their expectations over whether inequality will *increase* or *decrease* crime rates. These explanations can be roughly categorized into three types.

Explanations of the first type all make use of *social distance* theory (also referred to as "status distance" or "status heterogeneity" theory) (Blau, 1977; McPherson & Smith-Lovin, 1987; Simmel, 1955). Social distance theory is grounded in Blau's (1977) macrosociological theory, which holds that heterogeneity will increase intergroup contact while inequality will decrease intergroup contact in a given social structure. Holding ethno-racial heterogeneity constant, then, overall inequality should be expected to lower crime rates in general (Sampson, 1986) and interracial inequality ought to reduce interracial crimes in particular (Messner & Golden, 1992) because of diminished inter-group contact. This explanation has not been explicitly applied to intraracial inequality, although it logically follows that inequality between members of the same race may reduce inter-group contact along some other dimension (e.g., occupational status) and therefore lower intra-racial crime rates in areas that are highly segregated. However, interactions between neighborhood residents represent a necessary, if not sufficient, condition for the realization of shared values and maintenance of effective social controls (Bellair, 1997; Morenoff, Sampson, & Raudenbush, 2001; Patillo, 1998). Thus, social distance resulting from overall or interracial inequality may also increase crime through social disorganization (Hipp, 2007; Shihadeh & Steffensmeier, 1994; Wang & Arnold, 2008). It should be noted that these two social distance mechanisms are not mutually exclusive, so estimations of the inequality-crime relationship may measure some aggregation of their effects.

The second type of explanation utilizes some theory of *group competition* (or "group threat" or "racial threat") (Blalock, 1967; Eitle, D'Alessio, & Stolzenberg, 2002; Quillian, 1995). Like the social distance explanations, these also have competing predictions. On the one hand, increases in interracial or intraracial inequality may reduce the ability to compete for scarce employment opportunities among the members of the disadvantaged group and therefore increase criminal offending as a coping method (Jacobs & Wood, 1999; Kovandzic, Vieratis, & Yeisley, 1998; Stolzenberg, Eitle, & D'Alessio, 2006). On the other hand, increases in interracial inequality may lower crime rates as perceptions of threat among the advantaged group, and perceptions of opportunities for successful competition among the disadvantaged group, decline (Hipp, 2007). One way of testing these competing predictions is to examine the effect of interracial inequality on racial offender-victim dyads, since it is plausible that inter-group inequality typically functions to *increase* offending among members of the *disadvantaged* group and *decrease* offending among members of the *advantaged* group. However, contrary to their expectations McCall and Parker (2005) found that white-black interracial inequality in labor force participation significantly predicted both black-on-white and white-on-black homicide counts.

Finally, the last type of explanation employs Cohen and Felson's (1979) *routine activities* theory. This theory holds that criminal offending is a function of the convergence in time and space of three conditions: motivated offenders, suitable targets, and an absence of capable guardians. To my knowledge, only one study has ever utilized this theory to explain the socioeconomic inequality-crime relationship. Hipp (2007) argued that overall inequality can be expected to increase criminal offending because it increases the availability of motivated offenders (i.e. people with fewer resources) and suitable targets (i.e. people with more resources). He also held that census tracts are ideal units for measuring this relationship because offenders will typically not travel farther than a few miles from their homes to commit a crime, so the convergence of the three conditions must occur within extremely local areas (2007:669).

Socioeconomic Inequality and the Racial Invariance Thesis

Blau and Blau (1982) argued that the criminogenic effects of racial socioeconomic inequality impact blacks more strongly than whites because they are the more relatively deprived of the two racial groups, but the Blaus were unable to provide any direct evidence supporting this contention because their dependent variables were aggregated offense rates. Subsequent research attempted to identify this expected effect discrepancy using racially disaggregated crime rates, with the balance of the evidence actually suggesting larger effects among whites rather than blacks (Harer & Steffensmeier, 1992; Ousey, 1999; Messner & Golden, 1992; Parker & McCall, 1997). Unfortunately, not only has more recent work tended to neglect this auxiliary assertion made by the Blaus (Hipp, 2007; McCall & Parker, 2005; Stolzenberg, Eitle, & D'Alessio, 2006), but it has also largely refrained from dialogue with research utilizing the primary theoretical framework for assessing how the effects of structural covariates of community crime rates vary across ethno-racial groups: the racial invariance thesis (Hernandez, Vélez, & Lyons, 2016; Steffensmeier, Ulmer, Feldmeyer, and Harris, 2010). The racial invariance thesis is rooted in Shaw and McKay's (1949) observations of the disparate ecological contexts of white and black youth in Chicago neighborhoods and was explicitly articulated by Wilson (1987) and Sampson and Wilson (1995). The thesis posits that communities with comparable structural conditions (especially structural disadvantage levels) should exhibit similar crime rates regardless of their ethno-racial compositions because these conditions, and the processes by which they lead to crime, are the same for all ethno-racial groups. As Sampson and Wilson (1995) observe, "the sources of crime appear to be remarkably invariant across race and rooted instead in the structural differences among communities" (1995:41).

Hernandez, Vélez, and Lyons (2016) provide a useful framework for conceptualizing racial invariance by separating the thesis into two empirical expectations.

First, accounting for average differences in community ecological conditions should narrow or eliminate ethno-racial gaps in criminal involvement if racial invariance is to be supported. Second, verification of the hypothesis also rests on a demonstration that the structural determinants of crime are similar in magnitude and direction across local areas of varying ethno-racial compositions. Because the question of whether resource disparity has more pernicious criminogenic effects for some ethno-racial groups than others has been a major concern in the racial socioeconomic inequality literature, I focus my attention on this second expectation of the racial invariance thesis, for which a lesser body of research evidence exists (Krivo & Peterson, 1996; Ousey, 1999; Peterson & Krivo, 2000; McNulty, 2001; Steffensmeier et al., 2010; Hernandez, Vélez, & Lyons, 2016). Earlier studies focused on the extent to which structural determinants of crime at the city or census tract level exhibited comparable effects on offending patterns among whites and blacks, with mixed results. For example, Krivo and Peterson (1996) failed to find evidence of a statistical interaction between neighborhood racial composition and any indicator of structural disadvantage for census tracts in Columbus, Ohio; they also reported that the largest differences in community crime rates appeared between average disadvantage levels (i.e. high vs. extreme) rather than between racial groups. In contrast, Ousey (1999) examined racially disaggregated homicide rates for 125 cities in 1990 and found that the effects of poverty, unemployment, and female-headed households were significantly larger for whites than for blacks.

A major advance in this line of inquiry was forwarded by Krivo and Peterson (2000) and McNulty (2001), who demonstrated that the hypothesized racially invariant effects of structural determinants on homicide could be observed if units with similarly low mean levels of disadvantage were examined. Structural disadvantage only *appeared* to affect crime rates among whites more severely, these authors argued, because whites and blacks in American cities are situated at completely different ranges of the empirically observable disadvantage spectrum (predominantly white communities at low end, predominantly black ones at the high end), a condition which McNulty referred to as the *restricted distributions problem*. Comparing the effects of disadvantage in randomly selected white and black communities is inappropriate, therefore, because marginal increases in poverty, unemployment, family disruption, and so on can be expected to be more qualitatively meaningful in communities with low levels of these (i.e. white neighborhoods) compared with communities with higher levels of them (i.e. black communities). Thus, analyzing data on 400 block groups in Atlanta, Georgia, for 1990-1992, McNulty (2001) found that a squared concentrated disadvantage term significantly and negatively predicted homicide in black but not white neighborhoods (suggesting the weaker effects of disadvantage at higher levels), and also that disadvantage effects do not significantly differ by race within the range of disadvantage where the two neighborhood types overlap.

More recent work on the second expectation of the racial invariance thesis has attempted to subject it to stricter evaluation by expanding the structural determinants, crime types, and ethno-racial groups for which it is expected to hold (Hernandez, Vélez, & Lyons, 2016; Steffensmeier et al., 2010). Using race-specific homicide and other violent crime offending data for over 200 census places in New York and California for 1999-2001, Steffensmeier et al. (2010) examined the extent to which indicators of disadvantage exhibited invariant criminogenic effects on whites, blacks and Hispanics.

Their results were mixed: they discovered virtually no differences across racial groups in the effect of the disadvantage indicators predicting homicide, but they found substantial and significant differences in their effects on the violent crime index. Hernandez, Vélez, & Lyons's (2016) analysis of nearly 9,000 census tracts in 87 large cities was more supportive: they found that out of 220 equality of regression coefficient tests, which determine whether independent variable effects between groups significantly differ, the vast majority (>80%) were statistically insignificant at the .10 level for a large set of known structural determinants of crime across units of varying ethno-racial compositions. Furthermore, they observed that at similar levels of disadvantage (to adjust for restricted distributions), coefficient confidence intervals for disadvantage, residential instability, and percent foreign born across the different ethno-racial neighborhood types overlapped considerably.

Nevertheless, neither Steffensmeier et al. nor Hernandez et al. considered whether any measure of racial socioeconomic inequality exhibits racially invariant effects; in fact, to my knowledge, only one study has done so. Ousey (1999) used an across-equation F-test procedure to assess whether the effect of intraracial income inequality on homicide offending significantly differed between whites and blacks, and of five structural predictors tested it was the only one which did *not* differ significantly at conventional levels between the two groups (1999:418). The evidence to date, then, on whether any dimension (e.g. income, labor force participation, educational attainment) of any type of racial socioeconomic inequality—overall, interracial, or intraracial—exhibits comparable effects on community crime rates regardless of ethno-racial composition remains inconclusive.

Summary

Blau and Blau (1982) extended prior work on the concept of relative deprivation (Stouffer, Lumsdaine, et al., 1949; Stouffer, Suchman, et al., 1949) and the theories of reference groups and anomie (Merton, 1938, 1968) by positing that racial socioeconomic inequality in democratic societies contribute to feelings of unjust deprivation, which then result in expressions of diffuse aggression made manifest in violent crimes. Although scholars found their argument novel and intuitively appealing, they varied in their ability to replicate the Blaus' findings even after race-specific variables were used and analyses were extended to include Latinos as well as whites and blacks (Golden & Messner, 1987; Harer & Steffensmeier, 1992; Hipp, 2007; Martinez, 1996; Stolzenberg, Eitle, & D'Alessio, 2006). Instead, this subsequent body of work has suggested that overall and especially intraracial socioeconomic inequality are more robust predictors of crime than is interracial inequality, although the extent to which these factors associate with crime net of absolute deprivation indicators like structural disadvantage is unclear. Also unknown is whether racial socioeconomic inequality affects both expressive (violent) and instrumental (property) crimes equally (Bailey, 1984; Messner, 1982; Hipp, 2007; Stolzenberg, Eitle, & D'Alessio, 2006). These uncertainties have resisted resolution irrespective of theoretical alternatives proposed to account for the inequality-crime link, including social distance, group competition, and routine activity explanations (Hipp, 2007; McCall & Parker, 2005; Stolzenberg, Eitle, & D'Alessio, 2006). Finally, extant research suggests that racial socioeconomic inequality may impact offending among whites more severely than among members of other ethno-racial groups (Harer & Steffensmeier, 1992; Ousey, 1999; Messner & Golden, 1992; Parker & McCall, 1997), yet more recent work has supported the view that criminogenic structural factors are racially invariant in their operation, especially for the relationship between structural disadvantage and homicide (Hernandez, Vélez, & Lyons, 2016; Steffensmeier et al., 2010). Unfortunately, these two areas of research have largely refrained from reference to one another.

PART II. THE CURRENT STUDY

Although extant research has made substantial headway into clarifying the relationship between racial socioeconomic inequality and crime since Blau and Blau's (1982) original investigation, a comprehensive delineation of its effects has thus far remained elusive. I therefore build on prior work in the current study by determining (1) whether racial socioeconomic inequality affects crime across neighborhoods of varying ethno-racial compositions net of structural disadvantage and (2) whether the criminogenic effects of racial socioeconomic inequality vary in magnitude and direction by neighborhood ethno-racial composition. For each of these aims, I examine overall, intraracial, and interracial inequality among residents in three ethno-racial neighborhood types: Majority White, Majority Black, and Majority Latino. I analyze the distribution of income across neighborhood residents as the primary dimension of inequality for all three disparity types, with disparity in educational attainment serving as a secondary dimension for interracial inequality. Incomparability in educational means in a context of universally accepted economic goals may be especially likely to induce criminogenic adaptations or expressions of diffuse aggression (Farnworth & Leiber, 1989), and both educational attainment and income inequality represent resource disparities linked in prior work with interracial gaps in violent offending (Vélez, Krivo, & Peterson, 2003). Following earlier work on community crime, I use the census tract as a proxy for neighborhoods and henceforth use the two terms interchangeably (Hernandez, Vélez, & Lyons, 2016; Hipp, 2007; Peterson & Krivo, 2010a).

The present analysis primarily extends investigations by Hipp (2007) and Hernandez, Vélez, and Lyons (2016), both of which utilized census tracts in their examinations of the relationship between income inequality and crime and the validity of the racial invariance thesis, respectively. Census tracts are an ideal unit of analysis for the present work for several reasons. Most importantly, all of the mechanisms theorized to link racial socioeconomic inequality with crime assume interactions between persons who live near one another or otherwise frequently encounter each other in face-to-face interactions (Hipp, 2007:668, Table 1). For example, if inequality leads to crime through referent group comparisons that result in in feelings of illegitimate deprivation, as relative deprivation/reference group theory holds, then it is more likely that criminogenic comparisons will be made with salient others in one's residential vicinity than with persons residing in other parts of a city. Similarly, if inequality affects crime through social distance/social disorganization or routine activities, then the breakdown of regulative social ties or the convergence of suitable targets and motivated offenders is likely to occur in localized spaces rather than across large metropolitan areas. Second, census tracts are also small enough units to avoid confounding racial socioeconomic inequality effects with other structural factors that may strongly correlate with inequality at highly aggregated levels, such as residential segregation (Krivo, Peterson, & Kuhl, 2009; Peterson & Krivo, 2010a; Massey & Denton, 1993). Finally, and conversely, census tracts are large enough to encompass the areas within which most offenders commit their crimes (Hipp, 2007:669), so it is likely that any offenses resulting from the putative inequality-crime relationship are committed within the same areas where resource disparities are observed.

As aforementioned, almost no studies have explored how racial socioeconomic inequality affects crime rates within neighborhoods that vary in their ethno-racial compositions or whether these effects operate uniformly across them, so my expectations about the empirical outcomes of the current study are necessarily general. Nevertheless, I propose four tentative hypotheses based on the findings of prior work. First, regarding the extent to which racial socioeconomic inequality will predict neighborhood crime net of structural disadvantage, extant research has found overall and intraracial inequality measures to be more reliable correlates than interracial inequality regardless of the ethno-racial group in question (Harer & Steffensmeier, 1992; Hipp, 2007; LaFree & Drass, 1996; Martinez, 1996; Messner, Raffalovich, & McMillan, 2001; Phillips, 1997; Shihadeh & Steffensmeier, 1994). Between overall and intraracial inequality, the latter appears to be the stronger and more robust of the two (Hipp, 2007:683; see also Tables 4 and 5). Thus, my first hypothesis is as follows:

> **H1**: Intraracial inequality will be the most consistently positive and significant predictor of neighborhood crime net of structural disadvantage, followed by overall inequality and then interracial inequality.

My next hypothesis concerns whether the effects of racial socioeconomic inequality on crime will be similar in magnitude and direction across Majority White, Majority Black, and Majority Latino neighborhoods. Since the most comprehensive test to date of this "second prong" of the racial invariance thesis failed to yield evidence of significant effect differences for the majority of the structural factors it assessed (Hernandez, Vélez, & Lyons, 2016), I expect to observe a similar pattern:

> **H2**: The majority of the effect estimates of racial socioeconomic inequality will not significantly differ in size or direction across majority White, majority Black, or majority Latino neighborhoods.

However, it is necessary to anticipate the possibility that the effects of some types of racial socioeconomic inequality may be more severe among residents of some ethno-racial neighborhood types than others, and this may be especially likely for crime types other than homicide (Steffensmeier et al., 2010). I therefore propose two additional hypotheses, the third concerning overall and intraracial inequality and the fourth regarding interracial inequality. I discussed in Part I how, on balance, existing research suggests that overall and intraracial inequality appear to affect criminal involvement more severely among whites than among other ethno-racial minorities, especially blacks (Harer & Steffensmeier, 1992; Ousey, 1999; Messner & Golden, 1992; Parker & McCall, 1997). So, my third hypothesis is as follows:

> **H3**: For overall and intraracial inequality effects that significantly differ across ethno-racial neighborhood types, the largest positive effects will be observed in majority White neighborhoods, followed by majority Latino and then majority Black neighborhoods.

Unlike overall and intraracial inequality, which are operationalized the same way irrespective of the ethno-racial group under consideration, interracial inequality is typically measured as a ratio of the average resources of one group to that those of another (but see Balkwell, 1990 for an exception). I therefore only assess how interracial inequality affects neighborhood crime levels among the ethno-racial groups implicated in the disparity (i.e. I examine the effects of white-black interracial inequality on crime in majority White and majority Black neighborhoods, white-Latino interracial inequality on crime in majority White and majority Latino neighborhoods, and so on). In cases where the effects of interracial inequality significantly differ in size and direction between ethno-racial neighborhood types, I draw on findings from Peterson and Krivo (2010a) to hypothesize which neighborhood types will be more severely affected. These authors note that in large urban places in the United States, across multiple indicators of structural disadvantage, predominantly white neighborhoods and predominantly black ones serve as community socioeconomic extremes: white neighborhoods have the lowest disadvantage levels, black neighborhoods exhibit the highest disadvantage levels, and other ethno-racial neighborhood types rank between them in their disadvantage indicators.

If, as Blau and Blau (1982) maintain, interracial inequality results in crime through perceptions of unjust deprivation based on ethno-racial identity, individuals who are worse off socioeconomically may experience these perceptions more intensely if they reside in neighborhoods composed primarily of more advantaged members of another ethno-racial group than if they live in neighborhoods dominated by members of their own ethno-racial group. This differential may occur as result of *priming* (Margolis, 1987), or the process by which individuals' awareness of segregation along some dimension is heightened when the segregated differences somehow become pronounced (see Hipp, 2011). Consolidated inequality based on ethno-racial identity may generate some threshold for feelings of unjust deprivation, but when this inequality occurs in contexts where one is an ethno-racial minority these feelings may become especially acute. Consequently, interracial inequality may have larger criminogenic effects among *members of the disadvantaged group* residing in *the more advantaged group's neighborhood*.[2]

However, which group holds relative advantage depends on the two groups being compared and the indicator used to rank them. For example, predominantly Latino areas tend to have both lower poverty rates and higher proportions of residents without college degrees than do predominantly black areas in the United States (Peterson & Krivo, 2010a:54), so on the first indicator Latino areas are more advantaged whereas on the second indicator black areas are more advantaged. Furthermore, the same group may be relatively advantaged in each of the neighborhood types where the indicator is considered but hold a larger advantage in one type compared with the other. For instance, whites may have higher median household incomes than blacks in both majority white and majority black areas, yet retain a greater interracial advantage in the neighborhoods where they predominate. Thus, my two-part fourth hypothesis is as follows:

> **H4**: For interracial inequality effects that significantly differ across ethno-racial neighborhood types, the largest positive effects will be observed in the neighborhood type (1) composed primarily of the advantaged group *and* (2) with the larger absolute interracial disparity in the inequality dimension considered.

The current study builds on prior research on the relationship between racial socioeconomic inequality and crime in five key ways. First, my study is consistent with the approach of assessing the effects of overall, intraracial, and interracial inequality on crime along multiple dimensions of inequality within the same analysis (McCall & Parker, 2005; Stolzenberg, Eitle, & D'Alessio, 2006), but it adds the less frequently considered dimension of inequality in educational attainment (see Vélez, Krivo, & Peterson, 2003 for an exception). Second, I heed the recommendation by Hipp (2007) to utilize units of analysis small enough to precisely capture the effects of racial socioeconomic inequality, but extend the scope of that study's analysis using a nationally representative sample. Third, I employ data on a large sample of neighborhoods drawn from multiple cities that permits appropriate comparisons of similarly situated majority White, majority Black, and majority Latino neighborhoods. These data also allow me to explore how neighborhood ethno-racial composition may condition the relationship between socioeconomic inequality and crime, a possibility which only a few studies have considered (Balkwell, 1990; Hipp, 2007). Fourth, I explicitly distinguish between measures of relative and absolute deprivation and provide a more robust evaluation of the former perspective by estimating the effects of racial socioeconomic inequality net of structural disadvantage. Finally, I explore the impact of racial socioeconomic inequality on multiple types of crime to more clearly determine whether it is equally predictive of both violent and property offenses.

PART III. METHODOLOGY

Data and Variables

The data for this analysis come from two sources. First, I employ data from the NNCS (Peterson & Krivo, 2010b). The purpose of this study was to compile crime and sociodemographic characteristics for all tracts within a nationally representative sample of large urban places (i.e. with a population of at least 100,000) in the United States for the year 2000. The resulting data for 9,593 census tracts in 91 cities allow for multi-level study of predictors of crime for locations that vary in their social, economic, and ethno-racial characteristics. These data are advantageous for the present study because the large sample (1) allows for comparison between neighborhoods that are varied in their ethno-racial compositions but comparable in levels of structural disadvantage, and (2) permits exploration of whether any ethno-racial neighborhood type is especially vulnerable (or resistant) to the criminogenic effects of racial socioeconomic inequality.

Second, although the NNCS includes measures of white-black interracial inequality in income and educational attainment and overall income inequality at the city level, it does not contain interracial inequality measures beyond whites and blacks, overall inequality measures at the tract level, or intraracial inequality measures at either the tract or city levels. To construct these, I merged the NNCS with additional census data extracted from the National Historical Geographic Information System (NHGIS) (Minnesota Population Center, 2011). Unmatched cases from the merge reduced the sample size to 9,564 tracts, which I further classified into cases whose ethno-racial compositions were at least 50% non-Hispanic White, non-Hispanic Black, or Hispanic.[3] These tracts constituted the Majority White, Majority Black, and Majority Latino ethno-racial neighborhood types, respectively.[4] In total, these neighborhoods spanned 6,329 census tracts embedded in 60 cities; the remaining 31 cities comprising 3,235 census tracts were excluded from the analytic sample. Table 1 presents the means and standard deviations by ethno-racial neighborhood type for the dependent, independent, and control variables that I analyze for this final sample. I discuss the operationalization of these variables next, referencing the values listed in Table 1 when pertinent.

Dependent Variables

I utilize three crime types for my dependent variables: homicide, robbery, and burglary. I use homicide as my measure of violent offending because it is widely recognized as the most reliably reported crime type (Steffensmeier & Haynie, 2000). I use burglary as my primary measure of property crime, but I supplement it with a

Table 1. Descriptive Statistics.

	MW Tracts		MB Tracts		ML Tracts	
	Mean	SD	Mean	SD	Mean	SD
Tract Level	N = 3,868		N = 1,216		N = 1,245	
Homicide Rate	.052	.128	.341	.373	.188	.282
Robbery Rate	2.551	4.192	8.184	7.225	4.983	5.445
Burglary Rate	10.554	8.782	17.730	11.868	10.875	11.266
W-B Median Household Income Ratio	1.579	1.788	1.382	1.410		
W-B % High School Graduates Ratio	1.081	.459	.984	.335		
W-L Median Household Income Ratio	1.391	1.313			1.030	.192
W-L % High School Graduates Ratio	1.296	.503			1.488	.449
L-B Median Household Income Ratio			1.339	1.216	1.443	1.337
L-B % High School Graduates Ratio			.789	.462	.525	.269
Disadvantage	-.631	.509	.674	.651	.764	.506
Foreign Born (%)	11.038	8.342	7.114	8.132	41.954	15.240
Residential Instability	-.016	.902	-.105	.796	.276	.740
Young Males (%)	16.246	6.501	13.366	3.335	18.284	3.656
Spatial Lag of Homicide	.693	.732	3.069	2.149	2.341	1.778
Spatial Lag of Robbery	29.715	26.039	73.812	34.690	63.098	36.150
Overall Income Inequality	.393	.060	.453	.058	.427	.050
Intraracial Income Inequality	.382	.057	.437	.055	.412	.050
City Level	N = 44		N = 9		N = 7	
W-B Median Household Income Ratio	1.435	.197	1.615	.242		
W-B % High School Graduates Ratio	1.094	.089	1.183	.094		
W-L Median Household Income Ratio	1.308	.168			1.236	.207
W-L % High School Graduates Ratio	1.496	.305			1.660	.484
L-B Median Household Income Ratio			1.130	.148	1.168	.194
L-B % High School Graduates Ratio			.897	.204	.625	.236
Disadvantage	-.416	.747	.496	.479	1.022	.801
W-B Index of Dissimilarity	46.182	19.698	66.941	11.070	59.331	16.809
Foreign Born (%)	12.465	7.986	6.916	3.584	37.794	20.877
Recent Movers (%)	53.172	6.414	51.875	3.746	52.538	3.849
Young Males (%)	16.002	2.586	16.055	2.655	15.884	2.095
Population	268139	177503	297526	170497	903503	128366
Black (%)	15.208	14.724	35.713	12.271	18.488	14.561
Manufacturing (%)	12.283	4.792	10.925	4.850	10.877	3.637
Overall Income Inequality	.441	.047	.481	.042	.499	.052
Intraracial Income Inequality	.418	.036	.456	.030	.454	.029
South	.318	.471	.667	.500	.429	.535
West	.250	.438	.000	.000	.571	.535

Note. W-B = White-Black; W-L = White-Latino; L-B = Latino-Black; MW = Majority White, MB = Majority Black; ML = Majority Latino.

measure of robbery because the latter is more reliably reported (Baumer, 2002; Baumer & Lauritsen, 2010). Although both robberies and burglaries are instrumental in nature (i.e. aimed toward the acquisition of something of value) and tend to occur between strangers, robbery is classified as a violent offense because it involves the use or threat of force. Thus, using all three crime types captures a mix of both violent and property offending. For each crime type, I utilize the three-year average rate per 1,000 tract residents in 1999-2001 to minimize the impact of annual fluctuations (Krivo, Peterson, & Kuhl, 2009).

As can be seen in Table 1, Majority Black neighborhoods have the highest mean rates of offending across all three crime types, but the disparity narrows as increasingly less serious offenses are considered. For example, the average homicide rate in Majority Black neighborhoods is over 6 times greater in Majority White neighborhoods and almost twice the mean rate in Majority Latino tracts, but the average burglary rate in Majority Black neighborhoods is just over 1.5 times greater than the rate in either Majority White or Latino tracts.

<u>Tract-Level Variables</u>

I utilize nine key independent variables. Serving as an indicator of absolute deprivation, the first is an index of *structural disadvantage*. This variable is operationalized as the average of the standardized scores of the following six measures: percent secondary sector low wage jobs, jobless rate for working population, percent professionals and managers (reverse coded), percent female-headed households, percent high school graduates (reverse coded), and poverty rate ($\alpha = .93$). The remaining eight variables are inequality measures serving as indicators of relative deprivation. The next is my measure of *overall income inequality*, the Gini coefficient.[5] The Gini coefficient measures the dispersion of income across *x* number of households and ranges from 0 to 1, where a value of 0 would indicate that each of the *x* households holds the same income quantity and a value of 1 would indicate that one household holds all of the available income and the other *x* - 1 households have none. Among the census tracts analyzed in the present study, Majority Black neighborhoods have the highest mean level of overall inequality (Gini coefficient = .453), followed by Majority Latino (Gini coefficient = .427) and Majority White neighborhoods (Gini coefficient = .393) (Table 1).

The third key variable is my measure of *intraracial income inequality*, the race-specific Gini coefficient. Following Hipp (2007), I constructed this measure in three steps: (1) I calculated a race-specific Gini value for each ethno-racial group of interest (in my case, Whites, Blacks, Latinos, and Other Groups); (2) multiplied each of these values by the proportion of the tract comprised by the group, and (3) summed these values.[6] Thus, the constructed measure represents the average income inequality across the members of each ethno-racial group within the tract, weighted by the size of each group (Hipp, 2007:675). I used household income data extracted from the NHGIS to construct both my overall and intraracial income inequality measures. The data are binned (i.e. households are sorted into categories of income ranges), so I use an operator in Stata designed to generate inequality measures from data coded this way: the robust Pareto Midpoint estimator (“rpme”) command (von Hippel, Scarpino, & Holas, 2015). Table 1 indicates that the rank ordering of ethno-racial neighborhood types for intraracial inequality is the same as for overall inequality, with Majority Black neighborhoods having the highest mean value (.437) and being followed by Majority Latino neighborhoods (.412) and finally Majority White neighborhoods (.382).[7]

The final six primary independent variables are my measures of *interracial inequality*. Three of these variables capture income disparities while the other three measure disparities in educational attainment. I employ median household income ratios for three ethno-racial pairs: White-to-Black, White-to-Latino, and Latino-to-Black. For these same pairs, I also utilize percent high school graduates ratios, defined as the percentage of the members of one group age 25 and over who are at least high school graduates divided by the percentage of the members of the other group who fit these same criteria. I constructed all six of these ratios using NHGIS data.[8] Two notable patterns regarding the interracial inequality measures can be identified in Table 1. First, the descriptive statistics confirm Peterson and Krivo's (2010a) general observation that mostly white neighborhoods tend to be more advantaged than mostly Latino ones, which in turn are more advantaged than mostly black tracts, on measures of household income and educational attainment (the mean values for the interracial inequality ratios are typically greater than 1). However, whites have a slightly lower average proportion of residents with at least a high school diploma than do blacks in Majority Black neighborhoods (mean = .984), and a lower average proportion of Latinos has reached this educational threshold than have blacks in both Majority Black (mean = .789) and Majority Latino neighborhoods (mean = .525). Second, the largest absolute interracial disparities tend to occur in the neighborhoods where the more advantaged group is in the majority. Yet this pattern reverses for the White-Latino percent high school graduates ratio where whites are more advantaged in Majority Latino neighborhoods (mean =

1.488) than in their own neighborhood type (mean = 1.296), and again for the Latino-Black high school graduates ratio where blacks are more advantaged in Majority Latino neighborhoods (mean = .525) than in their own neighborhood type (mean = .789).

I also control for five variables that have been found to correlate with violent crime in prior literature. The first three include the percentage of the total population that is *foreign-born*, a measure of *residential instability* (an average of the standardized scores of the percentage of renter-occupied units and the percentage of residents who are at least age 5 who lived in a different dwelling in 1995), and the percentage of the population that are *young males* (between the ages of 15 and 34). The last two are *spatial lags* for my homicide and robbery rate dependent variables (to control for spatial autocorrelation in violence).[9] Except for the percent foreign-born, these controls are expected to increase neighborhood crime rates.

<u>City-Level Controls</u>

In addition, I control for several variables measured at the city level. Each of the nine key independent variables at the tract level (i.e. structural disadvantage; overall income inequality; intraracial income inequality; White-Black, White-Latino, and Latino-Black median household income ratios; and White-Black, White-Latino, and Latino-Black high school graduates ratios) has a counterpart variable at the city level, operationalized in the same way. *Population* is the size of the city population in 2000. *Percent manufacturing* is the percent of the civilian population age 16 and over employed in manufacturing industries. *Percent black* is the percent of residents who are non-Hispanic black. *Percent recent movers* is the percent of the population age 5 and over who lived in a different house in 1995. *Percent foreign born* is the percent of the total population that is foreign born. *Percent young males* is the percent of the total population that is male and between the ages of 15-34, and the dichotomous variables *South* and *West* serve as region indicators (with East and Midwest as reference categories). Lastly, I utilize the standard city-level measure of residential segregation in prior literature, the *White-Black Index of Dissimilarity* (D).[10] Except for the percent foreign born and percent employed in manufacturing variables, these controls are expected to increase neighborhood crime rates.

Analytic Strategy

To determine the extent to which racial socioeconomic inequality predicts criminal offending net of structural disadvantage in neighborhoods that vary in their ethno-racial compositions, I estimate a set of hierarchical linear models (HLMs), with tracts as level-one units nested in cities as level-two units. Doing so allows for reliable estimation of regression coefficients and standard errors despite the non-independence of the observations. Multicollinearity prevents an estimation of the effects of the inequality variables simultaneously, so six model types are analyzed: (1) an estimation of the overall income inequality effect; (2) an estimation of the intraracial income inequality effect; (3) an estimation of the interracial inequality effect between members of the ethno-racial neighborhood types under consideration and either of the other two groups (for the median household income ratio); (4) an estimation of the interracial inequality effect between the group under consideration and the group not compared in the preceding model (for the median household income ratio); (5) a replication of the third model (for the percent high school graduates ratio); and (6) a replication of the fourth model (for the percent high school graduates ratio). These general models are estimated with and without a control for structural disadvantage, making 12 models in total for *each* ethno-racial neighborhood type-crime type pair. Since there are three ethno-racial neighborhood types and three dependent variables, a total of 3 * 3 * 12 = 108 models were estimated (see Appendices A-I for the coefficients of the full models).

For the models that estimate coefficients for the interracial inequality measures, I further specify that the analytic sample be reduced to census tracts with a nonzero percentage of both groups being compared. Since models are estimated by ethno-racial neighborhood type (where the ethno-racial composition of each tract is greater than 50% of one of the three groups), this simply means dropping any tracts with a nonzero percentage of the *other* group in the interracial comparison. For example, if I am estimating the effects of the white-black median household income ratio in Majority White neighborhoods, I only estimate the coefficient of this measure for tracts where percent black is greater than 0. In addition, except for categorical and continuous variables that are already centered around 0, I grand-mean center my measures. When regression model predictors are scaled this way, model intercepts can be interpreted as the crime rates that would be observed in a tract and city with average values on all of the predictors (see Appendices A-I). Moreover, coefficients for city-level controls can be interpreted as the effects on the average tract crime rate within the city, net of the neighborhood conditions. Finally, to normalize their skewed distributions and minimize the possibility of outliers, I log-transform the dependent variables and all six of the interracial inequality measures at the tract level (see Hipp, 2007); I add a negligible constant (.01) to each of these variables prior to transforming them to avoid taking the natural logarithm of 0.

To assess whether the effects of any inequality type vary significantly by ethno-racial neighborhood type, I conduct Z-tests using the formula recommended by Paternoster, Brame, Mazerolle, and Piquero (1998). The value provided by their equation indicates whether two coefficients are significantly different from one another based on their magnitudes and the sizes of their standard errors and is given by

$$z = b_1 – b_2 / sqrt\ (SEb_1^2 + SEb_2^2)$$

Because the racial invariance thesis holds that structural predictors of crime operate uniformly across ethno-racial groups, the majority of these tests comparing inequality coefficients will need to *fail* to reject the null hypothesis of no differences across Majority White, Black, and Latino neighborhoods for H2 to be supported. I conduct a strict test of this possibility by using 90% confidence levels (rather than conventional 95% confidence levels), which increase the likelihood of the null hypothesis being rejected for any two inequality coefficients. I am cognizant that failing to find evidence of significant differences between the ethno-racial neighborhood types (via statistically insignificant Z-tests) for the inequality coefficients is not equivalent to finding evidence that their effects are actually uniform (Altman & Bland, 1995). Nevertheless, this method has proven fruitful for identifying effects that significantly differ in magnitude and direction between whites, blacks, and Latinos in recent research on race, structural disadvantage, and crime (Hernandez, Vélez, & Lyons, 2016; Painter-Davis & Harris, 2016).

PART IV. RESULTS

Results will be presented by crime type, starting with homicide. I then consider the results for burglary and end with a discussion of the results for robbery. For ease of presentation, Tables 2-4 present HLM coefficients for the eight inequality measures only, as well as the results of the Z-tests comparing these coefficients across ethno-racial neighborhood types. Tables 5-13 presenting HLM coefficients for the full models can be found in Appendices A-I. In the narration that follows, I focus primarily on the inequality coefficients obtained while controlling for structural disadvantage because of the salience of these estimates for assessing my hypotheses.

Homicide

Table 2 presents the HLM coefficients and standard errors predicting the logged tract homicide rate in Majority White, Black, and Latino neighborhoods in Panels 1-3 and the z-scores comparing these coefficients in Panel 4. Within each ethno-racial neighborhood type, coefficients are estimated first without a control for structural disadvantage (indicated by "W/O D") and then net of this index (indicated by "W/ D"). Since Table 2 condenses the findings from 36 distinct models for ease of presentation, several of its aspects differ from conventional regression model coefficient tables and require explanation. First, the coefficients and standard errors listed in each column of Panels 1-3 are *not* estimated within the same model (multicollinearity between inequality measures precludes this approach); each coefficient-standard error pair is estimated via a separate model. Second, four interracial inequality coefficients are presented within each of these columns: one for each interracial comparison, first for the median household income ratio (designated "*I*") and then for the percent high school graduates ratio

Table 2. Summary of Coefficients from HLMs Predicting Tract Homicide Rate in Majority White, Black, and Latino Neighborhoods

		Panel 1					**Panel 2**					**Panel 3**				**Panel 4**		
		Majority White					**Majority Black**					**Majority Latino**				**Z-Tests**		
		W/O D		W/ D			W/O D		W/ D			W/O D		W/ D		WB	WL	LB
		b	SE	b	SE		b	SE	b	SE		b	SE	b	SE	z	z	z
Overall		1.962*	.366	1.543*	.359		4.529*	.663	1.943*	.686		3.158*	.836	2.042*	.864	-.517	-.533	.090
Intraracial		1.886*	.406	1.471*	.398		4.509*	.848	.481	.904		3.160*	.844	2.031*	.870	1.002	-.585	1.235
Inter. (*I*)	**WB**	.024	.034	.020	.033	**WB**	-.058	.030	-.026	.029	**WL**	-.147	.209	.043	.210			
Inter. (*I*)	**WL**	.032	.038	.064	.037	**LB**	-.039	.022	-.022	.021	**LB**	.074	.067	.035	.067			
Inter. (*E*)	**WB**	-.122	.085	.026	.083	**WB**	-.023	.053	.025	.051	**WL**	-.304*	.152	-.152	.153			
Inter. (*E*)	**WL**	.274*	.065	.104	.065	**LB**	-.034	.028	-.013	.027	**LB**	-.218	.116	-.072	.119			

Note. *p<.05 (two-tailed). Controls at the tract-level: %foreign born, %males aged 15-34, residential instability, and the spatial lag of homicide. Controls at the city-level: disadvantage, white-black residential segregation, population size, %black, %recent movers, %foreign-born, %males aged 15-34, %in manufacturing industries, Southern location, and Western location. Each model also includes a city-level inequality control variable which corresponds to its tract-level counterpart. W/O D = Without Disadvantage; W/ D = With Disadvantage; (*I*) = Median Household Income Ratio; (*E*) = Percent High School Graduate Ratio; WB = White-Black; WL = White-Latino; LB = Latino-Black. z-Statistics test the equality of regression coefficients between models which control for disadvantage and are only provided if at least one coefficient is significant. Bolded z-statistics at p<.1 (90% CI).

(designated "*E*"). Bolded letter pairs preceding each of the first three panels indicate the interracial comparison made within each ethno-racial neighborhood type. For example, in Majority White neighborhoods, the White-Black median household income ratio coefficient is estimated first, followed by the White-Latino median household income ratio, then the White-Black percent high school graduates ratio, and finally the White-Latino percent high school graduates ratio. Finally, the coefficients presented in Panels 1-3 have been estimated net of all of the same control variables listed in Part III *except* the city-level inequality variables; these are alternately included to match their tract-level counterparts being estimated by the model in question.

Overall, the coefficients in Panels 1-3 of Table 2 offer mixed support for H1. As expected, interracial inequality is the weakest predictor of neighborhood homicide; in fact, none of the interracial inequality coefficients are significantly associated with homicide net of disadvantage. But instead of intraracial income inequality being the most consistently positive and significant predictor of crime as hypothesized, overall income inequality is clearly the more robust covariate. Only the overall tract-level Gini coefficient significantly predicted tract homicide in all three ethno-racial neighborhood types, whereas the race-specific Gini coefficient associated with homicide only in Majority White and Latino neighborhoods (Panels 1 and 3). These findings provide some support for the importance of the relative deprivation perspective vis-à-vis absolute deprivation with respect to neighborhood homicide rates; however, they also demonstrate the clear substantive impact of structural disadvantage on community crime rates (Krivo & Peterson, 1996; Peterson & Krivo, 2010a; Wilson, 1987). The effect of overall inequality is attenuated in all three ethno-racial neighborhood types after disadvantage is controlled, with the strongest diminution occurring in Majority Black neighborhoods (a 57% decrease) followed by Majority Latino (35% decrease) and then Majority White neighborhoods (21% decrease). Similarly, net of disadvantage the intraracial income inequality coefficient drops by 89% (to insignificance) in Majority Black tracts, by 36% in Majority Latino tracts, and by 22% in Majority White tracts.

Turning to the z-scores presented in Panel 4 of Table 2, I find clear support for H2. Each value listed in Panel 4 corresponds to a Z-test comparing the coefficients for an inequality type estimated in two distinct neighborhood types, indicated by the row and column where each value is presented. (For instance, z = -.517 tests whether the coefficients for overall income inequality differ significantly in size and magnitude between Majority White and Majority Black neighborhoods, z = -.533 tests this same condition for Majority White and Majority Latino neighborhoods, and so on. Z-tests were conducted for the coefficients estimated net of disadvantage and the resulting z-scores are presented only if at least one of the coefficients in the comparison was significant.) None of the z-scores displayed in Panel 4 are significant at the 90% confidence level (p < .1; significant z-scores are presented in bold). Thus, consistent with the racial invariance thesis, no significant differences in magnitude or size are discernable for the effects of overall or intraracial income inequality on homicide rates between the three ethno-racial neighborhood types. This finding, coupled with the absence of significant coefficients for the interracial inequality variables, renders inapplicable any expectations about which ethno-racial neighborhood types may be particularly vulnerable or resilient to the criminogenic effects of racial socioeconomic inequality. H3 and H4, therefore, cannot be evaluated with respect to the tract homicide rate.

Burglary

Table 3 presents the HLM coefficients and standard errors predicting the logged tract burglary rate in Majority White, Black, and Latino neighborhoods in Panels 1-3 and the z-scores comparing these coefficients in Panel 4. The coefficients and z-scores in Table 3 are organized the same way as in Table 2 and can therefore be interpreted similarly. The coefficients displayed in Panel 2 suggest that, as with homicide, overall rather than intraracial income inequality is the more robust predictor of tract burglary rates, but this is only the case among Majority Black neighborhoods. Indeed, Panels 1 and 3 indicate that all three types of inequality are important predictors of burglary in Majority White and Majority Latino neighborhoods. Only the White-Latino median household income ratio does *not* significantly associate with the tract burglary rate in each of these ethno-racial neighborhood types, net of structural disadvantage.

Considered in their entirety, the coefficients in Panels 1 and 3 suggest that interracial inequality in educational attainment is more consistently relevant for neighborhood burglary than is interracial income inequality in both Majority White and Majority Latino neighborhoods: the burglary rate in each is significantly affected by two between-race comparisons in the percent high school graduates ratio but by only one between-race comparison in the median household income ratio. Moreover, overall and intraracial income inequality are salient predictors of crime in both neighborhood types. One unusual finding from Panel 3 is that although the Latino-Black high school graduates ratio coefficient is significant net of structural disadvantage, its sign is negative ($b = -.097$, $p < .05$). In other words, Latino-Black disparity in educational attainment actually *lowers* the tract burglary rate in Majority Latino neighborhoods. This pattern may not be

Table 3. Summary of Coefficients from HLMs Predicting Tract Burglary Rate in Majority White, Black, and Latino Neighborhoods

		Panel 1 Majority White					**Panel 2 Majority Black**					**Panel 3 Majority Latino**				**Panel 4 Z-Tests**		
		W/O D		W/ D			W/O D		W/ D			W/O D		W/ D		WB	WL	LB
		b	SE	b	SE		b	SE	b	SE		b	SE	b	SE	z	z	z
Overall		3.975*	.210	3.377*	.201		1.180*	.170	.606*	.180		2.390*	.283	1.975*	.303	**10.270**	**3.856**	**3.884**
Intraracial		4.015*	.234	3.442*	.223		1.502*	.224	.450	.245		1.870*	.294	1.350*	.315	**9.031**	**5.420**	**2.255**
Inter. (*I*)	**WB**	.053*	.020	.046*	.019	**WB**	-.006	.008	.004	.007	**WL**	-.092	.077	-.025	.077			
																2.074		**2.104**
Inter. (*I*)	**WL**	-.007	.022	.026	.021	**LB**	.000	.006	.004	.006	**LB**	.078*	.024	.054*	.023			
Inter. (*E*)	**WB**	-.006	.049	.147*	.046	**WB**	-.025	.013	-.010	.013	**WL**	.077	.056	.166*	.056			
																3.284	-.670	**-1.951**
Inter. (*E*)	**WL**	.296*	.038	.121*	.037	**LB**	-.018*	.007	-.012	.007	**LB**	-.176*	.041	-.097*	.043			

Note. *p<.05 (two-tailed). Controls at the tract-level: %foreign born, %males aged 15-34, and residential instability. Controls at the city-level: disadvantage, white-black residential segregation, population size, %black, %recent movers, %foreign-born, %males aged 15-34, %in manufacturing industries, Southern location, and Western location. Each model also includes a city-level inequality control variable which corresponds to its tract-level counterpart. W/O D = Without Disadvantage; W/ D = With Disadvantage; (*I*) = Median Household Income Ratio; (*E*) = Percent High School Graduate Ratio; W-B = White-Black; W-L = White-Latino; L-B = Latino-Black. z-Statistics test the equality of regression coefficients between models which control for disadvantage and are only provided if at least one coefficient is significant. Bolded z-statistics at p<.1 (90% CI).

all that unexpected, however, if we recall that blacks have a higher average proportion of residents with at least a high school diploma than do Latinos even in neighborhoods where the latter are in the majority (see Table 1). Thus, increases in this measure in most Majority Latino neighborhoods reflect growing *parity* rather than *inequality* between Latinos and blacks in their educational attainment levels and may signal a corresponding diminishment of feelings of unjust deprivation in such neighborhoods. Alternatively, the inverse relationship may indicate a widening of social distance or a lowering of group competition between Latinos and blacks in Majority Latino neighborhoods (Messner & Golden, 1992; Parker & McCall, 2005).

As with the tract homicide rate, controlling for structural disadvantage tends to attenuate racial socioeconomic inequality's effects on neighborhood burglary, ranging from inducing a 13% drop in the White-Black median household income ratio coefficient for Majority White neighborhoods to a 70% drop (to non-significance) in the intraracial income inequality coefficient for Majority Black neighborhoods. Yet again, atypical patterns emerge: the absolute value of the White-Black percent high school graduates ratio coefficient (for Majority White neighborhoods) and the White-Latino percent high school graduates ratio coefficient (for Majority Latino neighborhoods) grow 25 times and 2 times larger, respectively, after disadvantage is controlled.

Considering Panel 4 of Table 3 next, I find evidence contradictory to the expectations of H2: all but one of the z-scores indicate significant differences in the effects of the racial socioeconomic inequality variables across ethno-racial neighborhood types. This finding, however, allows for a test of my third and fourth hypotheses. Recalling that H3 expected the largest significantly different effects for overall and intraracial income inequality to emerge in Majority White neighborhoods (followed by Majority Latino and Majority Black neighborhoods), this hypothesis appears to be supported. Overall income inequality has a significantly larger impact on Majority White than on Majority Black neighborhood burglary rates (b = 3.377 > b = .606, z = 10.270), Majority White than on Majority Latino rates (b = 3.377 > b = 1.975, z = 3.856), and Majority Latino than on Majority Black rates (b = 1.975 > b = .606, z = 3.884), net of disadvantage. The same ranking is evinced for intraracial income inequality: the effect is significantly greater in Majority White than in Majority Black neighborhoods (b = 3.442 > b = .450, z = 9.031), Majority White than in Majority Latino neighborhoods (b = 3.442 > b = 1.350, z = 5.420), and Majority Latino than in Majority Black neighborhoods (b = 1.350 > b = .450, z = 2.255).

The z-scores listed for the interracial inequality coefficient comparisons in Panel 4 are presented in a slightly different fashion than those for overall or intraracial inequality. Unlike these first two types, each type of interracial inequality only applies in two of the three ethno-racial neighborhood types. Thus, only one z-score is presented for each interracial inequality pair (White-Black, White-Latino, and Latino-Black) where at least one coefficient in each neighborhood type was significant. Examining the z-scores for interracial income inequality first (located in the sixth row of Table 3, between the two interracial income inequality coefficient rows of Panels 1-3), Panel 4 indicates that the White-Black median household income ratio coefficient is significantly larger in Majority White than in Majority Black neighborhoods (b = .046 > b = .004, z = 2.074), and also that the Latino-Black median household income ratio coefficient is significantly greater in Majority Latino than in Majority Black neighborhoods (b = .054 > b = .004, z = 2.104).

Recall that H4 expected the largest significantly different effects for interracial inequality to emerge in the neighborhood type composed primarily of the advantaged group in the interracial comparison, given that this neighborhood type also exhibits the larger absolute disparity between the two groups. According to Table 1, whites have higher median household incomes in both Majority White and Majority Black neighborhoods, but the absolute disparity is greater in the former type (1.579 > 1.382); so H4 would expect the larger White-Black median household income ratio coefficient in Majority White neighborhoods, and this is indeed the case. Similarly, Latinos have higher median household incomes in both Majority Latino and Majority Black neighborhoods, but the absolute disparity is greater in the former type (1.443 > 1.339). H4 thus predicts the Latino-Black median household income ratio to have a larger impact in Majority Latino neighborhoods, and this is in fact observed.

Proceeding to the z-scores for interracial inequality in educational attainment, Panel 4 indicates that the White-Black percent high school graduates ratio coefficient is significantly larger in Majority White than in Majority Black neighborhoods (b = .147 > b = -.010, z = 3.284), and also that the Latino-Black percent high school graduates ratio coefficient is significantly greater in Majority Latino than in Majority Black neighborhoods (b = -.097 > b = -.012, z = -1.951). Per Table 1, whites are only relatively advantaged to blacks in average educational attainment in Majority White neighborhoods, but it is in these neighborhood types where the larger absolute disparity is found (1.081 – 1 = .081 > .016 = 1 – .984). Thus, H4's prediction in this case matches our observation of the significantly larger percent high school graduates ratio coefficient in Majority White neighborhoods. In contrast, because blacks are relatively advantaged to Latinos in average educational attainment in both Majority Black and Majority Latino neighborhoods, but the absolute disparity is larger in the *latter* (1 - .789 = .211 < .475 = 1 - .525), the neighborhood type with the largest interracial disparity and the neighborhood type with the relatively advantaged group do *not* match, so H4 is unsupported.

Why might Latino-Black educational attainment disparity exhibit an effect with a larger absolute value in Majority Latino neighborhoods than in Majority Black neighborhoods even though blacks are relatively advantaged in each neighborhood type? I speculated earlier that the negative sign for the Latino-Black percent high school graduates ratio coefficient in Majority Latino neighborhoods may result from increases on the measure reflecting growing parity rather than inequality in most Majority Latino neighborhoods, given that the mean for this ratio is *less* than 1.0 (see Table 1). To the extent that this is also the case in Majority Black neighborhoods (the coefficient in Table 3 is insignificant), the *weaker crime-reducing* effect in Majority Black neighborhoods may result from resident Latinos residing in locations with high proportions of more advantaged ethno-racial group members. Thus, growing parity in educational attainment may diminish feelings of unjust deprivation among Latinos in both Majority Latino and Majority Black neighborhoods, but such feelings may be more resilient in Majority Black neighborhoods because Latino’s perceptions of inequality may be more pronounced there (see Hipp, 2011).

Robbery

Table 4 presents the HLM coefficients and standard errors predicting the logged tract robbery rate in Majority White, Black, and Latino neighborhoods (Panels 1-3) and the z-scores comparing these coefficients (Panel 4). Once again, H1 receives mixed support: the interracial inequality measures show the fewest significant associations with the tract robbery rate, but *all six* of the overall and intraracial income inequality coefficients are positive and significant net of disadvantage. With respect to direction and statistical significance, Panels 1-3 suggest overall and intraracial income inequality are comparably predictive of robbery incidents across Majority White, Black, and Latino neighborhoods.

Among the interracial inequality measures, Majority White tracts appear to be the most consistently affected neighborhood type: only the White-Latino median household income ratio did *not* significantly associate with robbery after disadvantage was controlled. In comparison, Majority Latino neighborhoods were significantly impacted by just two of the interracial inequality measures (the Latino-Black median household income ratio and the White-Latino percent high school graduates ratio), and Majority Black neighborhoods were not significantly affected by any of these measures.[11] As was the case with the other two crime types, controlling for structural disadvantage attenuated the racial socioeconomic inequality measures' effects, ranging from a 5% drop (for the White-Black median household income ratio in Majority White neighborhoods) to a 61% drop (for the Latino-Black percent high school graduates ratio in Majority Latino neighborhoods). And once more, several coefficients rose after disadvantage was controlled: the White-Black percent high school graduates ratio coefficient in Majority

Table 4. Summary of Coefficients from HLMs Predicting Tract Robbery Rate in Majority White, Black, and Latino Neighborhoods

		Panel 1 Majority White					**Panel 2 Majority Black**					**Panel 3 Majority Latino**				**Panel 4 Z-Tests**		
		W/O D		W/ D			W/O D		W/ D			W/O D		W/ D		WB	WL	LB
		b	SE	b	SE		b	SE	b	SE		b	SE	b	SE	z	z	z
Overall		4.923*	.375	4.390*	.360		2.469*	.277	1.324*	.288		3.831*	.418	2.939*	.434	**6.650**	**2.573**	**3.101**
Intraracial		4.882*	.409	4.381*	.390		3.207*	.377	1.722*	.412		3.349*	.427	2.456*	.442	**4.687**	**3.266**	1.215
Inter. (*I*)	**WB**	.080*	.033	.076*	.032	**WB**	-.033*	.013	-.014	.012	**WL**	-.327*	.109	-.170	.107			
																2.633		**3.479**
Inter. (*I*)	**WL**	-.007	.038	.045	.036	**LB**	-.019*	.009	-.011	.009	**LB**	.151*	.034	.108*	.033			
Inter. (*E*)	**WB**	.094	.083	.326*	.080	**WB**	-.040	.023	-.012	.022	**WL**	.024	.078	.199*	.078			
																4.074	.714	
Inter. (*E*)	**WL**	.511*	.066	.271*	.064	**LB**	-.021	.012	-.011	.011	**LB**	-.228*	.060	-.090	.060			

Note. *p<.05 (two-tailed). Controls at the tract-level: %foreign born, %males aged 15-34, residential instability, and the spatial lag of robbery. Controls at the city-level: disadvantage, white-black residential segregation, population size, %black, %recent movers, %foreign-born, %males aged 15-34, %in manufacturing industries, Southern location, and Western location. Each model also includes a city-level inequality control variable which corresponds to its tract-level counterpart. W/O D = Without Disadvantage; W/ D = With Disadvantage; (*I*) = Median Household Income Ratio; (*E*) = Percent High School Graduate Ratio; W-B = White-Black; W-L = White-Latino; L-B = Latino-Black. z-Statistics test the equality of regression coefficients between models which control for disadvantage and are only provided if at least one coefficient is significant. Bolded z-statistics at p<.1 (90% CI).

White neighborhoods and the White-Latino percent high school graduates ratio coefficient in Majority Latino neighborhoods increased by more than twofold and sevenfold, respectively.

Panel 4 of Table 4 yields a similar lack of support for H2 and the racial invariance thesis as for burglary: all but two of the estimated z-scores indicate significant differences in the effects of the racial socioeconomic inequality variables across ethno-racial neighborhood types. I therefore proceed to assess H3 and H4. Overall income inequality does indeed affect Majority White neighborhoods more severely than either Majority Black (b = 4.390 > b = 1.324, z = 6.650) or Majority Latino neighborhoods (b = 4.390 > b = 2.939, z = 2.573), and Majority Latino neighborhoods more than Majority Black neighborhoods (b = 2.573 > b = 1.324, z = 3.101), as H3 predicts. However, the z-tests for intraracial income inequality only partially support H3: the coefficient is significantly larger in Majority White neighborhoods than Majority Black (b = 4.381 > b = 1.722, z = 4.687) and Majority Latino neighborhoods (b = 4.381 > b = 2.456, z = 3.266), but the size difference fails to reach statistical significance between Majority Latino and Majority Black neighborhoods (b = 2.456 > b = 1.722, z = 1.215, p > .1). I therefore fail to reject the null hypothesis of no differences between only these last two ethno-racial neighborhood types with respect to the effects of intraracial income inequality on neighborhood robbery.

Each of the three z-scores that indicate significant differences in magnitude for the interracial inequality coefficients between ethno-racial neighborhood types is consistent with the expectations of H4. Recall from the section on burglary that whites are relatively advantaged to blacks in median household income regardless of the ethno-racial neighborhood type, but the greater disparity exists in Majority White neighborhoods; that Latinos are relatively advantaged to blacks in median household income regardless of neighborhood type, but the larger inequality is found in Majority Latino neighborhoods; and that whites are relatively advantaged to blacks in percent high school graduates only in Majority White neighborhoods, but the greater absolute disparity is found in this neighborhood type. Thus, H4 would predict significantly larger effects of the White-Black median household income ratio in Majority White neighborhoods, larger effects of the Latino-Black median household income ratio in Majority Latino neighborhoods, and larger effects of the White-Black percent high school graduates ratio in Majority White neighborhoods. This ranking is indeed exhibited in Panel 4 of Table 4: White-Black income inequality has a greater impact on robbery rates in Majority White than Majority Black neighborhoods ($b = .076 > b = -.014$, $z = 2.633$), Latino-Black income inequality has a greater impact on robbery rates in Majority Latino than Majority Black neighborhoods ($b = .108 > b = -.011$, $z = 3.479$), and White-Black inequality in educational attainment has a greater impact on robbery rates in Majority White than Majority Black neighborhoods ($b = .326 > b = -.012$, $z = 4.074$).

PART V. DISCUSSION AND CONCLUSIONS

Blau and Blau's (1982) seminal work was pathbreaking in its suggestion that high rates of violent offending "are apparently the price of racial and economic inequalities" (1982:126). However, with some notable exceptions (e.g. Stolzenberg, Eitle, & D'Alessio, 2006), the body of evidence on the relationship between racial socioeconomic inequality and crime that has accumulated since has largely eroded the foundation of support for the salience of interracial inequality as a factor of criminal violence. Instead, more recent work has argued that intraracial inequality is the more plausible generator of perceptions of unjust deprivation, and demonstrated the empirical importance of this variable (and overall inequality to a lesser extent) as a covariate of violent offending (Harer & Steffensmeier, 1992; Hipp, 2007; LaFree & Drass, 1996; Martinez, 1996; Messner, Raffalovich, & McMillan, 2001; Phillips, 1997; Shihadeh & Steffensmeier, 1994). In the process, this research has also suggested that whites may be especially vulnerable to the criminogenic effects of racial socioeconomic inequality compared with other ethno-racial groups (Harer & Steffensmeier, 1992; Ousey, 1999; Messner & Golden, 1992; Parker & McCall, 1997).

Unfortunately, firm conclusions about this issue have remained elusive due to several persistent limitations of prior work, including the use of overly broad units of analysis (Hipp, 2007; Messner & Tardiff, 1986), failure to distinguish between or evaluate the respective effects of relative versus absolute deprivation (Bernard, Snipes, & Gerould, 2016; Pettigrew, 2015), and neglect of how the ethno-racial composition of neighborhood areas may condition the magnitude or size of effects (Hernandez, Vélez, & Lyons, 2016). I sought to address these limitations in the current study by using data from the NNCS (Peterson & Krivo, 2010b) and NHGIS (Minnesota Population Center, 2011) to examine how overall, intraracial, and interracial inequality shaped criminal offending patterns in Majority White, Majority Black, and Majority Latino neighborhoods for homicide, burglary, and robbery rates. Specifically, I explored whether racial socioeconomic inequality affects crime across neighborhoods of varying ethno-racial compositions net of structural disadvantage, and whether the criminogenic effects of racial socioeconomic inequality vary in magnitude and direction by neighborhood ethno-racial composition. My analysis revealed six main findings.

First, I found that racial socioeconomic inequality and structural disadvantage tended to have separate effects on neighborhood crime. Regardless of the neighborhood ethno-racial composition or crime type under consideration, structural disadvantage often reduced but did not eliminate a statistically significant inequality coefficient; if a coefficient was insignificant net of disadvantage, it usually was not significant *before* disadvantage was controlled. This finding questions the notion that socioeconomic disparity by itself does not contribute to criminal offending beyond the effects of absolute deprivation and suggests the importance of both the relative and absolute deprivation perspectives for understanding crime distribution patterns (Pettigrew, 2015).

Second, inequality type, class of offense, and neighborhood ethno-racial composition intersected in shaping the racial socioeconomic inequality-crime relationship after disadvantage was controlled. For Majority White and Majority Latino neighborhoods, both overall and intraracial income inequality were robust predictors of neighborhood crime rates regardless of the offense. But in Majority Black neighborhoods, while overall income inequality significantly predicted each type of crime, intraracial income inequality only affected robbery rates. Interracial inequality was an important factor for burglary and robbery rates in both Majority White and Majority Latino neighborhoods, with disparity in educational attainment being a slightly more consistent predictor than income inequality. Yet the interracial inequality measures never predicted crime rates in Majority Black neighborhoods, and at no point did they significantly associate with homicide rates in neighborhoods of any ethno-racial composition. These observations highlight the importance of exploring how varying kinds of racial socioeconomic inequality affect different types of crime in neighborhoods of different ethno-racial compositions (Hernandez, Vélez, & Lyons, 2016; Hipp, 2007; Stolzenberg, Eitle, & D'Alessio, 2006).

Third, my analyses indicate that overall and intraracial inequality are more consistent predictors of neighborhood crime than is interracial inequality, at least for disparities in household income and educational attainment. That intraracial inequality is a more robust offending covariate than interracial inequality is consistent with the contention made in prior work that members of one's own ethno-racial group comprise the more accurate reference group for crime-inducing status comparisons (Harer & Steffensmeier, 1992; Martinez, 1996; Shihadeh & Steffensmeier, 1994). However, my analyses also emphasize the importance of overall inequality as a structural factor of neighborhood crime in its own right. In fact, every coefficient for overall income inequality in Tables 2-4 is positive and statistically significant whether or not disadvantage is controlled, making it a more consistent predictor of neighborhood crime than intraracial inequality (in contrast to my first hypothesis). A possible reason that this finding diverges from those of some prior studies (e.g. Hipp, 2007; Messner & Tardiff,

1986) is that the NNCS offers a considerably larger sample of census tracts and thus provides greater variance in this measure. For instance, Messner and Tardiff (1986) failed to find evidence of a significant relationship between overall income inequality and the tract homicide rate, but their sample only included 26 census tracts in Manhattan, New York; and while the standard deviation for their Gini coefficient was .04 (1986:317), the standard deviations for this measure in my data were at least .05 for all three ethno-racial neighborhood types (see Table 1).

Fourth, I found that racial socioeconomic inequality exhibited effects that were statistically comparable in magnitude and direction across Majority White, Black, and Latino neighborhoods for the tract homicide rate alone, yielding only partial support for my second hypothesis. That the racial invariance thesis is more regularly supported for homicide than for other violent crimes like robbery is consistent with research by Steffensmeier et al. (2010), who observed virtually no differences in the effects of the indicators of structural disadvantage on homicide but discovered significant differences in the effects of these indicators on a violent crime index. My finding regarding racially variant effects of racial socioeconomic inequality on burglary is consistent with the work of Hernandez, Vélez, and Lyons (2016), who found after accounting for restricted distributions in structural disadvantage that the effects of disadvantage, residential instability, and percent foreign born do not significantly differ with respect to *violent* crime, but do significantly vary with respect to *property* crime. Steffensmeier et al. (2010:1158) list three reasons why structural factors may operate uniformly across ethno-racial groups in the production of crime rates only for homicide, all of which may apply to racial socioeconomic inequality: (1) homicide is the most reliably measured crime, (2) the invariance assumption only applies to the most serious crimes, or (3) recent changes in definitions of what actions constitute violent or property crimes have differentially impacted crime rate estimates across ethno-racial groups.

Fifth, in support of my third hypothesis, the effects of overall and intraracial income inequality on neighborhood burglary and robbery rates were significantly larger in Majority White neighborhoods than in either of the other two ethno-racial neighborhood types; this is consistent with the findings of prior research (Harer & Steffensmeier, 1992; Ousey, 1999; Messner & Golden, 1992; Parker & McCall, 1997). They were also significantly larger in Majority Latino than in Majority Black neighborhoods. I speculate, as do Harer and Steffensmeier (1992:1048), that socioeconomic inequality may impact whites more severely than other groups because a greater disjuncture between culturally-valued goals and institutionalized means for achieving those goals may exist in locales that are majority white than in other places (Merton, 1938, 1968). I suspect that many minorities residing in Majority Black or Majority Latino neighborhoods adjust their expectations for socioeconomic success downward based on their own or others' experiences and therefore feel less relatively deprived when they make status comparisons with members of their own ethno-racial group than do whites when they make intraracial comparisons.

Sixth, my findings suggest a general pattern consistent with my fourth hypothesis: between-race inequality is most pernicious where the largest absolute disparities are found *and* where the disadvantaged group in the interracial comparison is residing in a locale where the more advantaged group is in the majority. This finding is consistent with, but does not demonstrate, my speculation that feelings of unjust deprivation are most severe among persons who are both disadvantaged and residing in a place where their ethno-racial group is in the minority. Thus, one possible direction for resolving the theoretical controversy in extant research over which reference group is the most appropriate for exploring the effects of relative deprivation on crime (Hipp, 2007; Stolzenberg, Eitle, & D'Alessio, 2006) is to more adequately specify *where* interracial inequality may impact crime. It may be that disadvantaged persons only make criminogenic status comparisons with members of *another* ethno-racial group if they are a minority in their own neighborhood.

Future investigations can build on the current study in a number of ways. First, more research is needed to determine when and how interracial inequality influences local crime rates. My own analyses have suggested a pattern for where its effects become most pronounced, but I cannot provide more direct evidence for my explanation without offending measures that are disaggregated by race/ethnicity. One potential solution would involve an approach that could determine race-specific offending patterns from aggregate data, such as King's (1997) solution to the ecological inference problem. Another route would utilize data that include race-specific offending rates for relatively small units, such as data from the National Incident Based Reporting System (NIBRS), although unfortunately this source does not include data at the census tract level.

More broadly, additional research is required to systematically adjudicate between the mechanisms theorized to link racial socioeconomic inequality with crime. I have demonstrated that indicators of relative and absolute deprivation operate separately in influencing neighborhood crime distributions, but whether reference group, social distance, group competition, or routine activity theories account for this finding is unclear. Also relatively neglected is the competing predictions made by the social distance and group competition explanations, which only a few studies have attempted to disentangle (Hipp, 2007; McCall & Parker, 2005; Stolzenberg, Eitle, & D'Alessio, 2006). It may be that qualitative or mixed methods research methods are required to verify or eliminate competing explanations of the relationship between racial socioeconomic inequality and crime. Indeed, Pettigrew (2015) argues that any test of relative deprivation that does not utilize individual-level perceptions of dissatisfaction and injustice is incomplete. If he is correct, then the relationships discovered in the current study may be capturing something other than feelings of relative deprivation that contribute to criminal offending (i.e. social distance, group competition, or routine activity processes)—but mixed methods research would be required to ascertain this.

A third limitation of the current study that future research can build on is my inability to explore how variation in ethno-racial composition *within* the same ethno-racial neighborhood type moderates the relationship between racial socioeconomic inequality and crime. I specified that each of my ethno-racial neighborhood types be more than 50% of a single ethno-racial group to maximize the number of residents of *other* ethno-racial groups sharing the neighborhood, but this specification allows for a large of degree of variation in the composition each ethno-racial neighborhood type subsample. Racial socioeconomic inequality may have different effects on crime rates in a census tract that is 55% white and 45% black, for example, compared to one where whites make up 90% and blacks 10% of the tract. Thus, future research can build on the present work by purposively sampling neighborhoods where a single ethno-racial group is in the majority but other groups constitute a greater or lesser proportion of the neighborhoods.

Finally, future research can expand the set of inequality, crime, and ethno-racial neighborhood types that I consider in the present work. More studies should shift analytical attention away from income inequality and toward other kinds of socioeconomic disparity for which persons may be especially likely to make reference group comparisons, including inequality in educational attainment, labor force participation, and occupational prestige. Others can follow Hipp's (2007) model of testing different types of violent and property crimes that vary in the usual relationship between offender and victim. And still others can include ethno-racial groups besides whites, blacks, and Latinos, or else explore how racial socioeconomic inequality differentially affects ethnic subgroups within these categories (e.g. Mexicans, Puerto Ricans, and Cubans, since these represent the largest Latino subgroups in the United States; see Vélez, 2006).

In closing, the current study has emphasized the salience of racial socioeconomic inequality as a neighborhood structural characteristic with substantive implications for crime rates apart from structural disadvantage. Although the relative deprivation perspective has fallen out of favor somewhat among recent sociological research, the results of the present analysis suggest abandoning it or its reference group theory derivative is premature (Pettigrew, 2015). As inequality levels in the United States continue to shift with the nation's ethno-racial makeup, it is my hope that sociological criminologists will continue to advance our understanding of the relationship between racial socioeconomic inequality and crime.

NOTES

1. In the present study, I use the phrase “racial socioeconomic inequality” out of convenience to refer to interracial inequality (disparity between members of different ethno-racial groups), intraracial inequality (disparity between members of the same ethno-racial group), and/or overall inequality (disparity without reference to an ethno-racial group). Although overall inequality does not involve a racial or ethnic dimension, I still refer to it with this phrase because (1) most studies since Blau and Blau’s (1982) have compared the effects of interracial and/or intraracial inequality with overall inequality, and (2) researchers who utilize a measure of overall inequality still make an assumption about the role of race in the impact of inequality on crime—specifically, that it has none (e.g. Braithwaite, 1979).
2. Whatever its empirical merit, this speculation is based on a premise that cannot be corroborated using an aggregated dataset (such as the NNCS): that members of the disadvantaged group in an interracial comparison, residing in a neighborhood where members of the more advantaged group are in the majority, are the persons actually responding to unequal socioeconomic conditions with criminal offending. Thus, despite their basis in prior research or theory, any claims I make about the behavior of individuals in this paper are undermined by the ecological inference problem (Robinson, 1950). I address this limitation more fully in Part V.
3. Of the 29 dropped cases, 20 were designated in the NNCS as partial tracts (i.e. subsections of whole tracts that straddle census place boundaries and thus appear in more than one city). The other 9 represented combined tracts located in Seattle,

Milwaukee, and Detroit. In these and several other cities, police departments provided crime counts using 1980 or 1990 tract boundaries, so some of these tracts were combined in the NNCS so that data are comparable with 2000 census tracts.

4. In the census data for 2000, “Hispanic” and “Latino” refer to the same ethnic category, and thus in this paper I use the terms interchangeably. Since the question the U.S. census uses to determine whether a respondent is of Spanish/Hispanic/Latino origin is distinct from the question it uses to determine a respondent’s race, Latino-identified persons can be of any census racial identification.
5. Although some prior work has incorporated income distribution measures into indices of resource deprivation (e.g. Land, McCall, & Cohen, 1990; Wang & Arnold, 2008), the correlation between the Gini coefficient and the structural disadvantage index in the current study only ranges from low to moderate in magnitude. Pearson’s correlation coefficient between these two measures in Majority White, Black, and Latino neighborhoods is .209, .546, and .431, respectively.
6. “Other Groups” here includes U.S. census respondents who identified with any of the following racial categories: American Indian or Alaska Native; Asian; Native Hawaiian or Other Pacific Islander; Some Other Race Alone; or Two or More Races.
7. It should be noted that the more racially or ethnically homogenous a census tract is, the greater is the overlap between “overall” and “intraracial” income

inequality. In extremely segregated areas, the empirical distinction between them is likely trivial.

8. The NNCS contains measures of White-Black inequality in both household income and educational attainment at the tract level, but the interracial income inequality measure is the ratio of the White mean household income to the Black median household income for 1999. I could not replicate this mean/median ratio for other ethno-racial pairs using the NHGIS data, so to ensure consistency I simply used the NHGIS data to construct all six of my interracial inequality variables.
9. I do not have a spatial lag measure for the burglary rate and so do not include it in the models that predict this outcome.
10. This measure yields "the percentage of [the members of some racial group] who [would] have to move to achieve an 'even' residential pattern—one where every neighborhood replicates the racial composition of the city" (Massey & Denton, 1993:20).
11. Interestingly, if they *had* associated significantly with the dependent variable, they would have been interpreted as *lowering* the tract robbery rate: all four of the interracial inequality coefficients in Panel 2 of Table 4 exhibit negative signs. This pattern emerges only for robbery.

APPENDICES

Appendix A: Table 5

Table 5. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority White Tracts

	Overall		Intraracial		Inter. (W-B, *I*)		Inter. (W-L, *I*)		Inter. (W-B, *E*)		Inter. (W-L, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	1.962*	1.543*										
	(.366)	(.359)										
Intraracial			1.886*	1.471*								
			(.406)	(.398)								
Inter. (W-B, *I*)					.024	.020						
					(.034)	(.033)						
Inter. (W-L, *I*)							.032	.064				
							(.038)	(.037)				
Inter. (W-B, *E*)									-.122	.026		
									(.085)	(.083)		
Inter. (W-L, *E*)											.274*	.104
											(.065)	(.065)
Disadvantage		.602*		.647*		.651*		.659*		.632*		.642*
		(.043)		(.046)		(.045)		(.045)		(.045)		(.046)
Foreign Born (%)	-.005	-.016*	-.005	-.016*	-.005	-.016*	-.004	-.017*	-.005	-.016*	-.007*	-.017*
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Residential Instability	.143*	.130*	.145*	.132*	.206*	.176*	.193*	.168*	.195*	.164*	.194*	.173*
	(.035)	(.034)	(.037)	(.036)	(.035)	(.034)	(.034)	(.033)	(.034)	(.034)	(.034)	(.033)

Table 5. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority White Tracts (continued)

Young Males (%)	-.002	-.002	-.001	-.002	-.006	-.006	-.002	-.002	-.003	-.003	-.003	-.004
	(.005)	(.004)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Spatial Lag	.413*	.299*	.412*	.292*	.434*	.307*	.436*	.309*	.432*	.309*	.418*	.303*
	(.027)	(.027)	(.028)	(.029)	(.027)	(.028)	(.027)	(.028)	(.027)	(.028)	(.027)	(.028)
City Level												
Overall	-3.147*	-2.794*										
	(.964)	(.994)										
Intraracial			-4.978*	-4.790*								
			(1.386)	(1.415)								
Inter. (W-B, *I*)					-.230	-.116						
					(.184)	(.193)						
Inter. (W-L, *I*)							-.324*	-.241				
							(.161)	(.165)				
Inter. (W-B, *E*)									-.704	-.551		
									(.412)	(.433)		
Inter. (W-L, *E*)											-.122	.054
											(.095)	(.098)
Disadvantage	.126*	-.091	.195*	-.035	.098	-.136*	.107*	-.132*	.081	-.131*	.110*	-.129*
	(.056)	(.059)	(.061)	(.065)	(.054)	(.059)	(.053)	(.057)	(.059)	(.064)	(.054)	(.057)
W-B Index of Diss.	.005*	.005*	.007*	.007*	.005*	.004	.004	.004	.006*	.005*	.004	.003
	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)	(.002)	(.002)	(.002)	(.003)	(.002)	(.002)
Foreign Born (%)	-.006	.010*	-.011*	.007	-.010*	.008	-.008*	.009*	-.011*	.006	-.008	.006
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.005)	(.005)

Table 5. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority White Tracts (continued)

Recent Movers (%)	.008	.008	.007	.007	.005	.006	.005	.005	.008	.009	.005	.003
	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Young Males (%)	-.016	-.009	-.011	-.003	-.014	-.007	-.018	-.011	-.019	-.012	-.020	-.011
	(.015)	(.016)	(.016)	(.016)	(.015)	(.016)	(.015)	(.015)	(.015)	(.016)	(.015)	(.015)
Population	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	-.002	.005	-.004	.004	-.003	.005	-.004	.004	-.002	.005	-.003	.005
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Manufacturing (%)	-.012	-.015*	-.014*	-.018*	-.008	-.010	-.008	-.011	-.008	-.010	-.005	-.011
	(.007)	(.007)	(.007)	(.007)	(.006)	(.007)	(.006)	(.007)	(.006)	(.006)	(.006)	(.007)
South	.085	.107	.077	.095	.072	.094	.080	.104	.049	.080	.077	.078
	(.066)	(.069)	(.066)	(.067)	(.066)	(.070)	(.066)	(.068)	(.064)	(.069)	(.067)	(.069)
West	.114	.169*	.148	.199*	.108	.166*	.093	.160*	.113	.165*	.116	.164*
	(.078)	(.080)	(.078)	(.080)	(.078)	(.082)	(.077)	(.080)	(.076)	(.081)	(.077)	(.079)
Intercept	-.037	.311*	-.029	.351*	-.015	.358*	-.026	.355*	-.010	.350*	-.030	.355*
	(.045)	(.053)	(.045)	(.053)	(.044)	(.054)	(.045)	(.053)	(.044)	(.054)	(.045)	(.054)
Tract N	4434		3998		4095		4225		4137		4245	

Note. *p<.05 (two-tailed). W-B, *I* = White-Black Median Household Income Ratio; W-L, *I* = White-Latino Median Household Income Ratio; W-B, *E* = White-Black High School Graduates Ratio; W-L, *E* = White-Latino High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group.

Appendix B: Table 6

Table 6. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority Black Tracts

	Overall		Intraracial		Inter. (W-B, *I*)		Inter. (L-B, *I*)		Inter. (W-B, *E*)		Inter. (L-B, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	4.529*	1.943*										
	(.663)	(.686)										
Intraracial			4.509*	.481								
			(.848)	(.904)								
Inter. (W-B, *I*)					-.058	-.026						
					(.030)	(.029)						
Inter. (L-B, *I*)							-.039	-.022				
							(.022)	(.021)				
Inter. (W-B, *E*)									-.023	.025		
									(.053)	(.051)		
Inter. (L-B, *E*)											-.034	-.013
											(.028)	(.027)
Disadvantage		.717*		.857*		.776*		.780*		.788*		.805*
		(.066)		(.083)		(.065)		(.067)		(.066)		(.070)
Foreign Born (%)	-.007	-.000	-.002	-.004	-.008	-.000	-.009	-.004	-.008	.000	-.009	-.005
	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Residential Instability	.120*	-.079	.250*	.085	.296*	.009	.311*	.028	.290*	.007	.329*	.050
	(.053)	(.055)	(.063)	(.063)	(.052)	(.056)	(.053)	(.057)	(.053)	(.056)	(.055)	(.058)

Table 6. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority Black Tracts (continued)

Young Males (%)	-.019	.009	-.041*	-.013	-.036*	.000	-.044*	-.004	-.040*	-.003	-.050*	-.011
	(.012)	(.012)	(.014)	(.014)	(.012)	(.012)	(.013)	(.013)	(.012)	(.012)	(.013)	(.013)
Spatial Lag	.220*	.172*	.231*	.164*	.230*	.171*	.241*	.180*	.231*	.170*	.230*	.165*
	(.018)	(.018)	(.022)	(.022)	(.019)	(.019)	(.019)	(.019)	(.020)	(.020)	(.020)	(.020)
City Level												
Overall	-5.149*	-4.134										
	(2.266)	(2.233)										
Intraracial			-7.849*	-6.752*								
			(3.258)	(3.130)								
Inter. (W-B, *I*)					-.221	-.210						
					(.371)	(.360)						
Inter. (L-B, *I*)							.569	.331				
							(.401)	(.385)				
Inter. (W-B, *E*)									.298	-.263		
									(.806)	(.785)		
Inter. (L-B, *E*)											-.171	-.228
											(.314)	(.301)
Disadvantage	.222	.089	.238	.087	.162	.010	.213	.008	.220	.019	.158	-.024
	(.135)	(.133)	(.147)	(.142)	(.149)	(.145)	(.126)	(.122)	(.160)	(.156)	(.124)	(.120)
W-B Index of Diss.	.003	-.001	-.009	-.010	-.002	-.005	-.012	-.012*	-.008	-.007	-.010	-.011*
	(.007)	(.007)	(.006)	(.006)	(.010)	(.009)	(.006)	(.006)	(.010)	(.009)	(.006)	(.006)
Foreign Born (%)	.000	-.002	-.004	-.002	-.007	-.008	-.004	-.004	-.007	-.009	-.005	-.006
	(.009)	(.009)	(.008)	(.008)	(.009)	(.009)	(.008)	(.008)	(.009)	(.009)	(.009)	(.008)

Table 6. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority Black Tracts (continued)

Recent Movers (%)	.006	.013	-.006	-.005	.008	.015	-.006	.002	.003	.015	.000	.006
	(.020)	(.020)	(.021)	(.020)	(.021)	(.020)	(.019)	(.018)	(.022)	(.022)	(.020)	(.019)
Young Males (%)	-.028	-.043	-.028	-.029	-.051	-.058	-.019	-.037	-.050	-.058	-.035	-.044
	(.046)	(.045)	(.047)	(.045)	(.047)	(.046)	(.044)	(.042)	(.049)	(.048)	(.045)	(.043)
Population	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	-.013*	-.007	-.015*	-.006	-.017*	-.008	-.019*	-.009*	-.018*	-.008	-.019*	-.009
	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.004)	(.005)	(.005)	(.005)	(.005)
Manufacturing (%)	-.051*	-.061*	-.043*	-.060*	-.041*	-.051*	-.025	-.037*	-.040*	-.051*	-.022	-.038*
	(.018)	(.018)	(.018)	(.018)	(.017)	(.016)	(.015)	(.015)	(.017)	(.017)	(.016)	(.016)
South	.011	-.165	-.130	-.285*	-.081	-.236	-.038	-.212	-.109	-.245	-.132	-.293*
	(.148)	(.147)	(.144)	(.139)	(.152)	(.149)	(.131)	(.126)	(.155)	(.151)	(.142)	(.136)
West	-.179	.015	-.403	-.113	-.294	-.014	-.430	-.135	-.372	-.078	-.524*	-.201
	(.255)	(.252)	(.234)	(.226)	(.271)	(.264)	(.225)	(.218)	(.271)	(.265)	(.237)	(.229)
Intercept	-.116	-.580*	-.103	-.576*	-.017	-.523*	-.028	-.479*	-.067	-.539*	.013	-.451*
	(.129)	(.134)	(.131)	(.133)	(.134)	(.137)	(.116)	(.117)	(.148)	(.149)	(.113)	(.116)
Tract N	1937		1247		1759		1603		1729		1482	

Note. *p<.05 (two-tailed). W-B, I = White-Black Median Household Income Ratio; L-B, I = Latino-Black Median Household Income Ratio; W-B, E = White-Black High School Graduates Ratio; L-B, E = Latino-Black High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group.

Appendix C: Table 7

Table 7. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority Latino Tracts

	Overall		Intraracial		Inter. (W-L, *I*)		Inter. (L-B, *I*)		Inter. (W-L, *E*)		Inter. (L-B, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	3.158*	2.042*										
	(.836)	(.864)										
Intraracial			3.160*	2.031*								
			(.844)	(.870)								
Inter. (W-L, *I*)					-.147	.043						
					(.209)	(.210)						
Inter. (L-B, *I*)							.074	.035				
							(.067)	(.067)				
Inter. (W-L, *E*)									-.304*	-.152		
									(.152)	(.153)		
Inter. (L-B, *E*)											-.218	-.072
											(.116)	(.119)
Disadvantage		.428*		.452*		.509*		.514*		.465*		.486*
		(.093)		(.095)		(.092)		(.094)		(.091)		(.097)
Foreign Born (%)	.004	-.002	.003	-.003	.004	.003	.001	-.006	.004	-.003	-.001	-.007
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.005)
Residential Instability	.088	.035	.092	.021	.172*	.072	.126	.020	.179*	.080	.108	.008
	(.065)	(.065)	(.066)	(.067)	(.063)	(.065)	(.065)	(.067)	(.061)	(.064)	(.064)	(.066)

Table 7. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority Latino Tracts (continued)

Young Males (%)	.018	.026	.020	.033*	.011	.023	.027	.045*	.011	.022	.027	.046*
	(.013)	(.013)	(.014)	(.015)	(.013)	(.013)	(.015)	(.015)	(.013)	(.013)	(.015)	(.015)
Spatial Lag	.239*	.199*	.241*	.198*	.256*	.202*	.264*	.208*	.245*	.203*	.259*	.209*
	(.024)	(.025)	(.024)	(.025)	(.024)	(.026)	(.024)	(.025)	(.024)	(.025)	(.024)	(.025)
City Level												
Overall	-3.331	-2.884										
	(3.525)	(3.472)										
Intraracial			-11.473*	-10.341*								
			(5.068)	(4.955)								
Inter. (W-L, *I*)					.239	-.185						
					(.551)	(.551)						
Inter. (L-B, *I*)							.375	.678				
							(.626)	(.598)				
Inter. (W-L, *E*)									1.082*	.952*		
									(.261)	(.271)		
Inter. (L-B, *E*)											-1.383	-1.222
											(.724)	(.726)
Disadvantage	.191	.125	.349*	.278	.193	.085	.222	.151	.207	.135	.182	.108
	(.156)	(.154)	(.164)	(.162)	(.150)	(.150)	(.149)	(.144)	(.123)	(.127)	(.141)	(.142)
W-B Index of Diss.	.015	.013	.020*	.016*	.011	.010	.007	.002	.003	.001	.014*	.010
	(.008)	(.008)	(.008)	(.008)	(.007)	(.007)	(.008)	(.008)	(.006)	(.006)	(.007)	(.007)
Foreign Born (%)	-.019*	-.012	-.020*	-.013	-.021*	-.014	-.019*	-.012	-.017*	-.010	-.011	-.005
	(.009)	(.009)	(.008)	(.008)	(.008)	(.009)	(.009)	(.009)	(.008)	(.008)	(.009)	(.009)

Table 7. Hierarchical Linear Models Predicting Logged Homicide Rate in Majority Latino Tracts (continued)

Recent Movers (%)	.038	.035	.005	.001	.040	.037	.025	.019	.044	.039	.042	.036
	(.029)	(.029)	(.031)	(.030)	(.028)	(.028)	(.029)	(.028)	(.024)	(.024)	(.028)	(.028)
Young Males (%)	-.056	-.064	-.017	-.027	-.070	-.074	-.038	-.039	-.120*	-.123*	-.123	-.117
	(.065)	(.064)	(.063)	(.062)	(.062)	(.062)	(.065)	(.063)	(.055)	(.056)	(.066)	(.066)
Population	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	-.015	-.012	-.021*	-.018*	-.016	-.013	-.021*	-.017*	-.017*	-.015*	-.024*	-.020*
	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.009)	(.008)	(.007)	(.007)	(.009)	(.009)
Manufacturing (%)	-.006	-.009	-.036	-.038	.002	-.001	-.012	-.018	-.030	-.033	-.023	-.023
	(.026)	(.026)	(.026)	(.026)	(.021)	(.021)	(.024)	(.023)	(.020)	(.021)	(.023)	(.023)
South	-.157	-.072	-.168	-.072	-.231	-.128	-.362	-.258	-.570*	-.486	-.581	-.432
	(.316)	(.312)	(.295)	(.289)	(.302)	(.300)	(.322)	(.306)	(.278)	(.285)	(.318)	(.320)
West	.222	.230	.211	.214	.150	.178	.061	.087	-.279	-.261	-.253	-.167
	(.305)	(.301)	(.293)	(.287)	(.303)	(.300)	(.312)	(.297)	(.284)	(.289)	(.337)	(.338)
Intercept	-.183	-.489	-.220	-.535*	-.144	-.494	-.042	-.411	.166	-.155	.214	-.177
	(.277)	(.280)	(.263)	(.264)	(.268)	(.273)	(.276)	(.268)	(.235)	(.249)	(.289)	(.299)
Tract N	1342		1273		1331		1232		1331		1228	

Note. *p<.05 (two-tailed). W-L, *I* = White-Latino Median Household Income Ratio; L-B, *I* = Latino-Black Median Household Income Ratio; W-L, *E* = White-Latino High School Graduates Ratio; L-B, *E* = Latino-Black High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group.

Appendix D: Table 8

Table 8. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority White Tracts

	Overall		Intraracial		Inter. (W-B, *I*)		Inter. (W-L, *I*)		Inter. (W-B, *E*)		Inter. (W-L, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	3.975*	3.377*										
	(.210)	(.201)										
Intraracial			4.015*	3.442*								
			(.234)	(.223)								
Inter. (W-B, *I*)					.053*	.046*						
					(.020)	(.019)						
Inter. (W-L, *I*)							-.007	.026				
							(.022)	(.021)				
Inter. (W-B, *E*)									-.006	.147*		
									(.049)	(.046)		
Inter. (W-L, *E*)											.296*	.121*
											(.038)	(.037)
Disadvantage		.543*		.561*		.591*		.602*		.596*		.578*
		(.023)		(.025)		(.024)		(.024)		(.024)		(.025)
Foreign Born (%)	-.002	-.012*	-.003	-.012*	-.003	-.012*	-.001	-.012*	-.002	-.012*	-.003	-.012*
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Residential Instability	-.022	-.030	-.022	-.033	.109*	.078*	.104*	.076*	.107*	.076*	.096*	.074*
	(.020)	(.019)	(.021)	(.020)	(.020)	(.019)	(.020)	(.019)	(.020)	(.019)	(.020)	(.019)

Table 8. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority White Tracts (continued)

Young Males (%)	.021*	.019*	.020*	.018*	.016*	.014*	.015*	.014*	.017*	.015*	.016*	.014*
	(.003)	(.002)	(.003)	(.002)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
City Level												
Overall	-.460	.182										
	(1.579)	(1.557)										
Intraracial			-.405	.194								
			(2.187)	(2.145)								
Inter. (W-B, *I*)					-.670*	-.556*						
					(.284)	(.273)						
Inter. (W-L, *I*)							-.552*	-.438				
							(.250)	(.248)				
Inter. (W-B, *E*)									-.948	.147*		
									(.637)	(.046)		
Inter. (W-L, *E*)											-.051	.084
											(.158)	(.154)
Disadvantage	.198*	.013	.209*	.014	.221*	.022	.236*	.030	.205*	.014	.252*	.054
	(.082)	(.081)	(.089)	(.088)	(.078)	(.075)	(.078)	(.078)	(.087)	(.083)	(.079)	(.078)
W-B Index of Diss.	.010*	.010*	.009*	.010*	.017*	.017*	.013*	.014*	.015*	.015*	.012*	.013*
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.003)	(.003)	(.004)	(.004)	(.004)	(.003)
Foreign Born (%)	-.016*	-.002	-.016*	-.000	-.010	.005	-.012*	.003	-.013*	.002	-.014*	-.000
	(.006)	(.006)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.006)	(.006)

Table 8. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority White Tracts (continued)

Recent Movers (%)	.052*	.052*	.055*	.054*	.048*	.048*	.046*	.046*	.050*	.050*	.047*	.045*
	(.012)	(.012)	(.012)	(.012)	(.012)	(.011)	(.012)	(.012)	(.012)	(.011)	(.012)	(.012)
Young Males (%)	-.054*	-.048*	-.056*	-.050*	-.048*	-.041	-.040	-.034	-.057*	-.049*	-.048*	-.042
	(.025)	(.024)	(.025)	(.024)	(.023)	(.022)	(.024)	(.023)	(.023)	(.022)	(.024)	(.023)
Population	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	-.004	.000	-.004	.001	-.003	.001	-.005	-.000	-.002	.002	-.005	-.000
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Manufacturing (%)	.011	.008	.010	.007	-.000	-.003	.000	-.002	.002	-.000	.006	-.000
	(.011)	(.011)	(.011)	(.011)	(.009)	(.009)	(.010)	(.010)	(.009)	(.009)	(.010)	(.010)
South	-.104	-.091	-.121	-.106	-.116	-.100	-.140	-.118	-.165	-.140	-.133	-.126
	(.118)	(.117)	(.117)	(.115)	(.112)	(.108)	(.115)	(.114)	(.113)	(.108)	(.118)	(.115)
West	-.062	-.026	-.069	-.035	-.028	.009	-.085	-.036	-.039	.001	-.047	-.020
	(.133)	(.131)	(.132)	(.129)	(.126)	(.121)	(.129)	(.128)	(.127)	(.122)	(.132)	(.129)
Intercept	.037	.365*	.036	.376*	.049	.403*	.064	.421*	.064	.418*	.047	.403*
	(.084)	(.084)	(.083)	(.083)	(.079)	(.078)	(.082)	(.082)	(.080)	(.078)	(.083)	(.083)
Tract N	4724		4257		4364		4500		4409		4515	

Note. *p<.05 (two-tailed). W-B, *I* = White-Black Median Household Income Ratio; W-L, *I* = White-Latino Median Household Income Ratio; W-B, *E* = White-Black High School Graduates Ratio; W-L, *E* = White-Latino High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group. Models for burglary do not include a spatial lag control.

Appendix E: Table 9

Table 9. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority Black Tracts

	Overall		Intraracial		Inter. (W-B, *I*)		Inter. (L-B, *I*)		Inter. (W-B, *E*)		Inter. (L-B, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	1.180*	.606*										
	(.170)	(.180)										
Intraracial			1.502*	.450								
			(.224)	(.245)								
Inter. (W-B, *I*)					-.006	.004						
					(.008)	(.007)						
Inter. (L-B, *I*)							.000	.004				
							(.006)	(.006)				
Inter. (W-B, *E*)									-.025	-.010		
									(.013)	(.013)		
Inter. (L-B, *E*)											-.018*	-.012
											(.007)	(.007)
Disadvantage		.143*		.197*		.195*		.164*		.200*		.180*
		(.017)		(.021)		(.016)		(.017)		(.016)		(.018)
Foreign Born (%)	-.007*	-.005*	-.005*	-.005*	-.008*	-.006*	-.008*	-.006*	-.009*	-.006*	-.008*	-.006*
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Residential Instability	.097*	.061*	.107*	.078*	.153*	.083*	.144*	.086*	.155*	.085*	.145*	.084*
	(.014)	(.014)	(.017)	(.017)	(.014)	(.015)	(.014)	(.015)	(.014)	(.015)	(.015)	(.016)

Table 9. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority Black Tracts (continued)

Young Males (%)	.007*	.012*	.005	.012*	.000	.010*	.002	.010*	.001	.011*	.001	.011*
	(.003)	(.003)	(.004)	(.004)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)	(.004)
City Level												
Overall	-1.178	-.919										
	(2.609)	(2.576)										
Intraracial			-.735	-.408								
			(3.692)	(3.634)								
Inter. (W-B, *I*)					-.813*	-.846*						
					(.385)	(.374)						
Inter. (L-B, *I*)							1.017*	.986*				
							(.452)	(.447)				
Inter. (W-B, *E*)									-.997	-1.182		
									(.883)	(.857)		
Inter. (L-B, *E*)											-.060	-.050
											(.356)	(.351)
Disadvantage	.134	.109	.139	.105	.015	-.031	.232	.191	.034	-.025	.147	.103
	(.131)	(.129)	(.144)	(.142)	(.130)	(.126)	(.124)	(.122)	(.148)	(.143)	(.123)	(.121)
W-B Index of Diss.	.007	.005	.005	.004	.015*	.013	.001	-.000	.013	.012	.006	.004
	(.008)	(.008)	(.008)	(.008)	(.008)	(.007)	(.007)	(.007)	(.009)	(.009)	(.007)	(.006)
Foreign Born (%)	-.004	-.005	-.007	-.007	-.003	-.004	-.009	-.009	-.005	-.006	-.007	-.007
	(.009)	(.009)	(.008)	(.008)	(.008)	(.007)	(.008)	(.008)	(.008)	(.007)	(.008)	(.008)

Table 9. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority Black Tracts (continued)

Recent Movers (%)	.052*	.051*	.048*	.047*	.054*	.053*	.044*	.044*	.058*	.059*	.047*	.046*
	(.023)	(.022)	(.023)	(.022)	(.022)	(.021)	(.022)	(.022)	(.023)	(.023)	(.023)	(.023)
Young Males (%)	-.105*	-.105*	-.105*	-.101*	-.099*	-.100*	-.092	-.093	-.107*	-.108*	-.102*	-.101*
	(.052)	(.051)	(.052)	(.051)	(.048)	(.047)	(.049)	(.048)	(.050)	(.048)	(.051)	(.050)
Population	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	-.007	-.006	-.009	-.007	-.007	-.005	-.011*	-.009	-.006	-.004	-.010	-.008
	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Manufacturing (%)	.029	.029	.029	.026	.030	.028	.017	.015	.031*	.029	.029	.026
	(.017)	(.017)	(.017)	(.017)	(.015)	(.015)	(.017)	(.016)	(.016)	(.015)	(.017)	(.016)
South	.070	.043	.063	.035	.130	.098	-.005	-.034	.051	.018	.053	.022
	(.177)	(.175)	(.171)	(.169)	(.169)	(.164)	(.167)	(.165)	(.169)	(.164)	(.174)	(.172)
West	-.539*	-.510*	-.545*	-.497*	-.515*	-.472*	-.517*	-.480*	-.618*	-.585*	-.574*	-.528*
	(.246)	(.243)	(.242)	(.238)	(.235)	(.229)	(.236)	(.233)	(.248)	(.240)	(.252)	(.248)
Intercept	-.062	-.155	-.082	-.187	.021	-.100	-.095	-.193	.036	-.073	-.056	-.157
	(.162)	(.161)	(.166)	(.164)	(.152)	(.148)	(.150)	(.149)	(.168)	(.163)	(.157)	(.155)
Tract N	2085		1358		1903		1740		1873		1609	

Note. *p<.05 (two-tailed). W-B, *I* = White-Black Median Household Income Ratio; L-B, *I* = Latino-Black Median Household Income Ratio; W-B, *E* = White-Black High School Graduates Ratio; L-B, *E* = Latino-Black High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group. Models for burglary do not include a spatial lag control.

Appendix F: Table 10

Table 10. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority Latino Tracts

	Overall		Intraracial		Inter. (W-L, *I*)		Inter. (L-B, *I*)		Inter. (W-L, *E*)		Inter. (L-B, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	2.390*	1.975*										
	(.283)	(.303)										
Intraracial			1.870*	1.350*								
			(.294)	(.315)								
Inter. (W-L, *I*)					-.092	-.025						
					(.077)	(.077)						
Inter. (L-B, *I*)							.078*	.054*				
							(.024)	(.023)				
Inter. (W-L, *E*)									.077	.166*		
									(.056)	(.056)		
Inter. (L-B, *E*)											-.176*	-.097*
											(.041)	(.043)
Disadvantage		.113*		.142*		.180*		.202*		.197*		.192*
		(.030)		(.032)		(.029)		(.030)		(.030)		(.031)
Foreign Born (%)	-.011*	-.013*	-.011*	-.013*	-.011*	-.014*	-.011*	-.014*	-.010*	-.014*	-.012*	-.014*
	(.001)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Residential Instability	.057*	.052*	.077*	.066*	.124*	.098*	.128*	.096*	.109*	.077*	.133*	.102*
	(.023)	(.023)	(.024)	(.024)	(.023)	(.023)	(.024)	(.024)	(.023)	(.023)	(.023)	(.024)

Table 10. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority Latino Tracts (continued)

Young Males (%)	.014*	.016*	.010	.014*	.009	.013*	.004	.010	.009	.013*	.001	.008
	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.006)	(.006)	(.005)	(.005)	(.006)	(.006)
City Level												
Overall	1.248	1.517										
	(1.937)	(1.999)										
Intraracial			1.301	1.968								
			(2.901)	(3.014)								
Inter. (W-L, *I*)					-.817*	-1.017*						
					(.298)	(.308)						
Inter. (L-B, *I*)							.663	.805*				
							(.349)	(.364)				
Inter. (W-L, *E*)									-.099	-.203		
									(.201)	(.215)		
Inter. (L-B, *E*)											.992*	1.052*
											(.469)	(.485)
Disadvantage	.153	.136	.147	.121	.121	.072	.209*	.180	.203*	.171	.206*	.173*
	(.084)	(.086)	(.094)	(.098)	(.081)	(.084)	(.080)	(.083)	(.085)	(.090)	(.084)	(.086)
W-B Index of Diss.	.000	-.000	.002	.000	.007	.006	-.002	-.005	.004	.004	.002	.000
	(.005)	(.005)	(.005)	(.005)	(.004)	(.004)	(.005)	(.005)	(.004)	(.005)	(.004)	(.004)
Foreign Born (%)	-.013*	-.012*	-.013*	-.010*	-.013*	-.010*	-.016*	-.012*	-.014*	-.010*	-.015*	-.012*
	(.005)	(.005)	(.005)	(.005)	(.004)	(.004)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)

Table 10. Hierarchical Linear Models Predicting Logged Burglary Rate in Majority Latino Tracts (continued)

Recent Movers (%)	.045*	.045*	.045*	.045*	.040*	.041*	.033*	.034*	.038*	.039*	.031*	.032*
	(.015)	(.015)	(.015)	(.016)	(.014)	(.014)	(.014)	(.015)	(.015)	(.016)	(.015)	(.016)
Young Males (%)	-.097*	-.098*	-.093*	-.096*	-.090*	-.090*	-.066	-.066	-.085*	-.082*	-.049	-.044
	(.035)	(.036)	(.035)	(.037)	(.032)	(.033)	(.034)	(.035)	(.035)	(.037)	(.038)	(.039)
Population	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	-.003	-.002	-.001	-.001	-.004	-.004	-.003	-.002	-.002	-.002	-.000	.001
	(.004)	(.005)	(.005)	(.005)	(.004)	(.004)	(.004)	(.005)	(.005)	(.005)	(.005)	(.005)
Manufacturing (%)	.009	.010	.008	.009	-.010	-.011	-.008	-.010	.002	.004	.015	.016
	(.014)	(.015)	(.015)	(.016)	(.012)	(.012)	(.013)	(.014)	(.014)	(.015)	(.014)	(.014)
South	.329	.356	.357*	.392*	.224	.249	.220	.248	.364	.443*	.484*	.556*
	(.177)	(.182)	(.176)	(.182)	(.168)	(.173)	(.183)	(.191)	(.187)	(.199)	(.193)	(.199)
West	-.074	-.066	-.055	-.047	-.186	-.192	-.145	-.145	-.045	.003	.136	.180
	(.175)	(.180)	(.176)	(.183)	(.169)	(.173)	(.179)	(.186)	(.191)	(.202)	(.203)	(.209)
Intercept	-.118	-.208	-.148	-.258	-.035	-.149	-.098	-.241	-.193	-.374*	-.334	-.507*
	(.168)	(.174)	(.167)	(.175)	(.159)	(.164)	(.165)	(.174)	(.172)	(.185)	(.183)	(.191)
Tract N	1489		1401		1478		1354		1478		1350	

Note. *p<.05 (two-tailed). W-L, I = White-Latino Median Household Income Ratio; L-B, I = Latino-Black Median Household Income Ratio; W-L, E = White-Latino High School Graduates Ratio; L-B, E = Latino-Black High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group. Models for burglary do not include a spatial lag control.

Appendix G: Table 11

Table 11. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority White Tracts

	Overall		Intraracial		Inter. (W-B, *I*)		Inter. (W-L, *I*)		Inter. (W-B, *E*)		Inter. (W-L, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	4.923*	4.390*										
	(.375)	(.360)										
Intraracial			4.882*	4.381*								
			(.409)	(.390)								
Inter. (W-B, *I*)					.080*	.076*						
					(.033)	(.032)						
Inter. (W-L, *I*)							-.007	.045				
							(.038)	.036				
Inter. (W-B, *E*)									.094	.326*		
									(.083)	(.080)		
Inter. (W-L, *E*)											.511*	.271*
											(.066)	(.064)
Disadvantage		.841*		.894*		.903*		.890*		.909*		.852*
		(.042)		(.044)		(.043)		(.043)		(.043)		(.044)
Foreign Born (%)	.004	-.010*	.005	-.010*	.005	-.010*	.005	-.011*	.005	-.010*	.002	-.012*
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Residential Instability	.150*	.129*	.151*	.130*	.288*	.247*	.290*	.255*	.287*	.245*	.285*	.257*
	(.035)	(.033)	(.036)	(.035)	(.034)	(.033)	(.034)	(.033)	(.034)	(.032)	(.034)	(.033)

Table 11. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority White Tracts (continued)

Young Males (%)	.018*	.018*	.015*	.015*	.010*	.011*	.009*	.010*	.012*	.012*	.010*	.010*
	(.005)	(.004)	(.005)	(.005)	(.005)	(.004)	(.005)	(.005)	(.005)	(.004)	(.005)	(.005)
Spatial Lag	.022*	.018*	.021*	.018*	.024*	.020*	.024*	.020*	.024*	.020*	.023*	.020*
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
City Level												
Overall	-5.275*	-4.320*										
	(1.655)	(1.669)										
Intraracial			-4.462	-3.405								
			(2.385)	(2.347)								
Inter. (W-B, *I*)					-.051	.095						
					(.303)	(.297)						
Inter. (W-L, *I*)							-.210	-.025				
							(.257)	(.256)				
Inter. (W-B, *E*)									-.278	-.019		
									(.693)	(.670)		
Inter. (W-L, *E*)											-.043	.178
											(.154)	(.151)
Disadvantage	.288*	-.022	.334*	.000	.349*	.029	.312*	-.008	.293*	-.005	.325*	.014
	(.091)	(.092)	(.103)	(.102)	(.086)	(.086)	(.083)	(.084)	(.098)	(.095)	(.083)	(.083)
W-B Index of Diss.	.015*	.015*	.011*	.012*	.009*	.010*	.011*	.012*	.010*	.010*	.011*	.011*
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.003)	(.003)	(.004)	(.004)	(.003)	(.003)
Foreign Born (%)	-.008	.015*	-.014*	.011	-.012*	.013*	-.012*	.012*	-.013*	.013*	-.013*	.008
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)

Table 11. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority White Tracts (continued)

Recent Movers (%)	-.006	-.006	.003	.003	-.007	-.005	-.010	-.010	-.009	-.007	-.010	-.012
	(.013)	(.013)	(.013)	(.013)	(.013)	(.012)	(.012)	(.012)	(.013)	(.013)	(.012)	(.012)
Young Males (%)	.003	.010	-.008	-.001	-.011	-.004	.002	.008	-.009	-.001	-.007	.002
	(.025)	(.025)	(.026)	(.025)	(.024)	(.024)	(.023)	(.023)	(.025)	(.024)	(.023)	(.023)
Population	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	.003	.013*	.002	.013*	-.000	.011*	-.002	.009*	.001	.012*	-.000	.010*
	(.004)	(.004)	(.005)	(.004)	(.004)	(.004)	(.004)	(.004)	(.005)	(.005)	(.004)	(.004)
Manufacturing (%)	-.036*	-.039*	-.034*	-.038*	-.031*	-.035*	-.029*	-.033*	-.029*	-.033*	-.030*	-.039*
	(.012)	(.012)	(.012)	(.012)	(.011)	(.010)	(.010)	(.010)	(.011)	(.010)	(.010)	(.010)
South	.008	.014	-.060	-.055	-.063	-.059	-.071	-.059	-.052	-.035	-.069	-.082
	(.118)	(.119)	(.120)	(.118)	(.116)	(.114)	(.112)	(.111)	(.120)	(.116)	(.113)	(.111)
West	.090	.170	.077	.149	.080	.162	.019	.120	.068	.150	.070	.133
	(.134)	(.135)	(.136)	(.134)	(.132)	(.129)	(.128)	(.127)	(.137)	(.132)	(.127)	(.125)
Intercept	.010	.506*	.033	.570*	.058	.590*	.073	.597*	.055	.589*	.049	.569*
	(.082)	(.087)	(.084)	(.087)	(.080)	(.083)	(.078)	(.082)	(.084)	(.085)	(.078)	(.081)
Tract N	4434		3998		4095		4225		4137		4245	

Note. *p<.05 (two-tailed). W-B, *I* = White-Black Median Household Income Ratio; W-L, *I* = White-Latino Median Household Income Ratio; W-B, *E* = White-Black High School Graduates Ratio; W-L, *E* = White-Latino High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group.

Appendix H: Table 12

Table 12. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority Black Tracts

	Overall		Intraracial		Inter. (W-B, *I*)		Inter. (L-B, *I*)		Inter. (W-B, *E*)		Inter. (L-B, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	2.469*	1.324*										
	(.277)	(.288)										
Intraracial			3.207*	1.722*								
			(.377)	(.412)								
Inter. (W-B, *I*)					-.033*	-.014						
					(.013)	(.012)						
Inter. (L-B, *I*)							-.019*	-.011				
							(.009)	(.009)				
Inter. (W-B, *E*)									-.040	-.012		
									(.023)	(.022)		
Inter. (L-B, *E*)											-.021	-.011
											(.012)	(.011)
Disadvantage		.298*		.293*		.359*		.317*		.364*		.318*
		(.027)		(.036)		(.028)		(.027)		(.028)		(.029)
Foreign Born (%)	-.003	.001	.001	.000	-.004	.000	-.004	-.000	-.005	-.000	-.003	-.000
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Residential Instability	.237*	.158*	.213*	.166*	.329*	.198*	.304*	.190*	.330*	.201*	.301*	.192*
	(.023)	(.023)	(.029)	(.028)	(.023)	(.024)	(.023)	(.024)	(.023)	(.024)	(.024)	(.025)

Table 12. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority Black Tracts (continued)

Young Males (%)	-.002	.010*	.006	.016*	-.010	.007	-.006	.010	-.011*	.006	-.010	.007
	(.005)	(.005)	(.006)	(.006)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.006)	(.006)
Spatial Lag	.005*	.005*	.006*	.005*	.006*	.005*	.005*	.005*	.006*	.005*	.005*	.004*
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
City Level												
Overall	-.539	-.247										
	(1.830)	(1.786)										
Intraracial			-.566	-.077								
			(2.781)	(2.764)								
Inter. (W-B, *I*)					-.181	-.253						
					(.264)	(.264)						
Inter. (L-B, *I*)							.228	.144				
							(.359)	(.372)				
Inter. (W-B, *E*)									.028	-.274		
									(.574)	(.569)		
Inter. (L-B, *E*)											-.315	-.313
											(.250)	(.256)
Disadvantage	.030	-.008	.043	.003	.019	-.044	.116	.061	.046	-.034	.109	.055
	(.099)	(.097)	(.117)	(.116)	(.096)	(.096)	(.102)	(.105)	(.106)	(.105)	(.095)	(.097)
W-B Index of Diss.	.011	.008	.010	.008	.015*	.012*	.010	.007	.012	.011	.010*	.007
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.005)	(.006)	(.006)	(.006)	(.005)	(.005)
Foreign Born (%)	.002	-.000	-.003	-.003	.002	-.001	-.003	-.005	.002	-.001	-.005	-.007
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)

Table 12. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority Black Tracts (continued)

Recent Movers (%)	.009	.010	.012	.011	.007	.009	.015	.016	.006	.010	.010	.010
	(.016)	(.016)	(.018)	(.018)	(.015)	(.015)	(.017)	(.018)	(.016)	(.016)	(.017)	(.017)
Young Males (%)	-.033	-.037	-.035	-.034	-.023	-.027	-.046	-.052	-.023	-.028	-.041	-.045
	(.035)	(.034)	(.038)	(.038)	(.033)	(.033)	(.037)	(.038)	(.033)	(.033)	(.036)	(.037)
Population	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	.005	.006	.003	.006	.003	.007	.001	.004	.003	.007	-.000	.003
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Manufacturing (%)	-.007	-.011	-.011	-.015	-.006	-.012	-.016	-.021	-.006	-.012	-.019	-.024
	(.013)	(.013)	(.015)	(.015)	(.011)	(.011)	(.013)	(.014)	(.012)	(.011)	(.013)	(.013)
South	-.068	-.129	-.053	-.104	-.041	-.101	-.097	-.158	-.063	-.125	-.066	-.126
	(.121)	(.118)	(.127)	(.126)	(.113)	(.113)	(.124)	(.129)	(.112)	(.111)	(.123)	(.126)
West	-.525*	-.465*	-.497*	-.437*	-.461*	-.383*	-.584*	-.540*	-.496*	-.427*	-.635*	-.579*
	(.190)	(.185)	(.198)	(.197)	(.181)	(.180)	(.194)	(.199)	(.185)	(.183)	(.199)	(.202)
Intercept	.075	-.130	-.007	-.164	.081	-.153	.031	-.164	.055	-.162	.014	-.172
	(.111)	(.110)	(.123)	(.124)	(.102)	(.104)	(.116)	(.121)	(.111)	(.111)	(.111)	(.116)
Tract N	1937		1247		1759		1603		1729		1482	

Note. *p<.05 (two-tailed). W-B, *I* = White-Black Median Household Income Ratio; L-B, *I* = Latino-Black Median Household Income Ratio; W-B, *E* = White-Black High School Graduates Ratio; L-B, *E* = Latino-Black High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group.

Appendix I: Table 13

Table 13. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority Latino Tracts

	Overall		Intraracial		Inter. (W-L, *I*)		Inter. (L-B, *I*)		Inter. (W-L, *E*)		Inter. (L-B, *E*)	
	1	2	3	4	5	6	7	8	9	10	11	12
Tract Level												
Overall	3.831*	2.939*										
	(.418)	(.434)										
Intraracial			3.349*	2.456*								
			(.427)	(.442)								
Inter. (W-L, *I*)					-.327*	-.170						
					(.109)	(.107)						
Inter. (L-B, *I*)							.151*	.108*				
							(.034)	(.033)				
Inter. (W-L, *E*)									.024	.199*		
									(.078)	(.078)		
Inter. (L-B, *E*)											-.228*	-.090
											(.060)	(.060)
Disadvantage		.299*		.308*		.385*		.392*		.420*		.404*
		(.045)		(.046)		(.044)		(.044)		(.045)		(.046)
Foreign Born (%)	-.002	-.006*	-.003	-.007*	-.004	-.008*	-.004	-.009*	-.003	-.008*	-.005*	-.009*
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Residential Instability	.132*	.109*	.166*	.134*	.234*	.173*	.214*	.150*	.211*	.137*	.221*	.155*
	(.033)	(.033)	(.034)	(.034)	(.033)	(.033)	(.033)	(.033)	(.033)	(.033)	(.033)	(.033)

Table 13. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority Latino Tracts (continued)

Young Males (%)	.020*	.024*	.012	.020*	.011	.019*	.011	.024*	.012	.020*	.008	.023*
	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.008)	(.008)	(.007)	(.007)	(.008)	(.008)
Spatial Lag	.010*	.009*	.010*	.009*	.011*	.009*	.010*	.009*	.011*	.009*	.010*	.009*
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
City Level												
Overall	-3.883*	-3.358*										
	(1.551)	(1.684)										
Intraracial			-8.908*	-7.737*								
			(2.097)	(2.530)								
Inter. (W-L, *I*)					-.078	-.330						
					(.231)	(.245)						
Inter. (L-B, *I*)							.401	.632*				
							(.254)	(.262)				
Inter. (W-L, *E*)									.087	-.062		
									(.142)	(.156)		
Inter. (L-B, *E*)											.508	.656
											(.356)	(.374)
Disadvantage	.071	.010	.164*	.091	.035	-.052	.110	.044	.055	-.021	.100	.029
	(.073)	(.076)	(.073)	(.079)	(.067)	(.070)	(.065)	(.066)	(.067)	(.071)	(.071)	(.073)
W-B Index of Diss.	.009*	.007	.012*	.010*	.006	.005	.000	-.004	.006	.004	.005	.001
	(.004)	(.004)	(.003)	(.004)	(.003)	(.003)	(.003)	(.004)	(.003)	(.003)	(.003)	(.003)
Foreign Born (%)	-.000	.005	-.003	.003	-.003	.004	-.005	.001	-.003	.004	-.004	.002
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)

Table 13. Hierarchical Linear Models Predicting Logged Robbery Rate in Majority Latino Tracts (continued)

Recent Movers (%)	.029*	.026	.020	.016	.039*	.036*	.025	.020	.035*	.029*	.018	.013
	(.014)	(.014)	(.014)	(.015)	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)	(.014)	(.014)
Young Males (%)	-.060	-.063*	-.053	-.056	-.087*	-.087*	-.045	-.045	-.088*	-.083*	-.041	-.031
	(.030)	(.032)	(.028)	(.030)	(.028)	(.029)	(.029)	(.029)	(.029)	(.031)	(.033)	(.034)
Population	.000	.000	.000	.000	.000	.000	.000*	.000*	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Black (%)	.011*	.012*	.009*	.011*	.011*	.012*	.009*	.011*	.010*	.012*	.009*	.012*
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Manufacturing (%)	-.023	-.026*	-.032*	-.036*	-.012	-.018	-.022*	-.032*	-.012	-.016	-.008	-.011
	(.012)	(.013)	(.011)	(.012)	(.009)	(.010)	(.010)	(.010)	(.011)	(.012)	(.011)	(.012)
South	-.141	-.118	-.158	-.138	-.243	-.200	-.245	-.244	-.266	-.175	-.140	-.040
	(.144)	(.152)	(.124)	(.137)	(.129)	(.135)	(.128)	(.132)	(.150)	(.160)	(.157)	(.164)
West	.016	-.020	.018	-.031	-.068	-.102	-.071	-.144	-.079	-.070	.031	.068
	(.139)	(.146)	(.124)	(.136)	(.131)	(.136)	(.126)	(.129)	(.151)	(.161)	(.166)	(.172)
Intercept	.046	-.131	-.001	-.168	.107	-.116	.086	-.120	.113	-.173	.010	-.289
	(.125)	(.135)	(.109)	(.124)	(.111)	(.120)	(.107)	(.114)	(.126)	(.139)	(.141)	(.152)
Tract N	1342		1273		1331		1232		1331		1228	

Note. *p<.05 (two-tailed). W-L, *I* = White-Latino Median Household Income Ratio; L-B, *I* = Latino-Black Median Household Income Ratio; W-L, *E* = White-Latino High School Graduates Ratio; L-B, *E* = Latino-Black High School Graduates Ratio. Standard errors in parentheses. Odd-numbered models exclude a control for tract-level disadvantage, whereas even-numbered models include it. Models 5-12 limit the analytic sample to exclude tracts whose racial/ethnic compositions do not include members of the comparison racial/ethnic group.

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