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Unequal Neighbors in Diverse Neighborhoods: Accounting for Variation in the Impact of Relative Inequality on Neighborhood Crime

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UNEQUAL NEIGHBORS IN DIVERSE NEIGHBORHOODS: ACCOUNTING FOR VARIATION IN THE IMPACT OF RELATIVE INEQUALITY ON NEIGHBORHOOD CRIME

by

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ABSTRACT

Research demonstrates that crime rate differences across racially segregated urban communities are primarily attributable to uneven distributions of resources between neighborhoods. Less is known about the role economic inequality within neighborhoods, what I call relative inequality, plays in maintaining ethno-racial criminal disparities. In this dissertation I explore sources of variation in the impact of relative inequality on neighborhood crime by drawing on data from the 2010-2013 National Neighborhood Crime Study Panel (NNCS2-P). I find that relative inequality effects are attenuated in higher disadvantage neighborhoods and this interaction accounts for differences in effect size by neighborhood ethno-racial composition. Results also show that relative inequality effects are weakened in cities that are more segregated, have greater minority political empowerment, and have more neighborhood development organizations. These findings suggest that initiatives to integrate and economically revitalize disadvantaged neighborhoods will not be sufficient to reduce crime and disorder so long as neighbors remain unequal.

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1. INTRODUCTION

"Inequality is a bit like cinnamon. You definitely want to have a little of it to spice life up a bit, but too much of it can be very dangerous."

—John Oliver

American urban neighborhoods are widely imagined as having markedly unequal levels of crime and disorder. While not often overtly acknowledged, the reputation of neighborhoods as somewhere safe or better off avoided hinges in part on their racial or ethnic makeup (Quillian & Pager, 2001; Sampson, 2012). Statistics back these perceptions for serious interpersonal crimes: in 2010, neighborhoods that were majority nonwhite had average property crime rates between 20% and 50% greater, and violent crime rates between two and six times greater, than those of typical majority White neighborhoods (Krivo et al., 2021). As I elaborate below, the heightened risk of criminal victimization in majority nonwhite areas—and especially predominantly Black or African American areas—results from a historical and contemporary reality of divestment from and isolation of these communities that is reflective of the American racial structure. The term "racial structure" refers the total set of relations and practices that privilege a dominant racial group and subordinate other groups within a racialized social system (Bonilla-Silva, 2014).

In the United States, the racial structure gives rise to ethno-racial inequality in neighborhood crime principally through the persistence of racial residential segregation (Krivo et al., 2009; Sampson & Levy, 2020). Throughout much of the twentieth century, nonwhite residents were excluded from predominantly White neighborhoods through overtly racist means including redlining, restricted covenants, blockbusting, and occasionally outright violence (Massey & Denton, 1993; Rothstein, 2017). Even in the twenty-first century, decades after the passage of civil rights legislation and the end of de jure segregation of public spaces, many White Americans desire to live in residential areas that are primarily White and affluent. Agents of the housing market cater to these preferences through a variety of ostensibly race-neutral routines that nevertheless employ racially coded stereotypes and discriminatory institutional practices (Korver-Glenn, 2018). As a result, many Black, Latino, and other persons of color are restricted to poorer and more socially isolated neighborhoods, and societal rewards and access accumulate in exclusive and majority White spaces. This arrangement results in the mapping of ethno-racial inequality along segregated geographic areas of American cities, a pattern Ruth Peterson and Lauren Krivo term the "racial-spatial divide" (Peterson & Krivo, 2010a).

How is the American racial-spatial divide related to neighborhood criminal inequality? Sociological research demonstrates that the bulk of ethno-racial inequality in crime is attributable to highly uneven distributions of key resources *between* neighborhoods, a condition I refer to as *absolute* neighborhood inequality. Without a minimum level of these resources, neighborhood residents become unable to collectively maintain the normative and institutional structures required to keep interpersonal crimes rare or absent. For example, there is widespread agreement that the single most important factor that accounts for racial disparities in violent crime is structural disadvantage, a term that refers to the geographic concentration of poverty, joblessness, low educational attainment, and family disruption following the deindustrialization of and outmigration from urban cores in the latter half of the twentieth century (Pratt & Cullen, 2005; Wilson, 1987; Sampson et al., 2018). Extant work also points to the importance of residential mobility, mortgage lending, and immigrant composition within neighborhoods, as well as spatial proximity to disadvantage and crime in nearby areas, as together explaining much of the gap in crime levels across neighborhoods of different racial and ethnic profiles (Krivo et al., 2021; Mears & Bhati, 2006; Peterson & Krivo, 2010a; Sampson et al., 2005). These findings, along with related studies showing that structural factors have similar consequences for neighborhood crime irrespective of ethno-racial composition, are the foundation for the racial invariance thesis, the perspective that the sources of crime are invariant across racial/ethnic groups and grounded primarily in ecologically distinct community conditions (Sampson & Wilson, 1995; Steffensmeier et al., 2010; Hernandez et al., 2018).

Less is known, however, about the role economic inequality *within* neighborhoods, what I refer to as *relative* neighborhood inequality, plays in the maintenance of the American racial structure and ethno-racial inequality in neighborhood crime. I conceptualize this kind of inequality as relative because although a neighborhood may have the minimum level of resources needed for otherwise effective crime control, the degree of economic disparity among its residents may work against this goal. Much of the now classic work on racial socioeconomic inequality and crime focused on large metropolitan areas or cities rather than neighborhoods and drew on a variant of relative deprivation theory to argue that inequality effects on crime may vary between racial/ethnic groups (Blau & Blau, 1982; Harer & Steffensmeier, 1992; Merton, 1968; Messner & Golden, 1992). Relative deprivation theory argues that cognitive appraisals of unfair disadvantage relative to similar others motivate actions to correct the perceived imbalance, sometimes including crimes (Agnew, 1999; Pettigrew, 2015; Smith et al., 2012). In a landmark study, Blau and Blau (1982) argued that in the United States, a country in which wealth and status are thought be awarded by merit alone, the association of race with inequality would be especially likely to produce feelings of alienation and frustration among Black Americans and contribute to their involvement in criminal violence. Although some follow up studies supported this position, many subsequent investigations reported that inequality effects on violence were in fact greater for White Americans (for examples, see Harer & Steffensmeier, 1992, and Parker & McCall, 1997; for a review, see Torres, 2020).

Before debates around racial variation in the effects of inequality on crime could be adequately resolved, however, scholars largely pivoted away from this question as evidence mounted that much of the ethno-racial neighborhood crime gap, and macro-level criminal inequality in general, could be attributed to disparities in structural disadvantage (Peterson & Krivo, 2005; Pratt & Cullen, 2005; Wilson, 1987). Yet as income inequality and income segregation have risen during the twenty-first century, and particularly following the 2008 global financial crisis, relative inequality has received renewed attention as a structural source of crime at the neighborhood level (Chamberlain & Hipp, 2015; Hipp, 2007; Hipp & Kubrin, 2017; Wang & Arnold, 2008; Wenger, 2019). As part of this attention, researchers have begun to reconsider the possibility of racial variation in the impact of relative inequality on crime by using a variety of sub-city units of observation as neighborhood proxies and investigating whether relative inequality effects vary by racial/ethnic group (Wright et al., 2016) or neighborhood ethno-racial composition (McNulty et al., 2023; Torres, 2020).

With this dissertation, I aim to build on this recent line of research by documenting and exploring sources of variation in the impact of relative inequality on neighborhood crime. I carry out my investigation by drawing principally on data from the National Neighborhood Crime Study Panel (NNCS2-P), a panel dataset containing crime and sociodemographic information for nearly 9,000 census tracts within over 80 major U.S. cities for the Wave I (1999-2001) and Wave II (2010-2013) data collection periods of the NNCS. I combine the NNCS2-P with household income data drawn from the 2000 Census and the 2008-2012 American Community Survey 5-year estimates to produce my measure of relative inequality, the neighborhood level Gini index. To gather information on city-level sources of neighborhood variation in the relative inequality-crime relationship, I further supplement these data with information on Black and Latino elected officials, Black and Latino municipal police officers, and capacity of nonprofit organizations committed to reducing crime and strengthening local communities. I provide more detail on these data, their sources, and the samples and variables I use in Chapter 2.

Stacked against one another, the balance of previous studies on relative inequality, race, and crime tips toward stronger effects on White Americans or in majority White neighborhoods than among Blacks, Latinos, or other persons of color, in contrast to the racial invariance expectation (Harer & Steffensmeier, 1992; Smith, 1992; Torres, 2020; Wright et al., 2016; but see also Hipp et al., 2009; Stolzenberg et al., 2006). Yet because these studies were not able to measure the social psychological process most often hypothesized to be at play—relative deprivation—their authors have had to speculate about the distinct subjective experiences different racial/ethnic groups might have with relative inequality. Furthermore, there is evidence that when perceived inequality is measured directly, it is not associated with crime (Rogers & Pridemore, 2022). Rather than determine the precise processes behind ethno-racial differences in effect of relative inequality on crime, in this dissertation I approach the problem by asking a slightly different question: Is there a way to account for racial variation in the effects of relative inequality? I explore this question in Chapter 3.

Drawing on a variety of theoretical perspectives to argue that relative inequality and disadvantage may elevate crime rates by similar mechanisms, I hypothesize that disadvantage tempers the impact of relative inequality on crime, such that inequality effects appear lesser in segregated neighborhoods of color because average levels of disadvantage are so much higher there than in predominantly White neighborhoods. I find that after controlling for the interaction between relative inequality and disadvantage, differences in the effect size of relative inequality across different neighborhood ethno-racial compositions are diminished or eliminated.

If the inequality-disadvantage interaction accounts for racial variation in the impact of relative inequality on neighborhood crime at one point in time, might a similar dynamic help explain racial differences in the consequences of relative inequality for changes in neighborhood crime over time? That is, do starting levels and growth in relative inequality vary in their association with crime trajectories between racially segregated or mixed neighborhoods, and do the interactions between initial or changing levels of relative inequality and disadvantage account for this variation? I take up this question in Chapter 4. I use a longitudinal framework known as latent growth curve modeling to estimate overall and neighborhood composition-specific crime trajectories during the 2000s decade, and I explore how initial and changing levels of relative inequality and disadvantage operate independently and in tandem to shape these trajectories. I find that during a period in which the average crime rate trajectory formed an inverse "U-shape," with crime levels initially rising through the mid-2000s and then declining through the early 2010s, initial relative inequality and growth in disadvantage were associated with more extreme rises and falls in crime, whereas initial disadvantage predicted a more modest trajectory. Contrary to my expectations, I also find that net of interactions between relative inequality and disadvantage, there remain important differences in how within-neighborhood inequality at the start of the decade affected subsequent crime trajectories between neighborhoods of different racial and ethnic makeups.

The findings from the previous chapters spur a broader question: to what extent does the relationship between relative inequality and neighborhood crime vary in general? In Chapter 5, I approach this question by exploring the extent to which the effect of relative inequality on neighborhood crime varies in magnitude or direction across the cities included in the NNCS2-P. Prior research demonstrates that cities represent forums on which different actors vie for political, economic, and civic influence, occasionally with major consequences for the capacity of neighborhoods to maintain communities free from crime and disorder (Bursik & Grasmick, 1993; Logan & Molotch, 1987; Lyons et al., 2013; Vélez, 2001; Vélez et al., 2015). Although extant work has investigated how the impact of relative inequality is moderated by other markers of socioeconomic composition, to my knowledge no study has yet considered whether the impact of neighborhood-level relative inequality varies with non-economic city-level characteristics. I begin the work of filling this gap by developing and testing hypotheses around three specific constructs: racial residential segregation, minority political empowerment, and community organizational capacity. I find that indicators from all three constructs account for some between-city variation in relative inequality's impact, such that in cities where these urban features are more prevalent, the inequality-crime association is reduced.

In previewing my findings, I foreshadow a theme that runs throughout this dissertation. Given that relative inequality is a consistent predictor of serious interpersonal crimes and that its effect is weakest in the most disadvantaged and segregated neighborhoods, it is possible that the severity of its impact is inversely related to overall community vitality and wellbeing. That is, assuming neighborhoods become more well-off over time, if they remain unequal, economic disparities among residents will only become more consequential for crime. I therefore conclude by warning scholars, policymakers, and community organizers who seek to improve public safety in disadvantaged neighborhoods that relative inequality may act as a final hurdle to clear. I am not the first to draw this conclusion about economic inequality (see, for example, Burraston et al., 2018), but the evidence I marshal behind it is unique. The size and representativeness of the cities and neighborhoods that comprise the NNCS2-P sample, and its inclusion of crime and sociodemographic information at multiple time points, makes it an ideal and unparalleled data source for answering my research questions. It is only appropriate that I begin my dissertation by describing this source, the additional data I supplement them with, and my approach to analyzing them in more detail, a task that I take up in the next chapter.

2. DATA AND METHOD

The datasets I employ in this dissertation permit consideration of a question interwoven through each of my empirical chapters: does relative inequality have a more pernicious influence on violent and property crime in some areas than in others? Are communities of some racial or ethnic compositions especially vulnerable (or resilient) to relative inequality, and what resources can municipalities marshal to dull its edge? A challenge to my selection of data and methods for this project was that the primary concerns of past research have shifted over time. Classic studies investigated whether racial socioeconomic inequality in large urban areas had more severe effects on White or Black rates of violence (Blau & Blau, 1982; Harer & Steffensmeier, 1992; Messner & Golden, 1992). Following Wilson's (1987) landmark work on the consequences of structural disadvantage for the social organization of impoverished and socially isolated urban Black neighborhoods, later studies pivoted to focus on intra-neighborhood economic inequality but largely omitted consideration of differential impacts by race (Chamberlain & Hipp, 2015; Hipp, 2007; Wang & Arnold, 2008; Stucky et al., 2016). More recent research, however, has revisited this question by investigating whether neighborhood-level relative inequality has dissimilar effects on crime by racial/ethnic group (Wright et al., 2016) or across neighborhoods of varying ethno-racial compositions (McNulty et al., 2023; Torres, 2020).

In what follows a I provide a brief overview of the methodological considerations of past work before discussing why the NNCS data are an ideal data for my project with these issues in mind. I then describe the supplemental data I collected for this project, the sample and variables I use in each chapter, and my analytic strategies for answering my research questions.

Methodological Issues in the Study of Race, Relative Inequality, and Neighborhood Crime

Racially (In)variant Relative Inequality Effects. Assessments of whether key structural predictors accord with the racial invariance thesis have involved a widening array of considerations around evidence and scope (Hernandez et al., 2018; Sampson et al., 2018; Steffensmeier et al., 2010). Regarding relative inequality, shifts in the operationalization of inequality and unit of analysis—from a focus on inter-group inequality across large urban areas (Blau & Blau, 1982; Harer & Steffensmeier, 1992; Vélez et al., 2003) to race-neutral inequality at the neighborhood level (Hipp, 2007; Wang & Arnold, 2008; Wenger 2019)—have implications for how the racial invariance expectation is tested. Levels of intra-neighborhood income inequality, especially when defined by census boundaries (e.g., tracts or block groups), do not vary to the same degree across neighborhoods of different colors as disadvantage or crime rates. This means that exploring whether average differences in structural factors diminish ethno-racial gaps in neighborhood crime, as the bulk of prior assessments of racial invariance have done (Hernandez et al., 2018), is likely to be less relevant for relative inequality.

Instead, the few studies that have explored neighborhood differences in the relative inequality and crime relationship have assessed the expectation that effect size and direction will be similar across neighborhoods (McNulty et al., 2023; Torres, 2020). For example, Torres (2020) analyzed data from Wave I of the NNCS and found that relative inequality universally elevated neighborhood crime, but effects were significantly larger in predominantly Black or Latino census tracts for homicide and in predominantly White or integrated tracts for burglary or robbery. By contrast, McNulty et al. (2023) observed both the

Gini index and the index of concentration at the extremes (ICE) to have effects on violence that were statistically comparable across White, Black, and mixed racial composition block groups in Atlanta, Georgia. However, McNulty and colleagues also found that disadvantage was unrelated to violent crime in White block groups, likely reflecting their consistently low levels of disadvantage. The fact that disadvantage tends to vary minimally across the predominantly White communities of a single city, and that this distribution has little overlap with the disadvantage distribution across Black or Latino neighborhoods in the same area, is a barrier to accurate comparisons of how disadvantage impacts crime across neighborhoods of different colors in the United States (Krivo & Peterson, 2000; McNulty, 2001). This problem of "restricted distributions" poses a challenge to my research questions since I plan to explore how relative inequality and disadvantage interact in shaping crime levels for neighborhoods of distinct racial and ethnic profiles.

Relative Inequality and Neighborhood Crime. Three foci have emerged in recent research on relative inequality and neighborhood crime that bear on my methodological approach. First, recent work has begun to consider how neighborhood relative inequality interacts with macro-level characteristics at higher levels of aggregation. Such work has demonstrated that city-level variables condition the impacts of intra-neighborhood economic inequality and disadvantage, but so far analyses have been limited only to other socioeconomic moderators (Chamberlain & Hipp, 2015; Wenger, 2019). Second, studies have shown that in addition to income inequality within focal neighborhoods, the economic condition of nearby neighborhoods matters. More affluent neighborhoods that are geographically proximate to low-income or high-disadvantage neighborhoods have higher crime, over and above their own disadvantage or relative inequality levels (Chamberlain &

Hipp, 2015; Hipp & Kubrin, 2017; Stucky et al., 2016). Finally, past research has experimented with different units of analysis to operationalize neighborhoods and capture the appropriate frame of reference for "local" inequality. Extant work has commonly used government-defined small area units including block groups (McNulty et al., 2023), census tracts (Torres, 2020; Wang & Arnold, 2008), or ZIP codes (Wright et al., 2016). Less frequently, researchers have proposed their own definitions of neighborhoods, arguing that scholars who rely on government-defined areas underestimate the amount of inequality residents are exposed to because such units are defined in part by greater economic and sociodemographic homogeneity within than without (Hipp & Boessen, 2013; Hipp & Kubrin, 2017).

Because my principal focus is on the potentially disparate impacts of within-neighborhood inequality, although the consequences of between-neighborhood or spatial inequality for crime are undoubtedly important, they lie outside the scope of this dissertation. The other two themes of past work, however, are directly relevant to my questions. They suggest that determining whether neighborhoods of particular ethno-racial profiles are differentially affected by relative inequality requires careful consideration of the appropriate unit of analysis for capturing inequality and the incorporation of city-level factors that may account for or moderate its impact.

Why the NNCS?

The foregoing suggests that a unique data source is needed to determine whether the consequences of relative inequality for crime vary by neighborhood ethno-racial composition; whether this variation is attributable to the highly unequal distributions of disadvantage by race that exist across American cities; and whether variation in the impact of relative inequality between neighborhoods generally is attributable to city-level characteristics. The data must allow comparison of neighborhood areas that vary in their racial and ethnic compositions but have similar levels of income inequality and disadvantage, a difficult requirement to meet when neighborhoods are drawn from a single city, metropolitan area, or county (Peterson & Krivo, 2010a; Sampson, 2009). The ideal dataset would also operationalize neighborhoods in a manner appropriate to capturing local inequality effects on crime, include enough information on the urban areas surrounding neighborhoods to allow for multilevel analysis, and provide information over multiple years to permit exploration of whether any cross-sectional findings observed for relative inequality hold over time.

I meet these criteria by drawing on the NNCS2-P, the panel dataset that combines data from Waves I and II of the National Neighborhood Crime Study. Wave I of the NNCS provides reported crime and sociodemographic characteristics for 9,593 census tracts within a nationally representative sample of 91 large urban areas (i.e., cities with a population of at least 100,000) in 2000 (Peterson & Krivo, 2010b). Wave II updates this information for 10,206 census tracts within 85 of the Wave I cities for approximately one decade later (Krivo et al., 2023). The NNCS2-P combines these waves to comprise a total sample of 8,856 tracts across 81 cities for which crime data are available at both the Wave I (1999-2001) and Wave II periods (2010-2013), with all data normed to 2010 tract boundaries (Logan et al., 2014). Additionally, a subset of the NNCS2-P cities include data for some or all years from 2002 through 2009. The reported crime data are supplemented with sociodemographic information from the census, foreclosure data from Realty Trac, and mortgage lending data from the Home Mortgage Disclosure Act for the 2000 and 2008-2012 periods (Lyons et al., 2022). To allow for longitudinal analysis in Chapter 4 while permitting similar sample sizes and variables in Chapters 3 and 5, I analyze data from the NNCS2-P for all three of my empirical chapters in this dissertation, and hereafter refer to the 1999-2001 period as "Time 1" (T1) and the 2008-2012/2010-2013 periods as "Time 2" (T2).

The NNCS2-P is exceptional not only in its representativeness of large urban areas in the U.S.[1], but also in the capacity it grants researchers to compare neighborhood areas that vary in their racial and ethnic compositions yet have comparable socioeconomic conditions, thereby avoiding the problem of restricted distributions. The unit of analysis the NNCS2-P provides to operationalize neighborhoods, the census tract, is also ideal for answering my research questions. Census tracts may not always proxy neighborhoods in a socially meaningful sense, but they have been widely used in extant work as geographies that are appropriately sized to capture the degree of economic inequality to which residents are exposed in their everyday patterns of social interaction (Chamberlain & Hipp, 2015; Hipp, 2007; Stucky et al., 2016; Torres, 2020; Wang & Arnold, 2008). Moreover, the census tract is a sub-city area for which demographic information, including ethno-racial composition data, are readily available. If critics of census geographic units are correct that these areas understate the disparity residents routinely encounter (Hipp & Kubrin, 2017), then any variation I discover in the impact of relative inequality across neighborhoods using the NNCS2-P represent a conservative estimate of the true disparities that may exist by neighborhood race/ethnicity, and I return to this point in my conclusion.

[1] The cities in the NNCS2-P are similar in poverty, racial/ethnic composition, and serious violent and property crime to all U.S. cities with populations over 100,000 in 2010, but they are also more racially segregated, less concentrated in the Northeast/Midwest, and more concentrated in the West. For details see the appendix of Lyons et al. (2022).

Supplementing the NNCS: External Data Collection

I supplement the NNCS2-P with data from five other sources. First, I merged in household income data at the tract level drawn from the 2000 Census SF3 file and 2008-2012 American Community Survey 5-year estimates file.[2] The income data are binned, with counts of households falling into different income categories, and I use these data to construct relative inequality estimates. Next, to construct measures of minority political empowerment, I aggregated counts of Latino and Black mayors and city councilors for 2010. For Latino elected officials I obtained counts from the 2010 National Directory of Latino Elected Officials (NALEO), selecting any elected official with the following titles: “Mayor,” “Alderman,” “Alderwoman,” “Councilmember,” or “Councilor.” No comparable data source was available for the same period for Black elected officials, so I collected these data by browsing the websites of each city in the sample. To identify the mayor and number of members on the city council or analogous body (e.g., board of representatives or board of commissioners), I scanned meeting agendas, minutes, or comprehensive annual financial reports for lists of members as near to 2010 as was available. For six cities I obtained member lists for a year other than 2010, ranging from 2011 to 2014. To classify elected officials as Black, I first visually inspected available photographs to determine whether their ascribed or “street” race might appear as Black (Lopez & Hogan, 2021). I then examined members’ “About” pages or other background writings to confirm whether they self-identify as Black or African American. In many cases I was able to classify elected officials as Black both visually and via self-identification, but in some cases I used only one method. If it was

[2] Census data on tract-level household income were extracted from the Integrated Public Use Microdata Series (IPUMS) National Historical Geographic Information System (NHGIS) (Manson et al., 2023).

not possible to determine an officials' race through either method, I assumed they were not Black.

Fourth, I constructed measures of minority bureaucratic incorporation by aggregating counts by city of Latino and Black sworn police officers drawn from the Bureau of Justice Statistics Law Enforcement Management and Statistics (LEMAS) dataset for 2013, the collection period that most closely approximates T2. Finally, to index community organizational capacity in each city, I draw on tax-exempt charitable nonprofit organization data obtained from the National Center for Charitable Statistics (NCCS), hosted by the Center on Nonprofits and Philanthropy at the Urban Institute. The NCCS provides a variety of datasets containing descriptive and financial information about nonprofits in the United States supplied by these organizations to the Internal Revenue Service (IRS). Following Sharkey et al.'s (2017) approach to selecting community organizations, I specifically use data from the Cumulative Master File (CMF), a subset of the Business Master File (BMF) that provides a cumulative list of 501(c) organizations that have been granted recognized tax-exempt status by the IRS (NCCS, 2013), and further restrict the data to 501(c)3 organizations (i.e., charitable organizations, foundations, and religious entities). For the purposes of my dissertation, I also select only organizations that had a most recent tax return filing year inclusive of 2008 through 2016. This timeframe ensures that organizations were active for at least one year inclusive of the range for my variables drawn from the 2008-2012 ACS 5-year estimates, and 2016 was the most return tax return filing year at the time the NCCS data were collected.[3]

[3] The NCCS data for this project were collected in 2018. At the time of writing the NCCS BMF data can be obtained from the Urban Institute's website (Lecy, 2023): https://nccs.urban.org/nccs/datasets/bmf/.

Samples, Dependent Variables, and Primary Independent Variables

Samples by Chapter. Table 2.1 presents the analytic samples I use for each empirical chapter. Each sample is slightly smaller than the full NNCS2-P dataset because of missing values on key variables of interest, primarily my dependent variables and their spatial lags (described below). Chapters 3 (N = 8,236 tracts nested within 72 cities) and 5 (N = 7,830 tracts nested within 66 cities), which present analyses of the data for T2, draw on similar subsamples except that six additional cities that are missing information on Black and Latino sworn police officer counts are excluded from the Chapter 5 sample.[4] The Chapter 4 subsample (N = 2,757 tracts nested within 28 cities) is restricted only to those cities that are missing crime data for no more than four of the fifteen years spanning 1999-2013 to allow for longitudinal analysis, as well as tracts that have available mortgage lending and household income inequality data for both the T1 and T2 periods.[5]

[4] LEMAS data are unavailable for five cities in the NNCS2-P. For a sixth city (Hialeah, FL), the ratio of the percentage of Black police officers to the percentage of Black residents is > 14.0, far above the mean value of .9 for all cities in the sample. I therefore exclude this outlying case before constructing the minority (combined Black and Latino) police representation variable.

[5] The method I used to produce estimates of relative inequality returned missing values for six census tracts for the 2008-2012 period and for five tracts for 2000. Mortgage lending data were unavailable for three census tracts during 2008-2012 but were available for all sample tracts in 2000.

Table 2.1 Analytic Sample Sizes and Differences from Full NNCS2-P Sample for Chapters 3-5

Chapter	Analytic Sample	Difference from Full Sample
Chapter 3	8,236 census tracts within 72 cities	Narrowed to tracts that were non-missing on crime, spatial lags for crime, mortgage lending, and income inequality data for circa 2010
Chapter 4	2,757 census tracts within 28 cities	Narrowed to 1) tracts that were non-missing on mortgage lending and income inequality data for 2000 and 2010, plus 2) cities with <= 4 years of missing crime data from 1999 through 2013 for at least one of three crime types
Chapter 5	7,830 census tracts within 66 cities	Narrowed to 1) tracts that were non-missing on crime, spatial lags for crime, mortgage lending, and income inequality data for circa 2010, plus 2) cities that were non-missing on sworn police officer data for 2013

Dependent Variables. Table 2.2 lists the dependent and primary independent variables that represent the core of my focus across all three empirical chapters, their operationalizations, and their data sources. In each chapter I analyze two tract-level dependent variables: the rate of burglaries as my measure of property crime, and the combined rate of homicides and robberies as my measure of violent crime. I use multiple-year rates to minimize the effect of annual fluctuations for small units, such that my modal outcome is the four-year average crime rate per 1,000 residents during 2010-2013; the exception is for violent crime in Chapter 3, for which I use the sum count of homicides and robberies and my modeling strategy converts the predicted outcome into a rate (see "Analytic Strategies" below). As I estimate separate rates for each year from 1999 through 2013 in Chapter 4, my outcomes in that chapter are the annual burglary and violent crime rate. I focus on these offense types because burglary is among the most reliably reported property crimes, and homicide and robbery are the most reliably reported serious violent offenses (Baumer et al., 2018).

Neighborhood Ethno-racial Composition. To group census tracts by ethno-racial composition, I reproduce the 7-category classification used by Lyons et al. (2022). The first four are considered "segregated" neighborhoods: White, Black, and Latino neighborhoods have at least 70% of the population in the respective group, and Minority tracts have two non-White groups that together comprise at least 70% of the population but neither group alone reaches the 70% threshold. The remaining three are considered "multiethnic" neighborhoods: In White-Black Multiethnic neighborhoods, Whites and Blacks are the only two groups that when combined comprise at least 70% of the population, and neither group alone makes up 70% or more of the population. In White-Latino Multiethnic neighborhoods,

Table 2.2 Operationalizations for Dependent and Independent Variables and Their Data Sources

Variable	Operationalization	Source
Tract-Level		
Burglary rate	Four year average rate of burglaries per 1,000 residents, 2010-2013	NNCS2
Violent crime count	Four year sum count of homicides and robberies, 2010-2013 (Chapter 3 Only)	NNCS2
Violent crime rate	Four year average rate of homicides and robberies per 1,000 residents, 2010-2013	NNCS2
Nbhd. Ethno-Racial Type	***Dummy variables indicating area ethno-racial composition:***	NNCS2
White	White nbhd (1 = at least 70% of the nbhd population is non-Latino White, else = 0), the reference group	
Black	Black nbhd (1 = at least 70% of the nbhd population is non-Latino Black, else = 0)	
Latino	Latino nbhd (1 = at least 70% of the nbhd population is Latino, else = 0)	
Minority	Minority nbhd (1 = two non-White groups together comprise at least 70% of the nbhd population, but neither group comprises at least 70% of the population on their own, else = 0)	
White-Black Multiethnic	White-Black Multiethnic nbhd (1 = non-Latino White and non-Latino Black residents together comprise at least 70% of the nbhd population, but neither group comprises at least 70% of the population on their own, else = 0)	
White-Latino Multiethnic	White-Latino Multiethnic nbhd (1 = non-Latino White and Latino residents together comprise at least 70% of the nbhd population, but neither group comprises at least 70% of the population on their own, else = 0)	
Other Multiethnic	Other Multiethnic nbhd (1 = all other neighborhoods that do not fall into one of the other six categories, else = 0)	
Relative inequality	Gini index of household income inequality	Census
Disadvantage*	***Average of the standardized scores of six variables:***	NNCS2
Joblessness	Percentage of population age 16-64 who are unemployed or out of the labor force	
Professional workers	Percentage of employed civilian population age 16 and older working in management, business, and related occupations (reverse coded)	
College graduates	Percentage of population age 25 and older who are are college graduates (reverse coded)	
Female-headed families	Percentage of households that are female-headed families	
Secondary-sector workers	Percentage of employed civilian population age 16 and older employed in the six occupational categories with the lowest average incomes	
Poverty	Percentage of population that is below the poverty line	
City-Level (Chapter 5 Only)		
White-Black Segregation	White-Black Index of Dissimilarity	NNCS2

Table 2.2 Operationalizations for Dependent and Independent Variables and Their Data Sources (Cont.)

Variable	Operationalization	Source
White-Latino Segregation	White-Hispanic Index of Dissimilarity	NNCS2
Minority mayor	Dummy variable indicating whether the city has a Black or Hispanic/Latino mayor (1 = yes, 0 = no)	NAELO, city website
Minority city councilor rate	Sum of Black and Hispanic/Latino city councilors divided by the sum of the total population that are Black or Hispanic/Latino, multiplied by 100,000	NAELO, city website
Minority police representation	Percentage of Black or Hispanic/Latino sworn officers in the city's police department divided by the percentage of the total population that are Black or Hispanic/Latino (minority police incorporation ratio)	LEMAS
Crime prevention nonprofit rate	Rate per 100,000 residents of organizations with NTEE-CC codes I20 (Crime Prevention), I21 (Youth Violence Prevention), F42 (Sexual Assault Services), I31 (Halfway Houses for Offenders & Ex-Offenders), I40 (Rehabilitation Services), I43 (Inmate Support), and I44 (Prison Alternatives); and any other nonprofits with keywords in their names related to crime, policing, or corrections - see Sharkey et al. (2017) online supplement	NCCS
Neighborhood development nonprofit rate	Rate per 100,000 residents of organizations with NTEE-CC codes L25 (Housing Rehabilitation), L30 (Housing Search Assistance), L80 (Housing Support), L81 (Home Improvement & Repairs), P28 (Neighborhood Centers), S20 (Community & Neighborhood Development), S21 (Community Coalitions), S22 (Neighborhood and Block Associations), S30 (Economic Development), and S31 (Urban & Community Economic Development)	NCCS
Substance abuse program nonprofit rate	Rate per 100,000 residents of organizations with NTEE-CC codes F20 (Substance Abuse Dependency, Prevention & Treatment), F21 (Substance Abuse Prevention), and F22 (Substance Abuse Treatment)	NCCS
Workforce development program nonprofit rate	Rate per 100,000 residents of organizations with NTEE-CC codes J22 (Job Training) and J30 (Vocational Rehabilitation)	NCCS
Youth program nonprofit rate	Rate per 100,000 residents of organizations with NTEE-CC codes N60 (Amateur Sports), O20 (Youth Centers & Clubs), O21 (Boys Clubs), O22 (Girls Clubs), O23 (Boys & Girls Clubs), O30 (Adult & Child Matching Programs), O31 (Big Brothers & Big Sisters), O40 (Scouting), O50 (Youth Development Programs), O51 (Youth Community Service Clubs), O52 (Youth Development - Agricultural), O53 (Youth Development - Business), O54 (Youth Development - Citizenship), O55 (Youth Development - Religious Leadership), P27 (Young Mens or Womens Associations), and P30 (Children & Youth Services)	NCCS
Total community organizations rate	Rate per 100,000 residents of the sum of all five subcategories of community nonprofits	NCCS

*In longitudinal analyses involving change scores, the disadvantage index for Waves I and II is normed to the midpoint between the waves. See footnote 9 in Chapter 4.

Whites and Latinos are the only groups that when combined comprise at least 70% of the population, and neither group alone attains the 70% cutoff. Finally, Other Multiethnic neighborhoods include any other combination of ethno-racial groups. In Chapter 4 the neighborhoods are defined based on their compositions in T1, while in Chapters 3 and 5 they are based on their compositions in T2.

Relative Inequality. To operationalize relative inequality, I use the Gini index of household income inequality. The Gini index is among the most common measures of income dispersion and has a long history of application in studies of neighborhood crime (Chamberlain & Hipp, 2015; Hipp, 2007; Messner & Tardiff, 1986; Torres, 2020). Prior work has also shown the Gini index to be a consistent predictor of violence and highly correlated with alternative operationalizations of income inequality at different macro-level units of analysis, including neighborhoods and cities (McNulty et al., 2023; Roberts & Willits, 2015; Wenger, 2019). The Gini index can be interpreted as the ratio of the average income difference between pairs of households in an area to the average income of that area (Messner, 1982) and ranges from 0 (perfect equality where every household holds the same income) to 1 (perfect inequality where one household holds all available income). To produce the Gini index from binned household income data, I use the cumulative distribution function (CDF) interpolation method, which can be implemented using the *binsmooth* package in R (von Hippel et al., 2017). I estimate the tract-level Gini index at T2 for use in Chapters 3 and 5, and at T1 in Chapter 4 to compute the change in the Gini index between 2000 and 2008-2012 (Δ Gini = Gini index for T2 – Gini index for T1).[6]

[6] Published figures for the Gini index are available from 2008-2012 ACS 5-year estimates, but since no comparable figures are available for 2000, I produce my own estimates using the *binsmooth* R package at T1

Neighborhood Disadvantage. I measure neighborhood structural disadvantage with an index that averages the standardized scores on six variables: percent secondary sector low wage jobs, jobless rate for working population, percent professionals and managers (reverse coded), percent female-headed households, percent of adults age 25 and over who are college graduates (reverse coded), and poverty rate. I construct the disadvantage index at T1 and T2 to compute change in disadvantage in Chapter 4 ($\alpha = .93$ for 2000 and $\alpha = .92$ for 2008-2012). In Chapter 4 I norm the index to the midpoint between the periods (see chapter for details). Chapters 3 and 5 make sole use of the T2 index.

Racial Residential Segregation. In Chapter 5 I measure city-level residential segregation using the White-Black and White-Hispanic Index of Dissimilarity (D) for census tracts for the T2 period. This is a common index of segregation that captures the extent to which the distribution of two groups across tracts in a city deviates from an even distribution. D ranges from 0 to 100 and can be interpreted as the percentage of either group that would need to move from their tract of residence to achieve perfect integration (Peterson & Krivo, 2010a).

Minority Political Empowerment. As described in Chapter 5, I operationalize two facets of minority political empowerment: descriptive representation and bureaucratic incorporation.[7] I measure descriptive representation using two city-level variables: a dichotomous measure of whether a city has a Black or Latino mayor in or around 2010

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and T2 to hold constant the estimation method between periods. For 2008-2012, my estimates of the Gini index and the published figures at the tract-level are highly correlated in the NNCS2-P sample (Pearson's r = .900, N = 8,850 census tracts).

[7] My measures of descriptive representation and bureaucratic incorporation were originally developed separately for Blacks and Latinos. However, upon finding similar results for both groups and with no strong theoretical rationale for keeping them distinct, I combined the measures into single "minority" empowerment measures.

("minority mayor"), and the rate of Black and Latino city councilors per 100,000 Black and Latino residents for the same period ("minority city councilor rate"). The minority city councilor rate has a considerable positive skew, so I take the natural logarithm of this variable to normalize its distribution. As my indicator of bureaucratic incorporation, I employ the police incorporation ratio, defined as the ratio of the percentage of Black and Latino sworn police officers in the city police department in 2013 to the percentage that Black and Latino residents comprise of the total city population for 2008-2012 ("minority police representation") (see Vélez et al., 2015). Values on the police incorporation ratio that are < 1 indicate that Blacks and Latinos are underrepresented on the police force relative to their share of the city population, and values > 1 indicate overrepresentation of Blacks and Latinos on the police force.

Community Organizations. To measure a city's capacity of community-oriented nonprofit organizations, in Chapter 5 I follow Sharkey et al.'s (2017) selection and operationalization of community organizations dedicated to strengthening community life or reducing crime. I use the National Taxonomy of Exempt Entities Core Code (NTEE-CC) system to choose 501(c)3 organizations that fall within one of five organization categories (refer to Table 2.2 for the codes included in each category): (1) crime prevention, (2) neighborhood development, (3) substance abuse prevention, (4) job training/workforce development for disadvantaged populations, and (5) recreational and social activities for youth. I construct category-specific rates by dividing the number organizations that were active for at least one year from 2008-2016 by the city population for 2008-2012 and multiplying the quotient by 100,000. I also construct a total rate of community organizations by summing the counts of organizations across all five categories. Each of the community organization rate variables are logged to normalize their distributions.

Tract- and City-Level Controls

Tract-Level Demographics. Table 2.3 presents my tract- and city-level control variables, their operationalizations, and the chapters they appear in. Beginning with the tract-level, I control for three demographic characteristics: the share of the population that is young and male, population size, and immigrant composition (using an index that averages the standardized scores on percentage of the population is foreign-born, percentage of the population that arrived in the U.S. within the last 10 years, and percentage of households in which no one age 14 and over speaks English very well). As with the disadvantage index, the immigration index is normed to the midpoint between T1 and T2 in Chapter 4 and measured only for T2 in the other chapters (α = .96 for 2000 and α = .93 for 2008-2012).

Tract-Level Housing Conditions. In Chapters 3 and 5 I measure residential instability with an index averaging the standardized scores on percentage of the population who are renters and percentage of the population age 5 and over who lived in a different residence five years ago (α = .71 for 2008-2012); in Chapter 4 I capture a similar construct using only the percentage of renters at each period. I include three additional housing condition indicators at T1 and T2: the percentage of total housing units that are vacant ("vacant housing"), the total dollar amount of home loans ("residential loans"), and the rate of foreclosures ("foreclosure rate"). In Chapter 4 the residential loan amount variable is specified as the amount per housing unit and the T1 and T2 amounts are in 2000 constant dollars. The foreclosure rate is the average number of foreclosures over 1999-2001 for T1

Table 2.3 Operationalizations for Tract- and City-Level Controls*

Variable	Operationalization	Chapter(s)
Tract-Level		
Young males	Percentage of the population that is male age 15-34	3,4,5
Residential instability	***Average of the standardized scores of two variables:***	3,5
Renters	Percentage of occupied housing units that are renter-occupied	4
Recent movers	Percentage of population age 5+ who lived in a different residence in 2005 (Wave II)	
Immigration**	***Average of the standardized scores of three variables:***	3,4,5
Foreign born	Percentage of the population that is foreign-born	
New immigrants	Percentage of the population that is foreign-born and entered the U.S. since 1990 (Wave I) or 2000 (Wave II)	
Linguistically isolated	Percentage of households in which no one age 14+ speaks English very well	
Residential loans	Total amount of loans originated (in 1,000s of dollars) in 2010 (Wave II)	3,5
Residential loans per unit	Total amount of loans originated per housing unit in 2000 (Wave I) or 2010 (Wave II) (in 1,000 constant 2000 dollars)	4
Vacant housing	Percentage of total housing units that are vacant	3,4,5
Foreclosure rate	Average foreclosure rate per 1,000 total housing units over 1999-2001 (Wave I) or 2010-2013 (Wave II)	3,4,5
Crime rate spatial lags	Average value for tracts that are geographically adjacent to the focal census tract, computed by multiplying the rate for the focal tract by a row-standardized first order spatial contiguity matrix using queen criteria	3,5

Table 2.3 Operationalizations for Tract- and City-Level Controls* (Cont.)

Variable	**Operationalization**	**Chapter(s)**
Population size	Total resident population	4
City-Level		
Disadvantage	Operationalized the same way as at the tract level	3,5
Manufacturing	Percentage of employed civilian population age 16+ working in a manufacturing industry	3,5
Population	Operationalized the same way as at the tract level	3,5
Black	Percentage of the population that is non-Latino Black	3,5
Recent movers	Operationalized the same way as at the tract level	3,5
Foreign-born	Operationalized the same way as at the tract level	3,5
Young males	Operationalized the same way as at the tract level	3,5
South	Dummy variable indicating whether the city is located in the South Census Region (1 = South, else = 0)	3,5
West	Dummy variable indicating whether the city is located in the West Census Region (1 = West, else = 0)	3,5

*Unless otherwise specified, variables are operationalized the same way at both data collection waves in Chapter 4 or only at Wave II in Chapters 3 and 5.
**In longitudinal analyses involving change scores, the immigration index for Waves I and II is normed to the midpoint between the waves. See footnote 9 in Chapter 4.

and over 2010-2013 for T2 per 1,000 total housing units in 2000 and 2010, respectively. Each of these three housing condition indicators are logged to normalize their distributions.

Tract-Level Crime Rate Spatial Lags. To control for levels of crime in surrounding census tracts that may influence crime levels in a focal tract in Chapters 3 and 5, I include the spatial lags of the burglary rate and combined homicide/robbery rate for T2. I calculated the spatial lags by multiplying the burglary, homicide, and robbery rate variables by a row-standardized first-order spatial contiguity matrix using queen criteria (i.e., in which spatially adjacent communities in all directions are considered contiguous). All elements of the matrix diagonal are set to 0, indicating that a tract is never a neighbor to itself. The resulting new variables represent the mean rate for each crime type across tracts that are geographically adjacent to the focal tract. The violent crime rate spatial lag is the sum of the lags for the homicide and robbery rates.

City-Level Controls. In Chapters 3 and 5 I include several city-level control variables measured for T2 and operationalized the same way as their tract-level counterparts: disadvantage, population size, and shares of the population that are recent movers, foreign born, and young males. Four additional controls are unique to the city-level: percent of the civilian population age 16 and over employed in manufacturing industries ("manufacturing jobs"), share of the population that is Black ("percent Black"), and two dichotomous variables, South and West, to serve as region indicators (with East and Midwest as reference categories).

Analytic Strategies

To answer the research questions that are the focus of Chapters 3, I fit a series of cross-sectional multilevel regression models with tracts as level-one units nested in cities as level-two units. As I treat the city-level variables strictly as controls in this chapter, the primary purpose of this approach is reliable estimation of model parameters despite the inherent clustering in my data that renders census tracts as non-independent observations. For property crime, I take the natural logarithm of the burglary rate to normalize its distribution and use ordinary least squares (OLS) regression models to predict the logged rate. Because homicides and robberies are rare events at the tract level, I leave the violent crime outcome as a count and estimate a set of negative binomial regression models. Like Poisson regression, negative binomial regression is a commonly used statistical model for predicting counts, but it adjusts for outcomes with variance values that exceed mean values with the inclusion of an overdispersion parameter. For violent crime I also specify exposure by tract population size, which transforms the count outcome into a per capita rate (Osgood, 2000).

The analytic strategy for Chapter 5 is similar, as the design is again cross-sectional and multilevel. However, in addition to specifying multilevel models to adjust for clustering, in this chapter I estimate the variation around the mean estimates of my dependent variable intercepts and slope terms for neighborhood ethno-racial composition and the Gini index across cities, which I specify as random effects. I then explore the extent to which between-city variation in the Gini index slope term is explained by my hypothesized city-level moderator variables by specifying cross-level interaction effects. In Chapter 4, in which I examine crime data available for most years from 1999-2013, I fit a series of latent growth curve (LGC) models, which I describe in more detail in that chapter.

Because my statistical software does not allow me to fit multilevel negative binomial regression models predicting the violent crime count that include interaction effects using the NNCS2-P data, in Chapters 4 and 5 I use the four-year average rate of homicides and robberies instead of the summed count, and I use logged rates for both property and violent crime. Finally, in all three empirical chapters I grand-mean center my continuous tract- and city-level independent variables. Mean centering allows model intercepts to be interpreted as the crime rates that would be observed in a tract and city with average values on all covariates.

Looking Ahead

This chapter has outlined the data sources, samples, and variables I will use to describe and attempt to account for differences in how relative inequality shapes crime across urban neighborhoods. As an initial foray into this topic, I begin in the next chapter by revisiting an old question in macro-level studies of racial inequality and crime: does the impact of relative inequality vary by race/ethnicity and, in particular, are effects stronger for Whites or in predominantly White communities? As I will show, adopting a structural framework for the inequality-crime nexus can provide clues for how to account for apparent variation in the effects of relative inequality on neighborhoods of different colors.

3. ACCOUNTING FOR ETHNO-RACIAL VARIATION IN THE EFFECT OF RELATIVE INEQUALITY ON NEIGHBORHOOD CRIME

Although early research asserted that economic inequality has an unequal influence on crime between White and Black Americans (Blau & Blau, 1982; Harer & Steffensmeier, 1992; Merton, 1938), the recent resurgence of work on relative inequality has largely pivoted away from the focus on differential impacts by race or ethnicity or ethno-racial gaps in neighborhood crime (Chamberlain & Hipp, 2015; Hipp & Kubrin, 2017; Stucky et al., 2016; Wenger, 2019). This shift is curious because a finding that the direction or magnitude of relative inequality effects on crime varied across neighborhoods of different ethno-racial compositions would counter one of the most widely accepted perspectives on neighborhood criminal inequality, the racial invariance thesis. The notion that the primary causes of crime are rooted in deeply unequal ecological conditions between segregated areas—as opposed to putative characteristics of demographic groups—has received widespread empirical support in the neighborhood crime literature, especially for the relationship between structural disadvantage and violence (Hernandez et al., 2018; Sampson et al., 2018). Yet the few studies that have examined relative inequality and crime suggest effects are stronger for White Americans or in communities that are majority White (e.g., Torres, 2020; Wright et al., 2016; but see also McNulty et al., 2023).

The most prominent explanations for the association between relative inequality and crime rely on variants of the social psychological mechanism at the core of relative deprivation theory. Specifically, economic disparities are held to induce social comparisons in which individuals appraise themselves as unfairly deprived relative to similar others, leading to feelings of frustration that sometimes manifest in acquisitive or violent crimes

(Smith et al., 2012). Scholars have elaborated on this idea by arguing that perceptions of and meanings attributed to relative deprivation vary across racial or ethnic groups, thereby accounting for differential impacts (Cernkovich et al., 2000; Harer & Steffensmeier, 1992; Merton, 1968). Yet critics have levied numerous critiques upon relative deprivation as the primary mechanism linking economic inequality with crime, including that the central construct is typically inferred rather than measured (Sampson & Wilson, 1995); that when measured it has not received empirical support (Chamlin & Cochran, 2006; Rogers & Pridemore, 2022); and that it is reductionist, explicating an aggregate-level phenomenon in individual-level terms (Tutle, 2022).

There is thus a puzzle in the relative inequality and crime literature. Past work indicates relative inequality is a reliable predictor of neighborhood crime and generally has stronger effects for White Americans than for persons of color, but it is not clear that relative deprivation is the process underlying either the association of relative inequality with crime or its uneven effects by race. Rather than pin down the exact mechanisms behind this disparity, however, could there be a way to account for it instead? In this chapter, I revisit the question of racial variation in relative inequality's impact on crime by exploring an approach to "explain away" this variation. I argue that a number of theoretical perspectives suggest relative inequality may affect crime via similar mechanisms as structural disadvantage and, consequently, incremental increases in either factor are substantively less important for raising crime rates the greater the level of the other factor. I hypothesize, in short, that disadvantage "weakens" or tempers the impact of relative inequality on crime, and vice-versa. If so, because distributions of disadvantage are themselves highly unequal across racially segregated residential areas, the impact of relative inequality on crime may also vary between neighborhoods of different ethno-racial compositions.

Relative Inequality, Crime, and Differential Impacts by Race

Most early explanations of how relative inequality affects crime are rooted in relative deprivation theory. This orientation can be traced to Robert K. Merton who, in developing his classic theory of structural strain, articulated an early hypothesis concerning racial difference that served as a springboard for later accounts of race-specific relative inequality effects. Merton (1938) argued that the discrepancy between cultural goals of the “American Dream” and unequal access to legitimate means for achieving those goals pressures some individuals to commit acquisitive crimes. However, he also suggested this strain does not apply as forcibly to Black Americans, as they may internalize the dominant culture’s values of pecuniary success yet be cognizant of the significant barriers that stand in the way of their socioeconomic success. Several scholars leveraged this idea to hypothesize that not only upward mobility, but also social comparisons with more advantaged others, are of less subjective relevance to Black Americans and other persons of color than they are to White Americans (Cernkovich et al., 2000; Harer & Steffensmeier, 1992; Smith, 1992). This perspective is neatly summarized by Cernkovich et al. (2000):

> …Whites may not anticipate or expect failure to same extent as African Americans, and such failure, when it does occur among Whites, may generate high levels of anger and frustration and result in criminal behavior in some instances. In short, even though African Americans experience greater levels of objective deprivation, Whites may experience greater levels of subjective or relative deprivation. (Cernkovich et al., 2000, p. 162)

If this hypothesis is correct, more intense feelings of relative deprivation among White than Black Americans can be viewed as a feature of the U.S. racial structure. Historic and contemporary housing market discrimination, as well as deindustrialization and depopulation of urban cores, have ensnared many Black residents and other persons of color in impoverished and isolated neighborhoods. Due to both spatial and social distance, therefore, few people of color view White or affluent neighbors as similar enough to themselves to be considered realistic referents or to trigger relative deprivation (Mears & Bhati, 2006; Harer & Steffensmeier, 1992).

Other accounts posit that relative inequality affects crime rates to a greater extent among people of color, and especially Black and Latino Americans. Blau and Blau (1982) suggested that economic inequality was the primary driver of high rates of violent crime among Black residents of U.S. metropolitan areas. They argued that persistent consolidation of Black racial identity with low socioeconomic status is perceived as especially unfair in an allegedly meritocratic nation, yielding intense feelings of alienation and frustration that result in high rates of violence within Black communities. Subsequent work has provided some support for the Blaus' arguments in finding that interracial economic inequality elevates crime among Blacks and Latinos (Hipp et al., 2009; Stolzenberg et al., 2006), yet one analysis found that interracial and overall income inequality have weaker effects on recidivism among Latino compared with White or Black youth (Wright et al., 2016). Each of these studies explains findings of differential impacts by speculating that the experience of relative deprivation varies in subjective significance across racial or ethnic groups.

Missing from these accounts are any measures of the primary social psychological mechanism theorized to be at play, namely, cognitive appraisals of an unfair disadvantage relative to similar others. Without such measures, relative deprivation cannot be inferred from objective demographic information like levels of income dispersion alone (Pettigrew, 2015), and neither can qualitatively distinct experiences of relative deprivation by race or ethnicity. Partially for these reasons, and due to a growing recognition that smaller area units were more appropriate for assessing relevant theories (Hipp, 2007; Stucky et al., 2016), more recent work has analyzed the relationship between relative inequality and crime at the neighborhood level while omitting a consideration of variation in impact by race. Fortunately, however, this body of research has proposed a wider suite of theoretical perspectives to explain the inequality-crime link in addition to relative deprivation theory, and in so doing provides an alternative framework through which to account for the uneven influence of relative inequality on crime by neighborhood ethno-racial composition.

The Moderating Impact of Disadvantage

Neighborhood crime research has proposed two major alternative interpretations of the relative inequality and crime association. Each perspective is widely viewed as supplemental to, rather than mutually exclusive with, possible relative deprivation effects. First is the application of social disorganization theory, which stems from propositions advanced in Blau's (1977) macro-sociological theory. Blau argued that inequality raises the status gap between people of different economic backgrounds and thereby decreases informal social interactions between them. His theory implies inequality is detrimental to social capital, defined as benefits obtained through social relationships and their underlying norms conducive to cooperation (e.g., trust and reciprocity) (Kawachi & Berkman, 2000; Portes, 1998), because inequality prevents or breaks down those relationships. Scholars of neighborhood crime have noted the affinity of these ideas with the systemic reformulation of social disorganization theory, which holds that crime results when local communities are unable to realize shared values or solve collective problems (Bursik, 1988; Shaw & McKay, 1942). They have thus argued that localized income inequality increases crime by elevating social distance between neighbors and impeding the interactions necessary for effective crime prevention, thereby weakening a neighborhood's capacity to keep crime at bay (Stucky et al., 2016; Wang & Arnold, 2008; Wenger, 2019).

Additionally, neighborhood scholars have framed relative inequality effects by drawing on a set of related perspectives collectively referred to as opportunity theories. Principal of these is routine activities theory, which holds that crime events take place during potential offenders' and victims' everyday activities when a motivated offender encounters a suitable target in the absence of any capable guardian (Cohen & Felson, 1979). Focusing more explicitly on the timing and location of crime events, environmental criminologists have built on routine activities theory to propose that certain areas or situations reliably act as crime generators (i.e., create opportunities for crime among persons present for other reasons) or attractors (i.e., draw offenders already intent on committing a crime to a specific area) because they provide an abundance of enticing targets with few or ineffective guardians. Such areas are typically familiar to would-be offenders and represent nodes around which usual patterns of interaction take place (e.g., work sites, schools, shopping centers, travel depots, or recreation areas) or stops along a pathway to one of these routine activities (Brantingham & Brantingham, 1993, 2011). Researchers have applied these perspectives to assert that within-neighborhood income inequality raises potential offenders' motivation to commit crime while simultaneously providing them access to suitable targets in the form of desirable property on victims or near their homes; thus, net of levels of guardianship, higher relative inequality should increase crime rates (Chamberlain & Hipp, 2015; Hipp, 2007).

Notably, the social processes hypothesized to link relative inequality with crime in this recent body of work have also been argued to mediate the impact of structural disadvantage on violent crime. Starting with relative deprivation theory, Agnew (1999) has argued that communities high in structural disadvantage have a high prevalence of residents who routinely experience a variety of stressors, including feeling unfairly deprived compared with similar others, that they sometimes cope with by committing crimes. In the social disorganization tradition, Sampson and colleagues have shown that structural disadvantage partially elevates violent crime through its effects on indicators of social capital, including the size of friendship networks, rates of participation in voluntary organizations, and the combination of mutual trust and willingness to engage in informal social control actions that they term collective efficacy (Morenoff et al., 2001; Sampson & Groves, 1989; Sampson et al., 1997). Finally, environmental criminologists argue that disadvantaged communities not only act as crime generators and attractors, but also that would-be offenders from disadvantaged communities are most likely to commit crimes within these neighborhoods or in ones with similar physical, social, and economic characteristics, because they feel most comfortable navigating these spaces and believe they are most capable of carrying out a crime successfully within them (Brantingham & Brantingham, 1995; see also Mears & Bhati, 2006).

Although the mechanisms articulated by these theoretical perspectives are distinct, the point for my purposes is that past work has applied each perspective to explain the positive association of neighborhood crime with both structural disadvantage and relative inequality. If these factors share any combination of the above mechanisms in how they elevate community crime rates, then there is reason to suspect relative inequality has a reduced impact in the most disadvantaged neighborhoods. Increments in relative inequality in neighborhoods with already high levels of disadvantage may be less substantively meaningful in raising relative deprivation-related stress, diminishing social capital, or further drawing together motivated offenders and suitable targets in the context of routine activities. In more affluent communities, by contrast, sharp income divisions may be more notable and disruptive to the social fabric in ways that raise incentives to commit crimes while lowering effective guardianship. This dynamic would be similar to the “floor” and “ceiling” effects discussed in literature on external investments and neighborhood crime (e.g., Saporu et al., 2011; Vélez, 2001), but in this case neighborhoods with high levels of disadvantage would represent the “ceiling” within which the impact of income dispersion on crime would be lowest. In fact, at least one prior study supports the notion that structural disadvantage tempers the impact of income inequality on crime (Burraston et al., 2018), but because this analysis was carried out at the county level, the implications for neighborhood crime are not clear.

Accounting for Ethno-Racial Variation in the Effect of Relative Inequality

I argue in this chapter that relative inequality has unequal effects on crime by neighborhood ethno-racial composition because disadvantage, with its highly unequal average levels between White and non-White neighborhoods, moderates the impact of relative inequality. This argument subsumes several hypotheses. First, I maintain that relative inequality will elevate serious violent and property crime across all neighborhoods in the NNCS2 cross-sectional sample. To my knowledge only Chamberlain and Hipp (2015) have assessed the impact of income inequality on crime for a large sample of urban neighborhoods spanning more than one or a few cities, and their study used data from the first wave of the NNCS.

H1: Relative inequality will be positively associated with neighborhood crime.

However, I suspect that relative inequality will have "diminishing returns" in terms of its impact on crime as neighborhood disadvantage grows. Because both relative inequality and disadvantage may raise crime rates through similar mechanisms, the impact of either factor on crime rates may weaken in areas with high levels of the other. Thus, the relative inequality-crime association may hit a "ceiling" in more disadvantaged neighborhoods because relative inequality's capacity to meaningfully affect community relative deprivation, social organization, or routine activities will decline in communities with already high levels of disadvantage.

H2: There will be a negative interaction effect between relative inequality and disadvantage, such that relative inequality has smaller effects on crime at higher levels of disadvantage.

Next, I expect that the influence of relative inequality on crime will be lesser on average in predominantly non-White or multiethnic neighborhoods than in mostly White areas. Prior research has largely accounted for this disparity in effect size by arguing that the inability to achieve economic success comparable with one's neighbors generates a stronger sense of relative deprivation among Whites than persons from other racial or ethnic groups.

H3: When White neighborhoods are the reference category, there will be negative interaction effects between neighborhood ethno-racial composition type and relative inequality, such that relative inequality has smaller effects in predominantly non-White or multiethnic areas.

Finally, I hypothesize that relative inequality has smaller effects in non-White and multiethnic areas compared with White neighborhoods because the former areas have higher average levels of disadvantage, and disadvantage tempers the influence of relative inequality on crime.

H4: The coefficients representing interaction effects between neighborhood ethno-racial composition type and relative inequality will reduce to non-significance after controlling for an interaction effect between relative inequality and disadvantage.

Data

To evaluate these hypotheses, I draw on a cross-sectional subset of the NNCS2-P. My two outcome measures, the summed count of homicides and robberies and the logged mean rate of burglaries per 1,000 population over 2010-2013, are based on crimes reported by police departments in each city included in the sample. My independent and control variables were constructed from sociodemographic data drawn from 2008-2012 American Community Survey and 2010 Home Mortgage Disclosure Act data. My analytic sample for this chapter comprised 8,236 census tracts nested within 72 cities.

Descriptive statistics for all tract- and city-level measures are presented in Table 3.1. Neighborhood areas experienced an average of 44 combined homicide and robbery incidents and more than 10 burglaries over the four-year reporting period. The mean Gini index value for the entire sample was .424 and ranged from a minimum average of .409 in Latino neighborhoods to a maximum average of .458 in Black neighborhoods. A one-way analysis of variance indicates that the mean values of the Gini index significantly differ across the seven ethno-racial neighborhood categories ($F = 95.34$, $p < .001$), but given that the Gini index can plausibly range from 0 to 1, the differences in means are modest. These differences

Table 3.1 Descriptive Statistics.

	Mean	SD
Tract-Level (N = 8,236)		
Violent crime count	44.005	49.858
Burglary rate	10.211	8.350
Ethno-Racial Nbhd. Type		
White	.274	
Black	.119	
Latino	.099	
Minority	.051	
White-Black Multi.	.082	
White-Latino Multi.	.122	
Other Multi.	.253	
Gini	.424	.062
White	.413	.058
Black	.458	.061
Latino	.409	.053
Minority	.432	.059
White-Black Multi.	.441	.071
White-Latino Multi.	.420	.055
Other Multi.	.422	.064
Disadvantage	.012	.846
Young males (%)	15.913	6.002
Residential instability	-.002	.881
Immigration	.027	.948
Residential loans	29668.43	43903.12
Vacant housing (%)	11.315	8.403
Foreclosure rate	14.889	18.978
Sp. Lag (Homicide/robbery rate)	3.370	3.156
Sp. Lag (Burglary rate)	10.235	6.914
City-Level (N = 72)		
White-Black Index of Diss.	44.888	16.749
Disadvantage	.032	.916
Manufacturing (%)	9.625	3.777
Population	450,450	577,095
Black (%)	17.977	14.492
Recent movers (%)	18.731	4.749
Foreign-born (%)	17.683	12.696
Young males (%)	15.767	2.215
South	.361	
West	.278	

may not be great enough to explain a substantive portion of the gaps in crime between the different neighborhood types, as has been demonstrated for structural disadvantage (Krivo et al., 2021; Peterson & Krivo, 2010a; Sampson et al., 2005), but this does not preclude the possibility that relative inequality has an unequal impact on crime between them (Torres, 2020).

Before turning to the results of my regression models, I first consider the bivariate distribution of my tract-level disadvantage and Gini indices. Because I hypothesize that relative inequality effects on crime will be weakened in areas with high disadvantage, it is important that my sample contain enough neighborhoods that are high on the Gini index but low on disadvantage, high on disadvantage but low on the Gini index, and near the average on both variables. I explore this possibility in Figure 3.1, which cross-tabulates categorical versions of my Gini index and disadvantage variables at four levels: Extremely Low (less than 1 standard deviation below the mean), Low (between 1 standard deviation below the mean and the mean), High (between the mean and 1 standard deviation above the mean), and Extremely High (greater than 1 standard deviation above the

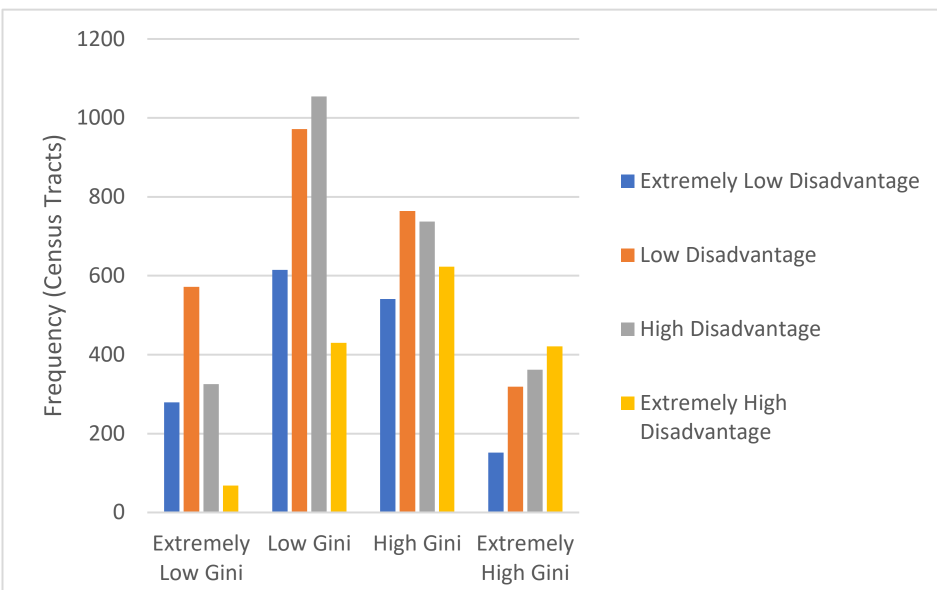

Figure 3.1. Neighborhood Distribution of by Level of Gini Index and Disadvantage, 2008-2012.

mean). This figure shows that although most of the 8,236 neighborhoods in my sample fall into the ranges just below or above the mean on either variable, there are well over 200 census tracts in 14 of the 16 possible level combinations. The only exceptions are tracts with extremely high values on the Gini index and extremely low values on disadvantage (n = 152), and tracts with extremely low values on the Gini index and extremely high values on disadvantage (n = 68).

Additionally, I investigate how cross-tabulations on the categorical versions of my Gini and disadvantage indices vary by ethno-racial neighborhood type. Are there sufficient frequencies of neighborhoods with high and low values on each variable across neighborhoods of different colors? Figure 3.2 and Table 3.2 speak to this question. Two general conclusions can be drawn from Figure 3.2, which presents a scatterplot of the two variables and color-codes census tracts by their ethno-racial composition. First, the Gini and disadvantage indices are positively but weakly correlated at tract level across the full sample (Pearson's r = 0.2). Second, although some neighborhood categories cluster at the higher or lower end of disadvantage (compare White neighborhoods

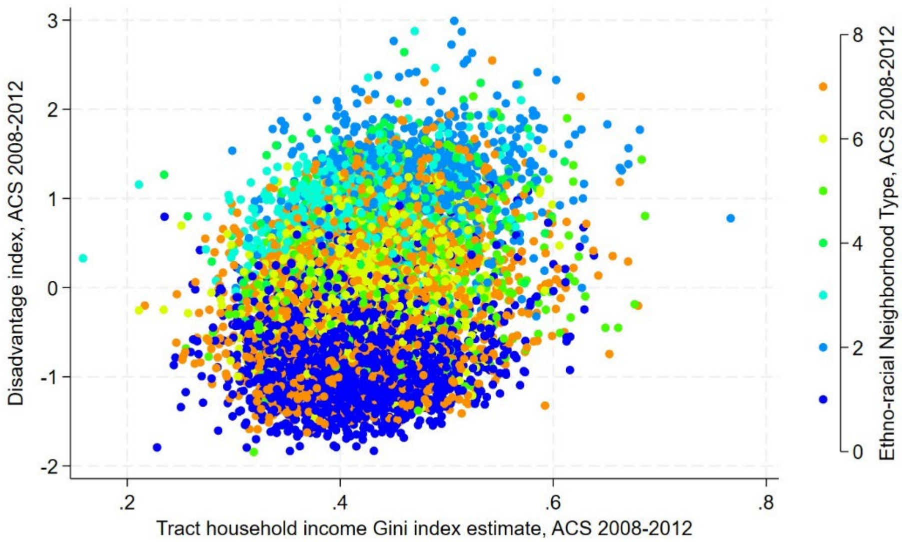

Figure 3.2. Scatterplot of Tract-Level Gini Index and Disadvantage, by Ethno-Racial Neighborhood Type, 2008-2012.

Table 3.2 Crosstabulation of Disadvantage by Gini Index, by Neighborhood Type, 2010-2013*

White Neighborhoods (N = 2,256)				
	Extremely Low Gini	Low Gini	High Gini	Extremely High Gini
Extremely Low Disadvantage	180	447	380	97
Low Disadvantage	229	383	254	98
High Disadvantage	27	86	32	29
Extremely High Disadvantage	1	3	7	3
Black Neighborhoods (N = 981)				
	Extremely Low Gini	Low Gini	High Gini	Extremely High Gini
Extremely Low Disadvantage	0	0	0	0
Low Disadvantage	5	12	9	8
High Disadvantage	20	116	107	56
Extremely High Disadvantage	17	134	275	222
Latino Neighborhoods (N = 816)				
	Extremely Low Gini	Low Gini	High Gini	Extremely High Gini
Extremely Low Disadvantage	0	0	0	0
Low Disadvantage	3	4	7	3
High Disadvantage	98	226	121	25
Extremely High Disadvantage	33	151	108	37
Minority Neighborhoods (N = 420)				
	Extremely Low Gini	Low Gini	High Gini	Extremely High Gini
Extremely Low Disadvantage	0	1	0	0
Low Disadvantage	11	20	9	4
High Disadvantage	26	87	68	25
Extremely High Disadvantage	6	46	74	43
White-Black Multiethnic Neighborhoods (N = 675)				
	Extremely Low Gini	Low Gini	High Gini	Extremely High Gini
Extremely Low Disadvantage	7	16	14	10
Low Disadvantage	57	84	83	63
High Disadvantage	23	81	76	61

Extremely High Disadvantage	1	19	40	40
White-Latino Multiethnic Neighborhoods (N = 1,005)				
	Extremely Low Gini	Low Gini	High Gini	Extremely High Gini
Extremely Low Disadvantage	8	16	20	5
Low Disadvantage	88	189	162	50
High Disadvantage	49	170	135	47
Extremely High Disadvantage	3	21	25	17
Other Multiethnic Neighborhoods (N = 2,081)				
	Extremely Low Gini	Low Gini	High Gini	Extremely High Gini
Extremely Low Disadvantage	84	135	127	40
Low Disadvantage	179	280	240	93
High Disadvantage	82	288	198	119
Extremely High Disadvantage	7	56	94	59

**Note.* Extremely Low = less than 1 SD below the mean, Low = between 1 SD below the mean and the mean, High = between the mean and 1 SD above the mean, Extremely High = greater than 1 SD above the mean.

= 1 with Black neighborhoods = 2), there is wide variation along the values of the Gini index irrespective of ethno-racial composition (scatterplot points appear all along the horizontal axis regardless of color). The visual information contained in Figure 3.2 is also presented in tabular form in Table 3.2, which lists tract frequencies at each combination of levels on the Gini and disadvantage indices separately by neighborhood type. Because some neighborhood types lack any census tracts in the Extremely Low Disadvantage category, in subsequent figures that present predicted rates of crime I focus only predictions at the Low, High, and average values of the Gini index and disadvantage.

In the next section, I begin with the findings from multilevel negative binomial models predicting homicide and robbery. As explained in Chapter 2, these models specify population as a variable exposure, which transforms the analysis into a per-capita rates of violence. I then consider the findings from the multilevel OLS models predicting the logged burglary rates. Models first estimate average differences in crime across the ethno-racial neighborhood types and then assess the extent to which the Gini index accounts for the neighborhood crime gaps. Next, I estimate an interaction effect between relative inequality and disadvantage, paying attention to its size, direction, and robustness to controls. I then estimate interaction terms between the ethno-racial neighborhood categories and relative inequality to determine whether any of the neighborhood types' crime levels are affected less strongly than are those of White neighborhoods. Finally, I assess whether the ethno-racial neighborhood type by relative inequality interaction effects are reduced upon the inclusion of the interaction between relative inequality and disadvantage.

Results

Violence. Table 3.3 presents the results from the multilevel negative binomial regression models predicting the homicide and robbery per capita rate. Model 1, the baseline model, only includes coefficients for the ethno-racial neighborhood type dummy variables, with White neighborhoods as the reference category. These coefficients, all of which were significant at $p < .001$, indicate that predominantly non-White census tracts have higher average violent crime rates than White tracts. Turning next to Models 2-4, the coefficient for the Gini index is positive and significant in Model 2 and remains so net of structural disadvantage in Model 3 and the rest of the tract- and city-level controls in Model 4, lending support to my first hypothesis. However, Models 2-4 show that the inclusion of relative inequality accounts for little of the variation in violent crime rates between White and non-White neighborhoods. After controlling for the Gini index in Model 2 the ethno-racial neighborhood type coefficients decrease by only 3% on average compared with Model 1. By comparison, when the Gini index and structural disadvantage are controlled in Model 3 the corresponding average decrease is 46%, and with all controls added the average decrease is 53%. Thus, although neighborhood relative inequality is a reliable predictor of violence, the models so far suggest its contribution to explaining ethno-racial gaps in violent crime is modest.

I now explore whether structural disadvantage moderates the impact of relative inequality on violent crime. Matching the expectation of my second hypothesis, the interaction term in Model 5 is negative and significant, indicating that disadvantage tempers the influence of relative inequality. Figure 3.3 graphs this this dynamic, presenting the predicted counts of homicides and robberies at different percentiles of the Gini index for neighborhoods with low disadvantage (one standard deviation below the mean), average

Table 3.3 Mixed Effects Negative Binomial Regression of Violent Crime Counts on Disadvantage, Relative Inequality, and Nbhd. Types

	Model 1			Model 2			Model 3			Model 4			Model 5		
Tract-Level	b		SE	b		SE	b		SE	b		SE	b		SE
Black nbhd	1.517	***	.037	1.404	***	.035	.594	***	.044	.426	***	.041	.427	***	.041
Latino nbhd	.997	***	.041	1.092	***	.039	.263	***	.048	.197	***	.046	.148	**	.046
Minority nbhd	1.328	***	.049	1.322	***	.047	.535	***	.053	.364	***	.048	.350	***	.047
White-Black Multi. nbhd	.957	***	.040	.847	***	.039	.513	***	.039	.285	***	.035	.272	***	.035
White-Latino Multi. nbhd	.800	***	.036	.756	***	.035	.344	***	.037	.235	***	.033	.217	***	.033
Other Multi. nbhd	.790	***	.028	.755	***	.027	.360	***	.029	.216	***	.027	.207	***	.027
Gini				4.579	***	.161	4.125	***	.156	1.769	***	.153	2.128	***	.154
× Disadvantage													-2.218	***	.160
× Disadvantage Squared															
× Black															
× Latino															
× Minority															
× White-Black Multi.															
× White-Latino Multi.															
× Other Multi.															
Disadvantage							.465	***	.017	.259	***	.019	.306	***	.019
Disadvantage Squared															
Young males										.009	***	.002	.008	***	.002
Residential instability										.329	***	.014	.315	***	.014
Immigration										-.016		.014	-.037	*	.014
Residential loans (ln)										-.080	***	.008	-.083	***	.008
Vacant housing (ln)										.072	***	.007	.064	***	.007
Foreclosure rate (ln)										.079	***	.009	.069	***	.009
Homicide/robbery rate spatial lag										.084	***	.004	.082	***	.004
City-Level															
White-Black Index of Diss.										.014	**	.005	.013	**	.004
Disadvantage										.110		.062	.093		.060
Manufacturing jobs										-.054	***	.014	-.055	***	.014
Population										.000		.000	.000		.000
Percent Black										.001		.005	.002		.005
Recent movers										-.027		.016	-.024		.016

Foreign-born										-.011	*	.005	-.008		.004
Young males										.043		.029	.037		.028
South										.106		.110	.078		.107
West										.219		.132	.189		.129
Intercept	-5.658	***	.095	-5.625	***	.086	-5.281	***	.081	-5.069	***	.097	-5.020	***	.095

Note. *p < .05, **p < .01, ***p < .001.

Table 3.3 Mixed Effects Negative Binomial Regression of Violent Crime Counts on Disadvantage, Relative Inequality, and Nbhd. Types (Cont.)

	Model 6			Model 7			Model 8			Model 9		
Tract-Level	b		SE	b		SE	b		SE	b		SE
Black nbhd	.395	***	.042	.415	***	.041	.469	***	.043	.436	***	.042
Latino nbhd	.184	***	.046	.148	**	.046	.160	**	.047	.153	**	.046
Minority nbhd	.332	***	.048	.338	***	.047	.364	***	.048	.354	***	.048
White-Black Multi. nbhd	.228	***	.036	.248	***	.036	.278	***	.036	.279	***	.035
White-Latino Multi. nbhd	.177	***	.034	.188	***	.034	.226	***	.033	.220	***	.033
Other Multi. nbhd	.177	***	.028	.187	***	.028	.210	***	.027	.211	***	.027
Gini	1.820	***	.153	2.156	***	.154	2.811	***	.294	1.585	***	.310
× Disadvantage				-2.179	***	.178				-2.301	***	.209
× Disadvantage Squared				.407	*	.158						
× Black							-3.163	***	.449	.473		.553
× Latino							-2.482	***	.550	.523		.603
× Minority							-2.305	***	.614	.716		.665
× White-Black Multi.							-1.081	*	.479	.404		.491
× White-Latino Multi.							.392		.498	1.650	**	.505
× Other Multi.							-.462		.376	.681		.387
Disadvantage	.272	***	.019	.302	***	.019	.272	***	.019	.306	***	.019
Disadvantage Squared	-.084	***	.011	-.050	***	.012						
Young males	.007	***	.002	.007	***	.002	.008	***	.002	.008	***	.002
Residential instability	.343	***	.014	.324	***	.014	.322	***	.014	.316	***	.014
Immigration	-.035	*	.015	-.043	**	.014	-.023		.014	-.039	**	.014
Residential loans (ln)	-.087	***	.008	-.086	***	.008	-.081	***	.008	-.084	***	.008
Vacant housing (ln)	.071	***	.007	.065	***	.007	.069	***	.007	.064	***	.007
Foreclosure rate (ln)	.075	***	.009	.068	***	.009	.077	***	.009	.069	***	.009
Homicide/robbery rate spatial lag	.086	***	.004	.084	***	.004	.083	***	.004	.082	***	.004
City-Level												
White-Black Index of Diss.	.014	**	.004	.013	**	.004	.013	**	.005	.012	**	.004
Disadvantage	.094		.060	.082		.060	.112		.061	.095		.060
Manufacturing jobs	-.054	***	.014	-.055	***	.014	-.055	***	.014	-.055	***	.014
Population	.000		.000	.000		.000	.000		.000	.000		.000
Percent Black	.003		.005	.003		.005	.001		.005	.002		.005
Recent movers	-.026		.016	-.023		.016	-.026		.016	-.023		.016

Foreign-born	-.009		.005	-.007		.004	-.010	*	.005	-.008		.004
Young males	.041		.029	.036		.028	.041		.029	.036		.028
South	.090		.108	.069		.106	.099		.110	.082		.107
West	.224		.130	.190		.128	.204		.132	.194		.129
Intercept	-5.040	***	.096	-5.010	***	.094	-5.051	***	.097	-5.027	***	.095

Note. *p < .05, **p < .01, ***p < .001.

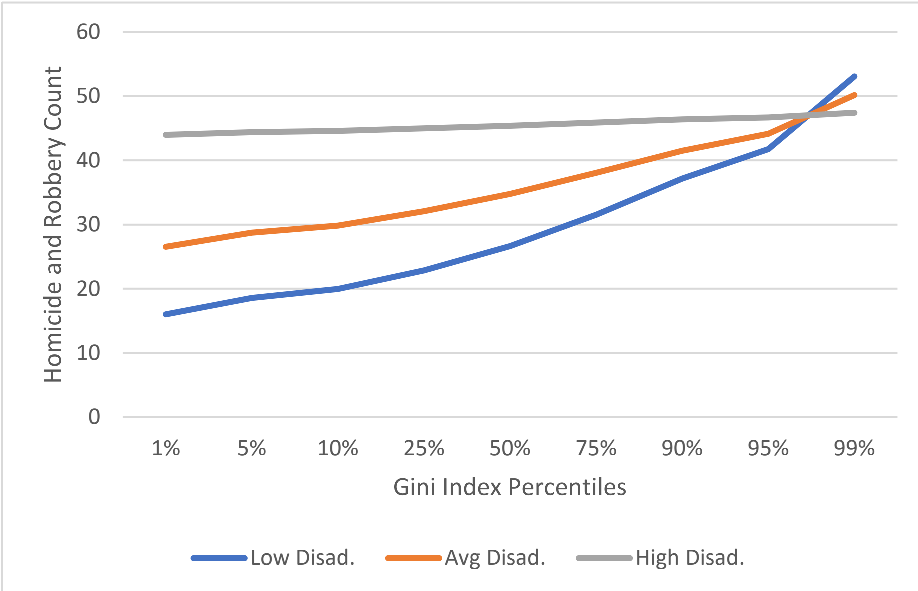

Figure 3.3. Predicted Sum Count of Tract Homicides and Robberies by Gini Index Percentiles at Low, Average, and High Disadvantage, 2010-2013.

disadvantage, and high disadvantage (one standard deviation above the mean), with all other variables held at their mean values. The figure shows that in low- and average-disadvantage tracts, violent crime rates start out low when relative inequality is low and rise at an accelerating pace as relative inequality rises, even surpassing the crime rates in high-disadvantage tracts at the highest percentiles of the Gini index. In high-disadvantage tracts, however, where homicide and robbery per capita rates are already high, the slope for the relative inequality-crime relationship is much reduced and approximately linear. Thus, the strongest impacts of relative inequality on neighborhood violent crime are limited to tracts with low or average disadvantage levels, whereas in tracts with high disadvantage the influence of relative inequality is much weaker.

Models 6-7 assess the robustness of the findings from the previous models by including a control for the squared term of disadvantage. Prior research examining disparities in crime across neighborhoods of differing ethno-racial compositions finds that regression models are properly specified with a squared term for disadvantage because the influence of disadvantage on crime reaches a “ceiling” in extremely high crime neighborhoods, beyond which further increases in disadvantage have little meaningful impact on crime rates (Krivo & Peterson, 2000; McNulty, 2001). When disadvantage squared is included alongside the main effect of disadvantage, relative inequality, and controls in Model 6, the coefficient is negative, indicating the effect of disadvantage is attenuated at extremely high levels. Nevertheless, the coefficient for the Gini index remains positive and significant. Model 7 builds on this model by adding the disadvantage by Gini index product term alongside a disadvantage squared by Gini index product term. The disadvantage squared by Gini index product coefficient is positive and significant. This suggests that where income inequality is high, the attenuation of the disadvantage at high levels is reduced. Yet my primary interaction of interest, the disadvantage by Gini index product term, remains negative and significant. Together, the results presented in Models 6 and 7 show that my finding for the main effect of the Gini index is not substantively changed by the inclusion of disadvantage squared, and neither is the disadvantage by Gini index product term altered by the inclusion of the disadvantage squared by Gini index product term.

Although the previous models indicate that relative inequality only accounts for a modest share of the variation in homicide and robbery rates between White and non-White neighborhoods, relatively inequality may nevertheless have an uneven impact on violence across neighborhoods of varying ethno-racial compositions. Recall that early studies diverged over whether relative inequality has stronger effects on crime among White or Black populations, and recent work argues relative inequality's impact is tempered among Latinos. Model 8 examines this possibility by interacting the six ethno-racial neighborhood dummy variables (excluding White neighborhoods) with the Gini index. Partially supporting my third hypothesis, the product terms are negative and significant for Black, Latino, Minority, and White-Black Integrated neighborhoods, indicating the impact of relative inequality is lesser in these communities than in predominantly White neighborhoods. In fact, given that the main effect for the Gini index (b = 2.811, p < .001) represents the impact in White tracts in Model 8, the product term for Black neighborhoods (b = -3.163, p < .001) indicates the Gini index is *negatively* related to violence in predominantly Black areas.

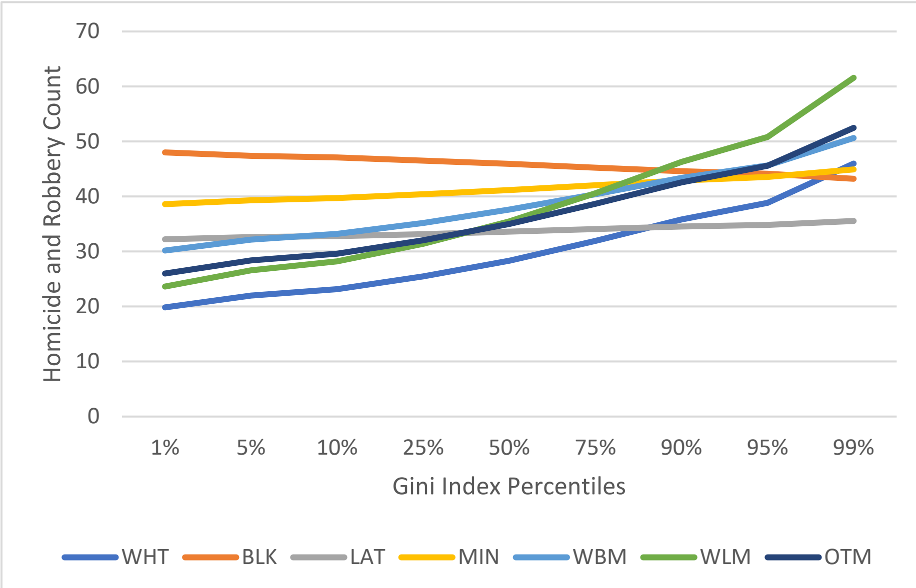

*Figure 3.4. Predicted Sum Count of Tract Homicides and Robberies by Gini Index Percentiles and Ethno-Racial Neighborhood Type, 2010-2013.**

**Note: WHT = White, BLK = Black, LAT = Latino, MIN = Minority, WBM = White-Black Multiethnic, WLM = White-Latino Multiethnic, and OTM = Other Multiethnic.*

Figure 3.4 illustrates these differences by graphing predicted counts of homicides and robberies at different percentiles of the Gini index for each neighborhood composition type, and the values of all other variables are constrained to their means. The figure shows that as inequality rises, violent crime counts ascend more steeply in White, White-Latino Multiethnic, and Other-Multiethnic neighborhoods than in Latino, Minority, or White-Black Multiethnic neighborhoods, and in Black neighborhoods the predicted count decreases as inequality increases.

Having established that disadvantage attenuates the impact of relative inequality and that relative inequality shapes violence more strongly in neighborhoods of some ethno-racial compositions than in others, I now explore whether these dynamics are related. Model 9 includes the same neighborhood type by Gini index interactions and controls as Model 8 but adds in the disadvantage by Gini index product term. Not only do I again find evidence that disadvantage reduces the impact of relative inequality (b = -2.301, p < .001), but once this interaction term is specified the ethno-racial neighborhood type by Gini index product terms for Black, Latino, Minority, and White-Black Integrated neighborhoods weaken to non-significance. Figure 3.5 visualizes this change by graphing the neighborhood type-specific homicide and robbery counts across Gini index percentiles predicted by Model 9. After adjusting for the disadvantage by Gini index product term, the slopes for the relative inequality effect are uniformly positive and much more similar in size between neighborhood types. This finding lends support to my fourth hypothesis that relative inequality has uneven impacts across neighborhoods of different colors because they have uneven average levels of disadvantage, and disadvantage moderates (i.e., tempers) the impact of relative inequality on crime.

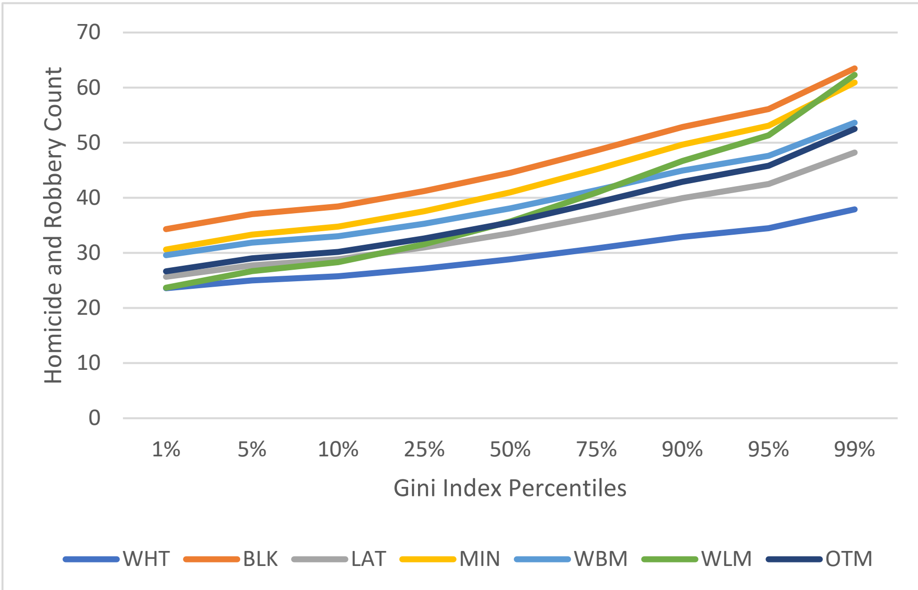

Figure 3.5. Predicted Sum Count of Tract Homicides and Robberies by Gini Index Percentiles and Ethno-Racial Neighborhood Type, Controlling for Gini Index Disadvantage Interaction, 2010-2013.

Burglary. The results from the OLS regression models predicting the logged burglary rate presented in Table 3.4 largely parallel those for homicide and robbery. As was the case for violence, each of the coefficients for the ethno-racial neighborhood type dummy variables in Model 1 are positive and significant, indicating higher average burglary rates in each neighborhood type than in White neighborhoods. Model 2 shows that adding relative inequality reduces the size of these coefficients by only a modest proportion, about 2.1% on average, yet the coefficient for the Gini index remains positive and significant after disadvantage and the remaining tract- and city-level controls are included in Models 3-4. Model 5 incorporates the disadvantage by Gini index interaction term and, again, the coefficient is negative and significant. Figure 3.6 graphs this effect, which presents predicted burglary rates at different percentiles of the Gini index for neighborhoods with low, average, or high disadvantage, while constraining other variables in the model to their means. Notably, in low- and average-disadvantage neighborhoods the Gini index and the burglary rate rise

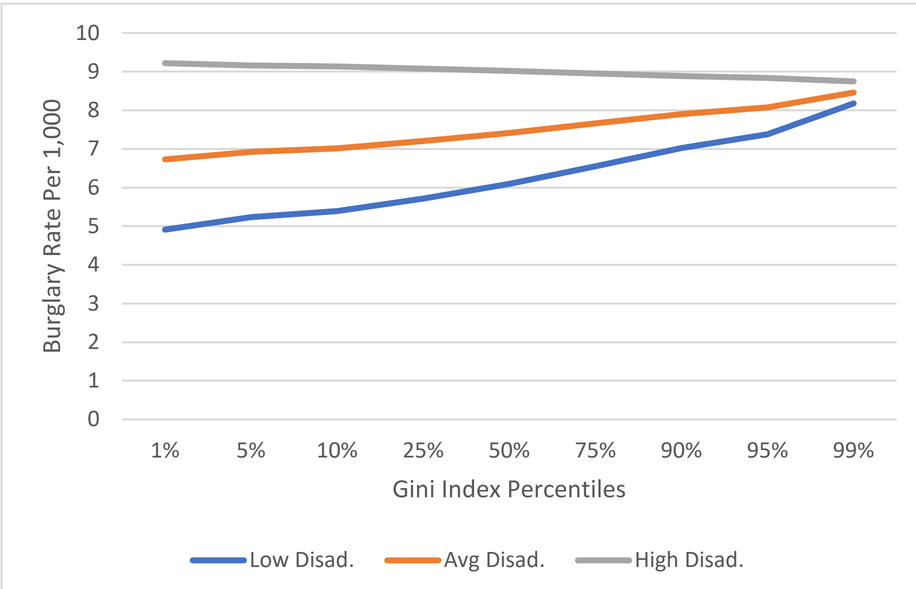

Figure 3.6. Predicted Average Tract Burglary Rate by Gini Index Percentiles at Low, Average, and High Disadvantage, 2010-2013.

Table 3.4 Mixed Effects OLS Regression of Burglary Rate (ln) on Disadvantage, Relative Inequality, and Nbhd. Types

	Model 1			Model 2			Model 3			Model 4			Model 5		
Tract-Level	b		SE	b		SE	b		SE	b		SE	b		SE
Black nbhd	.961	***	.025	.909	***	.025	.428	***	.032	.124	***	.031	.134	***	.031
Latino nbhd	.234	***	.027	.249	***	.027	-.258	***	.034	-.074	*	.034	-.097	**	.034
Minority nbhd	.597	***	.033	.578	***	.033	.108	**	.038	.101	**	.036	.099	**	.035
White-Black Multi. nbhd	.545	***	.028	.502	***	.027	.301	***	.028	.167	***	.026	.164	***	.026
White-Latino Multi. nbhd	.425	***	.024	.412	***	.024	.161	***	.026	.176	***	.024	.168	***	.024
Other Multi. nbhd	.330	***	.019	.314	***	.019	.099	***	.020	.107	***	.020	.106	***	.020
Gini				1.480	***	.113	1.045	***	.111	.647	***	.113	.765	***	.113
× Disadvantage													-1.112	***	.119
× Disadvantage Squared															
× Black															
× Latino															
× Minority															
× White-Black Multi.															
× White-Latino Multi.															
× Other Multi.															
Disadvantage							.286	***	.012	.204	***	.014	.227	***	.014
Disadvantage Squared															
Young males										.002		.001	.002		.001
Residential instability										.067	***	.010	.059	***	.010
Immigration										-.160	***	.011	-.172	***	.011
Residential loans (ln)										-.028	***	.006	-.029	***	.006
Vacant housing (ln)										.050	***	.005	.046	***	.005
Foreclosure rate (ln)										.095	***	.007	.090	***	.007
Homicide/robbery rate spatial lag										.039	***	.002	.038	***	.002
City-Level															
White-Black Index of Diss.										.007		.006	.006		.006
Disadvantage										.051		.076	.043		.075
Manufacturing jobs										-.024		.018	-.025		.018
Population										.000		.000	.000		.000
Percent Black										-.004		.006	-.004		.006
Recent movers										.007		.020	.009		.020

Foreign-born										-.002		.006	-.001		.006
Young males										.024		.036	.020		.036
South										.227		.137	.214		.136
West										.078		.165	.063		.164
Intercept	1.591	***	.077	1.618	***	.076	1.840	***	.073	1.826	***	.122	1.851	***	.121

Note. *p < .05, **p < .01, ***p < .001.

Table 3.4 Mixed Effects OLS Regression of Burglary Rate (ln) on Disadvantage, Relative Inequality, and Nbhd. Types (Cont.)

	Model 6			Model 7			Model 8			Model 9		
Tract-Level	b		SE	b		SE	b		SE	b		SE
Black nbhd	.117	***	.031	.130	***	.031	.148	***	.032	.136	***	.032
Latino nbhd	-.080	*	.034	-.098	**	.034	-.092	**	.035	-.094	**	.035
Minority nbhd	.086	*	.036	.092	**	.035	.100	**	.036	.101	**	.036
White-Black Multi. nbhd	.138	***	.027	.149	***	.027	.176	***	.027	.179	***	.027
White-Latino Multi. nbhd	.145	***	.025	.152	***	.025	.171	***	.025	.170	***	.024
Other Multi. nbhd	.087	***	.020	.095	***	.020	.102	***	.020	.107	***	.020
Gini	.676	***	.113	.770	***	.113	1.415	***	.207	.768	**	.227
× Disadvantage				-1.010	***	.130				-1.089	***	.158
× Disadvantage Squared				.038		.118						
× Black							-1.905	***	.340	-.074		.431
× Latino							-1.378	**	.407	.104		.460
× Minority							-1.481	**	.482	-.019		.526
× White-Black Multi.							-1.533	***	.347	-.769	*	.364
× White-Latino Multi.							-.213		.362	.453		.373
× Other Multi.							-.423		.266	.126		.277
Disadvantage	.211	***	.014	.228	***	.014	.211	***	.014	.226	***	.014
Disadvantage Squared	-.048	***	.008	-.027	**	.009						
Young males	.001		.001	.001		.001	.002		.001	.002		.001
Residential instability	.074	***	.010	.064	***	.010	.063	***	.010	.059	***	.010
Immigration	-.170	***	.011	-.176	***	.011	-.165	***	.011	-.173	***	.011
Residential loans (ln)	-.031	***	.006	-.030	***	.006	-.029	***	.006	-.029	***	.006
Vacant housing (ln)	.050	***	.005	.046	***	.005	.048	***	.005	.046	***	.005
Foreclosure rate (ln)	.091	***	.007	.088	***	.007	.093	***	.007	.089	***	.007
Homicide/robbery rate spatial lag	.039	***	.002	.038	***	.002	.038	***	.002	.038	***	.002
City-Level												
White-Black Index of Diss.	.007		.006	.006		.006	.007		.006	.006		.006
Disadvantage	.041		.075	.038		.075	.053		.076	.045		.075
Manufacturing jobs	-.025		.017	-.025		.017	-.025		.018	-.026		.018
Population	.000		.000	.000		.000	.000		.000	.000		.000
Percent Black	-.004		.006	-.004		.006	-.004		.006	-.004		.006
Recent movers	.008		.020	.010		.020	.008		.020	.010		.020

Foreign-born	-.001		.006	.000		.006	-.002		.006	-.001		.006
Young males	.023		.036	.020		.036	.022		.036	.019		.036
South	.216		.136	.209		.135	.216		.138	.210		.136
West	.079		.163	.065		.163	.068		.165	.062		.164
Intercept	1.842	***	.120	1.857	***	.120	1.841	***	.122	1.851	***	.121

Note. *p < .05, **p < .01, ***p < .001.

together, but in high-disadvantage neighborhoods the burglary rate gradually *decreases* as the Gini index level rises. In tracts with high levels of disadvantage at least, this suggests relative inequality has some protective effect against the highest rates of burglary.

Models 6 and 7 introduce the disadvantage squared and disadvantage squared by Gini index interaction, respectively. In both models, the main effect of relative inequality remains significant, and in Model 7 the disadvantage by Gini index product term also remains significant (the disadvantage squared by Gini index term itself does not significantly differ from 0). Model 8 displays the results of the neighborhood type by Gini index interactions, and once more the negative coefficients for Black, Latino, Minority, and White-Black Integrated tracts indicate these neighborhoods have a reduced impact of relative inequality on burglary rates comped to White neighborhoods. Figure 3.7 graphs these differences by presenting predicted burglary rates across Gini index percentiles for each neighborhood type, again with controls held at their means. In this figure the predicted burglary rate has a larger positive slope in White, White-Latino Multiethnic, and White-Other Multiethnic neighborhoods than in Latino neighborhoods, and the burglary rate

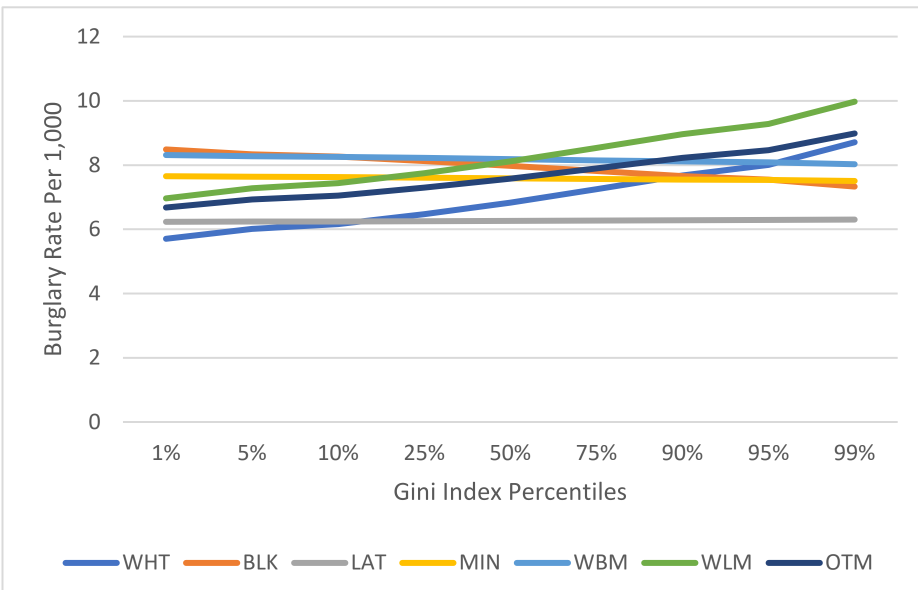

Figure 3.7. Predicted Average Tract Burglary Rate by Gini Index Percentiles and Ethno-Racial Neighborhood Type, 2010-2013.

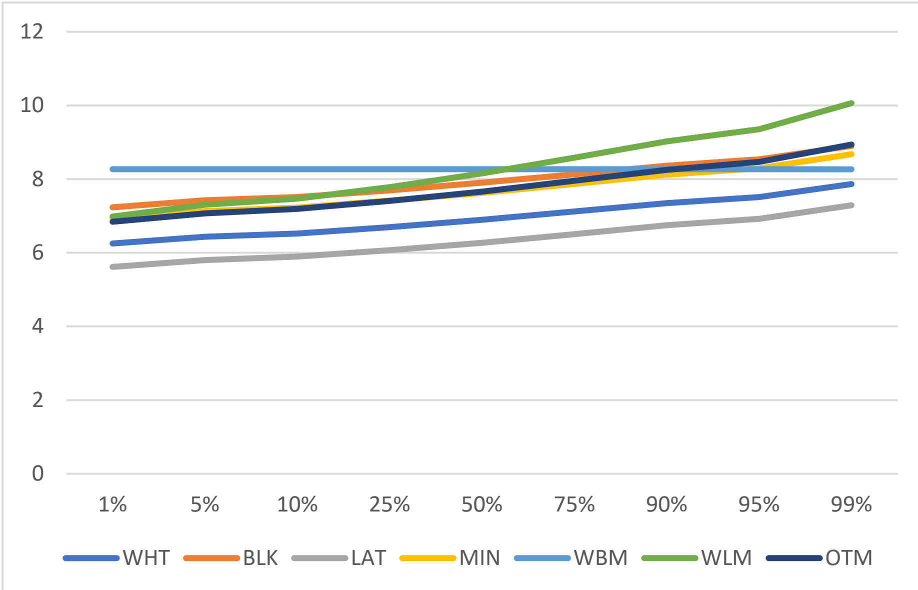

*Figure 3.8. Predicted Average Tract Burglary Rate by Gini Index Percentiles and Ethno-Racial Neighborhood Type, Controlling for Gini Index * Disadvantage Interaction, 2010-2013.*

declines with rising Gini index percentiles in Black, Minority, and White-Black Multiethnic areas. However, once the disadvantage by Gini index product term is included in Model 9, the product terms for Black, Latino, and Minority neighborhoods are reduced to non-significance, and the interaction effect for White-Black Multiethnic neighborhoods remains significant but falls by almost half (from b = -1.533 in Model 8 to b = -.769 in Model 9). The "flattening" of the relative inequality effect differences is depicted in Figure 3.8, which again reveals that upon the inclusion of the disadvantage by relative inequality interaction effect, the slopes of the Gini index effects on burglary rates become uniform in direction and similar in magnitude by ethno-racial neighborhood composition.

Conclusion

This chapter reexamined a question long present among studies of relative inequality and crime but rarely considered in neighborhood crime research: Does relative inequality have differential effects on crime by race or ethnicity? Most extant analyses of this question have compared the impact of relative inequality on racial/ethnic-specific crime rates across large urban areas and found that effects are attenuated among non-White groups compared with Whites. They conclude this disparity occurs because White Americans experience a stronger subjective sense of relative deprivation than do members of other groups, without any measures of the cognitive appraisals of unfair disadvantage at the core of relative deprivation theory. The lack of direct measures of different groups' experiences and attitudes has meant that it has not been possible to know definitively whether relative deprivation processes are behind the intra-neighborhood inequality and crime relationship or the extent to which such processes vary by racial/ethnic group.

Thus, rather than try to identify the precise social mechanisms that link relative inequality with neighborhood crime, in this chapter I explored an avenue for accounting for ethno-racial variation in the relative inequality effect. I drew on three frameworks commonly applied in recent relative inequality and neighborhood crime research—relative deprivation, social disorganization, and opportunity theories—to suggest that relative inequality and structural disadvantage may raise crime rates through similar means. I argued that if both relative inequality and structural disadvantage elevate crime by triggering social comparisons perceived as unfavorable and unfair, breaking down social ties required for mutual trust and effective crime control actions, or bringing motivated offenders and suitable targets into routine proximity, then relative inequality may have a weaker influence on crime where disadvantage is high. Such moderation may occur because incremental increases in income disparities may not meaningfully disrupt the social fabric of communities characterized by extreme structural disadvantage. Relative inequality would therefore have stronger effects on crime in White neighborhoods, not because it is of any greater subjective significance for White Americans, but because White neighborhoods have much lower average levels of disadvantage than do Latino, multiethnic, and especially Black neighborhoods. Analyzing cross-sectional data from the NNCS2-P, I found support for these hypotheses with four key findings.

First, I found that across more than 8,000 neighborhoods in over 70 cities, areas with greater household income inequality had higher levels of serious violent and property crime, net of structural disadvantage and other tract- and city-level controls. This finding is important as few studies have examined the impact of economic inequality on neighborhood crime beyond only one or a handful of cities, and mine is the first to do so for the 2010-2013 period covered by the NNCS2. Next, I discovered that relative inequality affects neighborhood crime rates in tandem with structural disadvantage. Among highly disadvantaged neighborhoods, increasing variability in income led to more modest increases in homicide and robbery, and in fact more income inequality was associated with *lower* burglary rates in such areas. In neighborhoods with low or average disadvantage levels, I observed the expected positive relationship for each outcome measure. This pattern is analogous to, but the reverse of, Saporu et al.'s (2011) finding that home loans have a stronger crime-reducing impact in more disadvantaged neighborhoods because every dollar invested there is more meaningful. I find that relative inequality has a *weaker* crime-*increasing* impact in the most disadvantaged areas, potentially because its consequences for residents' experiences with relative deprivation, neighborhood social organization, or routine activities are less meaningful there. My findings are also consistent with recent work showing that disadvantage tempers the impact of income inequality on violent crime across U.S. counties (Burraston et al., 2018).

However, I go beyond prior research by showing that this interaction effect accounts for differential effects of relative equality across neighborhoods of different colors.

Consistent with extant work, my third finding was that neighborhood ethno-racial composition conditioned the impact of relative inequality such that income disparities were less strongly associated with crime in White-Black multiethnic, Minority, or predominantly Black or Latino neighborhoods compared with mostly White areas. Yet after controlling for the disadvantage by relative inequality product term, these differences were no longer discernable for homicide and robbery, and for burglary they diminished to non-significance for all neighborhoods except White-Black multiethnic areas, for which the difference fell by half. This last finding supports the role that widely divergent distributions of disadvantage play in accounting for apparent differences in the effects of structural factors across neighborhood color lines (Berthelot et al., 2016; Hernandez et al., 2018; Krivo & Peterson, 2000; McNulty, 2001; Phillips, 2002).

Taken together, these patterns suggest relative inequality accords with the racial invariance expectation that racial/ethnic differences in crime are attributable to vastly unequal ecological conditions that map onto racially segregated communities. Relative inequality only apparently affects crime rates in neighborhoods of varying ethno-racial compositions differently when analyzed in isolation, because in fact relative inequality affects neighborhood crime rates similarly as it operates in tandem with disadvantage. To the extent this finding focuses attention on how disadvantage and relative inequality work together in complex ways, it can help broaden our understanding of the racial structural sources of crime. For example, even though neighborhood inequality in socioeconomic conditions and racial segregation declined during the 2000s (Firebaugh & Acciai, 2016), the concomitant decline in crime during this period may have been slowed in communities where disadvantage was decreasing but relative inequality remained high. Such a dynamic could have been especially likely in predominantly Black neighborhoods, which have higher average household income inequality levels than neighborhoods of other compositions (see Table 3.1) and which saw the smallest relative decrease in crime between 2000 and 2010 (Krivo et al., 2021). Thus, our understanding of the relationship between disadvantage and crime may be incomplete without considering current and prior levels of relative inequality.

This chapter explored how disadvantage moderates relative inequality in producing neighborhood violent and property crime and how this interaction accounts for apparent differences in the impact of relative inequality between predominantly White and non-White neighborhoods. While crucial for establishing this dynamic, the analysis was limited to only one point in time circa 2010. As hinted above, it may be necessary to apply a “dynamic racial structural perspective” (Lyons et al., 2022) to examine how past and changing levels of relative inequality and disadvantage have interacted to more fully understand how crime rates across neighborhoods of different colors have changed over time. This is the subject of the next chapter.

4. RELATIVE INEQUALITY AND NEIGHBORHOOD CRIME TRENDS: DOES THE INEQUALITY-DISADVANTAGE INTERACTION MATTER OVER TIME?

In the previous chapter, I revisited the view that economic disparities have effects on crime that vary in size or direction by offender race/ethnicity or neighborhood ethno-racial makeup. Rather than inferring from objective demographic information that racial/ethnic groups have categorically distinct experiences of relative deprivation, I drew on several theoretical perspectives to hypothesize that relative inequality appears to have lesser effects on crime in predominantly non-White communities because these areas have higher than average levels of structural disadvantage, and disadvantage tempers the relative inequality and crime association. After controlling for the interaction between relative inequality and disadvantage, I found that most differences in the impact of relative inequality on violent or property crime rates by neighborhood ethno-racial composition were considerably diminished or reduced to non-significance. My aim in the present chapter is to extend this framework to explore how relative inequality and disadvantage work in tandem to shape ethno-racial variation in neighborhood crime levels over time.

Since 1980 and continuing through the mid-2010s, income segregation rose and crime declined in most large U.S. cities (Reardon & Bischoff, 2011; Sharkey, 2018). These trends were not uniform at the neighborhood level, however. Although urban neighborhoods generally grew more homogeneous by household income, there remained wide variation in the extent of income inequality within census tracts during this period (Fry & Taylor, 2012); and while street crimes diminished considerably from their 1980 peak, serious violent and property crime rates held stable or increased among a minority of tracts (Baumer et al., 2018; Krivo et al., 2018). The persistence of variation in neighborhood relative inequality and neighborhood crime levels during the 2000s decade evokes the possibility of a longitudinal relationship, yet very few studies have explored this association (see Hipp & Kubrin, 2017 for an exception). Moreover, although extent work has drawn on social disorganization theory for insights on how changes in structural factors affect crime trends (Bursik & Grasmick, 1992; Bursik & Webb, 1982; Kikuchi & Desmond, 2010; Kubrin & Herting, 2003) and, more recently, ethno-racial inequality in neighborhood crime change (Krivo et al., 2018; Lyons et al., 2022), whether changes in relative inequality contribute to variation in ethno-racial neighborhood crime trends or impact some neighborhood trajectories more strongly than others remains unknown.

Thus, following the framework presented in Chapter 3, in this chapter I specifically ask: how did starting levels and changes in relative inequality shape neighborhood crime trends during the 2000s and early 2010s? Was there variation in how relative inequality affected crime trends by area ethno-racial composition? And did differences in starting levels or changes in disadvantage serve to account for this variation? I investigate these questions by analyzing the National Neighborhood Crime Study Panel (NNCS2-P), which combines the first and second waves of the NNCS and includes yearly crime data for a subset of cities. I employ latent growth curves (LGCs) to model change across 2,757 census tracts in 28 cities with property and violent crime data for most years between 1999 and 2013. In what follows, I begin by reviewing what we know about how structural features of neighborhoods affect change in crime and ethno-racial inequality in neighborhood crime trends. I then address specifically how relative inequality and disadvantage may operate interactively to shape crime trends across neighborhoods of different colors.

Relative Inequality and Ethno-Racial Variation in Neighborhood Crime Trends

A now considerable body of work has documented variation across neighborhoods in how crime has changed over time. Much past research draws on a social disorganization framework to identify structural factors that contribute to disparities in crime change, often finding that which predictors matter depend on the time periods and crime type examined. In a now classic pair of studies, Bursik and colleagues reexamined distributions of juvenile delinquency across the Chicago community areas originally studied by Shaw and McKay, finding that many neighborhoods deviated from the overall U-shaped trend in delinquency rates over 1930-1970 and that change in racial/ethnic composition was associated with delinquency rates only after 1950 (Bursik & Grasmick, 1992; Bursk & Webb, 1982). Later work examining U-shaped trends in neighborhood homicide or property crime rates during the 1980s and 1990s argued that increases over time in traditional structural predictors of social disorganization may disrupt the maintenance of neighborhood social networks and institutions, leading crime to decline more slowly and then rise more quickly (i.e., the "U-shape") where disadvantage and residential mobility rose (Kikuchi & Desmond, 2010; Kubrin & Herting, 2003). More recent work has sought to measure explicitly the variables that link changes in structural conditions to changes in crime, finding that increases in disadvantage and residential instability are associated with lowered expectations for intervening on behalf of public safety at a subsequent point in time, and that changes in social cohesion are inversely associated with later changes in violence (Hipp & Steenbeek, 2016; Wickes & Hipp, 2018).

Other studies have focused on how inequality in crime change overlaps with area ethno-racial composition. Much of this work concludes that declines in serious violent and property crime during the 1990s and 2000s were widespread and that crime decreased most in the poorest, most racially segregated urban neighborhoods (Friedson & Sharkey, 2015; Krivo et al., 2021; Sharkey, 2018). However, there were important variations in this overall pattern. Examining crime change across nearly 2,700 census tracts in 18 cities over 1999-2013, Krivo et al. (2018) categorized tracts as falling into one of three trajectories of homicide and burglary rate change—increasing, decreasing, or holding stable—and found that the distribution was highly unequal by ethno-racial composition, with predominantly Black neighborhoods much more likely to have experienced rising crime rates due to high or increasing disadvantage or home vacancies in the wake of the 2007-2008 global financial crisis. Drawing on panel data from an even broader sample of census tracts representing 75 cities from the NNCS2-P, Lyons et al. (2022) studied how both changes in neighborhood ethno-racial composition and socioeconomic resources or investments affected changes in crime between 2000 and 2010. They found that neighborhoods that remained or transitioned toward a segregated non-White population experienced uniquely high or increasing levels of disadvantage, home vacancies, foreclosures, and spatial proximity to high crime areas alongside decreases in mortgage lending. Furthermore, these factors accounted for much variation across neighborhoods in how much levels of homicide, robbery, and burglary declined during the decade.

What about household income inequality within neighborhoods? How might I expect initial levels and growth in relative inequality to shape neighborhood trends in serious violent and property crime during the 2000s decade? Past work finds that high or increasing levels of disadvantage are associated with crime trajectories that rise more steeply (or decline more gradually) than in neighborhoods where disadvantage remained stable over decreased. Thus, if relative inequality elevates crime via similar mechanisms as I argued in Chapter 3, high or increasing relative inequality may have similar consequences, leading to sharper increases in crime when crime levels are rising or, when they are falling, a deceleration in the rate of decline. This pattern would be consistent with findings from the only extant study I am aware of that directly examines the impact of changes in neighborhood-level income inequality on changes in crime during the 2000s. Examining quarter-mile and two and a half-mile circular buffers around city blocks as proxies for neighborhoods in Los Angeles, Hipp and Kubrin (2017) found that growth in income inequality in the broader area surrounding neighborhoods was associated with large increases in violent crime within neighborhoods. More importantly for my purposes, rising income inequality in neighborhoods themselves predicted a modest increase in violence when inequality in the broader area around neighborhoods also increased. This latter finding suggests the possibility that growth in focal area relative inequality may accelerate already rising crime trends and slow down the rate of decline of falling trends.

Additionally, there may be variation in how relative inequality affects crime trends across neighborhoods of different ethno-racial compositions, given that there is wide variation in average initial levels of disadvantage and in how much these levels changed over time (Krivo et al., 2021; Lyons et al., 2022). Following my logic from Chapter 3, if neighborhood residents' experiences with relative deprivation, social organization against crime, or opportunities to commit crimes in the context of their routine activities have already been critically affected by high or increasing structural disadvantage—in segregated Black or Minority neighborhoods, for example—then initial or change values of relative inequality may matter less for shaping crime trends in those communities. Conversely, in predominantly White or multiethnic neighborhoods with lower average levels of disadvantage, high or increasing relative inequality may be more consequential in determining crime trends. If this pattern holds, I further suspect that substantive differences in the impact of relative inequality on crime trends between neighborhood types would diminish or disappear after controlling for relative inequality-disadvantage interactions between initial levels of these factors, change levels, or both.

Does Inequality-Disadvantage Interaction Matter Over Time?

The foregoing discussion suggests the inequality-disadvantage interaction introduced in the previous chapter may extend to encompass interaction effects between starting *and* change values that help explain apparent differences in the impact of relative inequality on crime trajectories between neighborhoods of different colors. I now break down this expectation into discrete hypotheses.

First, I expect higher initial values and growth in relative inequality will, all else equal, predict growth in crime over time. As mentioned above, this means that higher values on either dimension will accelerate the pace of crime rate increases when crime is rising and decelerate the pace of crime rate decreases when crime is falling.

> H1: Higher initial values and growth in relative inequality will be associated with growth in crime.

However, I expect that the impact of relative inequality on crime trends will be attenuated in neighborhoods that started the period with already high levels of disadvantage or that experienced increases in disadvantage.

> H2: Interaction effects between initial or change values of relative inequality and disadvantage will be negative, such that the impacts of higher initial values and

growth in relative inequality on growth in crime are lower in neighborhoods that had higher initial values or experienced growth in disadvantage.

Next, since segregated non-White neighborhoods were more likely to start the period with higher disadvantage or experience growth in disadvantage during the 2000s decade (Krivo et al., 2018), I expect that the effects of relative inequality on crime change will be lesser in those areas than in predominantly White tracts.

H3: When White neighborhoods are the reference category, interaction effects between initial or change values of relative inequality and segregated non-White neighborhoods will be negative, such that the impacts of higher initial values and growth in relative inequality on growth in crime are lower in these neighborhoods.

Finally, because I suspect tempered impacts of relative inequality on crime trends in neighborhoods of color result from the higher average initial levels and changes in disadvantage, I expect that relative inequality effects will be similar by ethno-racial neighborhood type net of the relative inequality and disadvantage interaction effects.

H4: After controlling for interaction effects between initial or change values of relative inequality and disadvantage, the interaction terms between neighborhood type and initial or change values of relative inequality will reduce to non-significance.

Data and Method

For this chapter, I draw on data from the NNCS2-P, which combines Waves I and II of the NNCS. These data contain information on socioeconomic conditions and demographics from the census, foreclosure data from Realty Trac, and mortgage lending data from the Home Mortgage Disclosure Act for the 2000 and 2008-2012 periods. They also have violent (homicide and robbery) and property (burglary) crime incidents reported from city police departments for circa 2000 (inclusive of 1999-2001 if no data are missing) and 2010 (inclusive of 2010-2013 if no data are missing). The full sample comprises 8,856 census tracts within 81 cities. A subset of these cities has a fuller set of crime data for some or all years from 2002 through 2009, and I draw from this subset to conduct the longitudinal analysis proposed in the present chapter. I select from the full sample all cities with no more than four years of missing data for at least one of the three crime types of interest, producing an analytic sample of 2,757 census tracts within 28 cities (for a listing of the cities included in the sample and their years of available crime data, see Table 4.1). My outcome measures include the rate of violent crimes (homicides and robberies) and property crimes (burglaries) per 1,000 tract residents for every year in the timeframe.[8] To adjust for their considerable skew, in my regression models I use the natural logarithm of these rates.

Descriptive statistics are presented on the dependent and independent variables in Tables 4.2 and 4.3, respectively. Table 4.2 summarizes the distribution of the tract violent and property crime rates by year, revealing that average crime rates initially increased and then decreased in an inverse U-shaped pattern. Both rate averages rose to reach their maximum values in 2005, fell slightly and rose again to a local peak in 2008, and then declined or held stable in subsequent years. Table 4.3 summarizes my independent variables where, except for tract ethno-racial composition, the distribution of every predictor is

[8] Producing annual crime rates requires tract population estimates for each year. Population estimates are only available for decennial years in the NNCS2-P, so I used linear interpolation/extrapolation to obtain estimates for 1999, 2001-2009, and 2011-2013.

Table 4.1 Range and Count of Years with Available Crime Data in NNCS2-P Analytic Sample, by City and Crime Type*

	Burglary		Robbery		Homicide	
	Years	Count	Years	Count	Years	Count
1. Alexandria, VA	1999-2001, 2006-2013	11	1999-2001, 2003, 2005-2013	13	1999-2001, 2003-2013	14
2. Arlington, TX	2000-2001, 2005-2013	11	2000-2001, 2005-2013	11	2000-2001, 2005-2010, 2012-2013	10
3. Austin, TX	1999-2013	15	1999-2013	15	1999-2013	15
4. Carrollton, TX	1999-2013	15	1999-2013	15	1999-2013	15
5. Charlotte, NC	1999-2001, 2005-2013	12	1999-2001, 2005-2013	12	1999-2001, 2005-2008, 2010-2013	11
6. Chicago, IL	2000-2013	14	2000-2013	14	2000-2013	14
7. Cleveland, OH	1999-2013	15	1999-2013	15	1999-2005, 2008, 2010-2013	12
8. Columbus, OH	1999-2001, 2004-2012	12	1999-2001, 2004-2012	12	1999-2001, 2007	4
9. Dallas, TX	1999-2013	15	1999-2013	15	1999-2013	15
10. Dayton, OH	1999-2013	15	1999-2013	15	1999-2013	15
11. Fort Worth, TX	1999-2001, 2003-2013	14	1999-2001, 2003-2013	14	1999-2001, 2003-2013	14
12. Hartford, CT	1999-2001, 2005-2013	12	1999-2001, 2005-2013	12	1999-2001, 2005-2013	12
13. Kansas City, MO	1999-2006, 2008-2013	14	1999-2006, 2008-2013	14	1999-2006, 2008-2013	14
14. Long Beach, CA	1999-2013	15	1999-2013	15	1999-2004, 2006-2013	14
15. Madison, WI	1999-2013	15	1999-2013	15	1999-2002, 2004-2006, 2009-2013	12
16. Milwaukee, WI	1999-2001, 2005-2013	12	1999-2001, 2005-2013	12	1999-2001, 2005-2013	12
17. Oakland, CA	1999-2001, 2006-2013	11	1999-2001, 2006-2008, 2010-2013	10	1999-2001, 2006-2013	11
18. Overland Park, KS	1999-2001, 2003-2013	14	1999-2001, 2003-2005, 2007-2013	13	1999-2001, 2003-2013	14
19. Pasadena, CA	1999-2013	15	1999-2013	15	1999-2013	15
20. Pasadena, TX	1999-2001, 2006-2013	11	1999-2001, 2006-2013	11	1999-2001, 2006-2013	11
21. Plano, TX	1999-2001, 2004-2013	13	1999-2001, 2004-2013	13	1999-2001, 2004-2013	13
22. Portland, OR	1999-2013	15	1999-2013	15	1999-2006, 2008-2013	14
23. San Diego, CA	1999-2001, 2003-2013	14	1999-2001, 2003-2013	14	1999-2001, 2003-2013	14
24. Simi Valley, CA	1999-2001, 2005-2013	12	1999-2001, 2005-2013	12	1999-2001, 2005-2013	12
25. St. Louis, MO	1999-2013	15	1999-2002, 2004-2013	14	1999-2013	15
26. St. Petersburg, FL	1999-2013	15	1999-2013	15	1999-2013	15
27. Waco, TX	1999-2013	15	1999-2003, 2005, 2007-2011	11	1999-2013	15
28. Worcester, MA	1999-2001, 2003-2013	14	1999-2001, 2003-2013	14	1999-2001, 2003-2013	14

*Only cities with at least 11 years of available data (i.e., no more than 4 years of missing data) for at least one crime type are included.

summarized for its initial value (tract values in 2000) and change value (how much values changed between the start and end of the period, i.e., the 2008-2012 value minus the 2000 value).[9] Tracts are classified into ethno-racial neighborhood categories based on their composition in 2000 only. Table 4.3 shows that the average tract in my sample saw both disadvantage and relative inequality rise over time. Disadvantage, with an average value just below 0 in 2000 (initial Disadvantage mean = -.067), increased to an average value of .056 by circa 2010 (Δ Disadvantage mean = .123). The Gini index, which started the decade with an average value of .411, rose to an average value of .419 by end of the decade (Δ Gini = .008).[10]

Table 4.2 Descriptive Statistics for Dependent Variables (N = 2,757 tracts)

Violent Crime Rate			Burglary Rate		
Year	Mean	SD	Year	Mean	SD
1999	4.4	7.6	1999	14.4	21.6
2000	5.0	6.6	2000	12.6	11.0
2001	5.6	14.7	2001	14.1	26.1
2002	6.5	10.7	2002	14.4	15.7
2003	5.5	10.2	2003	13.4	16.6
2004	5.9	30.5	2004	14.1	25.4
2005	9.3	127.5	2005	20.9	215.1
2006	5.8	17.0	2006	14.7	54.2
2007	5.6	13.6	2007	14.1	34.6
2008	6.3	26.7	2008	15.3	56.8
2009	5.0	9.8	2009	13.0	19.6
2010	4.2	5.0	2010	12.3	10.1
2011	4.5	9.2	2011	13.0	18.3
2012	4.4	7.7	2012	11.9	14.1
2013	5.4	35.0	2013	13.0	76.0

Note. Rates are per 1,000 census tract residents for the listed year.

[9] For the disadvantage and immigration indices, standardized scores for each variable in the index at Time 1 and Time 2 were calculated relative to the same single standard, the midpoint between Time 1 and Time 2 (i.e., after averaging each indicator's value between 2000 and 2008-2012, the mean and standard deviation of this average were used to compute standardized scores). The standardized scores were then averaged at each time point and their difference computed to produce a change score. This procedure allows changes in the indices over time to reflect differences relative to the same standard, rather than a different standard for each time point (see Lyons et al., 2022).

[10] This change is small but matches national trends. As measured by the Gini coefficient, the 2000s decade saw income inequality change by a modest amount relative to the decades before and after. From 1970 to 2000 the U.S. Gini coefficient rose by approximately .02 each decade, and from 2010 to 2017 it decreased by about .03, but from 2000 to 2010 it rose by just .006 (Fry & Taylor, 2012; Horowitz et al., 2020; Reardon & Bischoff, 2011).

Table 4.3 Descriptive Statistics for Independent Variables*

	Mean	SD
Ethno-Racial Nbhd. Type		
White	.395	
Black	.126	
Latino	.035	
Minority	.049	
White-Black Multi.	.109	
White-Latino Multi.	.090	
Other Multi.	.197	
Gini	.411	.068
Disadvantage	-.067	.902
Young Males (%)	16.215	6.243
Immigration	-.071	.882
Renters (%)	48.899	25.143
Vacant housing (%)	7.198	5.874
Foreclosure rate	3.290	6.019
Population	3568.705	1529.078
Residential loans	15.432	36.787
Δ Gini	.008	.054
Δ Disadvantage[a]	.123	.373
Δ Young males (%)	-.383	4.463
Δ Immigration[a]	.038	.531
Δ Renters (%)	1.628	10.126
Δ Vacant housing (%)	4.567	6.852
Δ Foreclosure rate	10.633	20.798
Δ Population	224.387	1160.171
Δ Residential loans	-.858	32.611

[a]Standardized scores for each variable in the index were calculated relative to the midpoint between 2000 and 2008-2012 before taking their average for each time point and then computing the difference to produce a change score.

*Non-change score variables are measured only for 2000.

N = 2,757 tracts, across 28 cities.

To assess my hypotheses, I estimate a set of multilevel LGC models. In a LGC framework, the goal is to fit regression lines (or curves) for each observation (or neighborhood in my case, where crime rates are regressed on time in each neighborhood). Varying regression lines are then smoothed to produce summary measures that characterize the typical, but unobserved, trend for all neighborhoods in the sample (Kikuchi & Desmond, 2010). There are several key advantages to using LGC models over alternative techniques for modeling change (Preacher, 2019; Raudenbush & Bryk, 2002). First, because they draw on data from multiple time points across many observations, the LGC framework allows for explicit modeling of individual growth, including estimation of the initial level of a dependent variable and its rate of change over time. This degree of detail is not available in longitudinal study designs that rely on data at only two time points. Second, after estimating parameters that summarize the overall growth curve, LGC models permit exploration of how time-invariant or time-varying covariates account for variation around those parameters, a feature that is key for assessing my hypotheses of how initial values and changes in relative inequality and disadvantage shape trajectories of crime over time. Finally, LGC models are robust to many instances of missing data. Assuming data are missing at random, parameter estimates remain unbiased when cases are not measured at the same instances or at equally spaced intervals. This benefit is also critical to my study since, as evident in Table 2.1, the neighborhoods in my sample vary in how many years of crime data they have available depending on their host city.

Likelihood ratio tests indicate that the ideal model fit for either outcome variable is a quadratic function with both time terms specified as random effects. Thus, each model has intercept, linear time, and time-squared terms that vary randomly across neighborhoods, and the initial and change versions of the covariates are entered into the models to account for variation across these estimates. Given that I explore change in crime rates over time within neighborhoods that are themselves embedded within cities, I use a three-level modeling strategy. This strategy can be formally expressed by a set of equations at three levels. The first level is a year-level model.

LEVEL 1 – YEARS FROM 1999 THROUGH 2013

$$Yijk = \pi 0jk + \pi 1jk(Time) + \pi 2jk(Time)^2 + eijk \tag{1}$$

In Equation 1, Yijk is the logged property or violent crime rate during year i for neighborhood j in city k, π0jk is the mean crime rate of neighborhood j in city k in 1999, π1jk is the linear rate of change in neighborhood j's crime rate for a one-year increase in years since 1999, π2jk is the quadratic rate of change, and eijk is an error term, the extent to which the observed crime rate during year i for neighborhood j in city k deviates from the neighborhood mean crime rate.

Next, at the second level, the crime rate intercept, linear rate of change, and quadratic rate of change for each neighborhood are viewed as varying randomly around some citywide mean, and neighborhood-level covariates are entered into each equation to explain this variation.

LEVEL 2 – NEIGHBORHOODS (CENSUS TRACTS)

$$\pi 0jk = \beta 00k + \beta 0Z'jk + r0jk \tag{2}$$

$$\pi 1jk = \beta 10k + \beta 1Z'jk + r1jk \tag{3}$$

$$\pi 2jk = \beta 20k + \beta 2Z'jk + r2jk \tag{4}$$

In Equation 2, $\beta 00k$ is the mean crime rate in city k in 1999, $\beta 0Z'$ represents a set of time-invariant tract-level independent variables and their associated coefficients for neighborhood j in city k, and $r0jk$ is the deviation of neighborhood j's mean crime rate from the city mean. These parameters together define $\pi 0jk$, the average crime rate of neighborhood j at the start of the period. The parameters that sum to define the rates of change in crime over time terms, $\pi 1jk$ and $\pi 2jk$, have analogous interpretations: each slope term is defined by a citywide average, a set of tract-level covariates with their associated coefficients, and an error term.

Finally, at the third level, the average crime rate for each city is viewed as varying randomly around a grand mean, and a set of city-level fixed effects are included in the equation to adjust for unobserved heterogeneity across cities.

LEVEL 3 – CITIES

$$\beta 00k = \gamma 000 + \gamma 001(\text{CITY ID})k + u00k \tag{5}$$

In this final equation $\beta 00k$, the mean crime rate for city k at the period start, is defined as the sum of $\gamma 000$, the average crime rate across all cities; $\gamma 001(\text{CITY ID})k$, a categorical indicator for each city and its corresponding coefficient; and $u00k$, the deviation of city k's crime rate from the grand mean. Including categorical indicators of each city as fixed effects allows each city to serve as its own control and eliminate any bias resulting from time-invariant, systematic differences between cities. For simplicity, the city-level intercept and city indicator effect estimates are omitted from my LGC results tables.

I specify a series of OLS regression models predicting the logged crime rate, first for property crime (burglary) and then for violence (homicide and robbery). Given the low incident counts for homicides and robberies, the ideal modeling strategy for violence would likely be a negative binomial model, but limitations inherent in my data analysis software (Stata 17) preclude estimating LGC models with categorical outcomes using my data. I begin by estimating the "unconditional" model, which describes the average values of the growth curve without adjusting for any predictors. I next refit this model with only the ethno-racial neighborhood type and city indicator categorical variables predicting each parameter to explore how neighborhood type-specific growth curves vary from the aggregate trend. In subsequent models I sequentially add in initial and change levels of relative inequality, disadvantage, and the remaining independent variables. Net of all controls, I then separately add in interaction terms between initial and change versions of relative inequality and disadvantage, followed by interaction terms between relative inequality and the ethno-racial neighborhood types. Finally, alongside the inequality by neighborhood type interactions, I add back in the relative inequality by disadvantage interactions and assess the extent to which the former set of interaction terms diminish in size or significance.

Results

Before discussing my findings, I acknowledge that LGC models are complex and interpreting their output is not straightforward. It is difficult to discern patterns of interest solely by examining regression coefficients because LGC models include a full set of results for each time-level parameter, and unlike in a traditional regression model where coefficients can be interpreted one after another, the effects of the time terms and their covariates must be interpreted jointly. Thus, although I provide customary tables of regression coefficients in this dissertation and reference them in the text, I focus the upcoming discussion on figures that illustrate key findings of relevance to my research questions and hypotheses.

Table 4.4 Relative Inequality, Disadvantage, and Controls as Predictors of Latent Growth Curve Models for Burglary Rates (ln), 1999-2013

	Unconditional			Model 1			Model 2			Model 3			Model 4		
	b		SE	b		SE	b		SE	b		SE	b		SE
Intercept	1.107	***	.107	.823	***	.099	.940	***	.096	1.233	***	.098	1.517	***	.094
Ethno-Racial Nbhd Type															
Black				.640	***	.035	0.423	***	0.036	.129	**	.048	-.033		.048
Latino				.347	***	.053	0.304	***	0.052	-.026		.061	.114		.064
Minority				.505	***	.058	0.385	***	0.056	.053		.065	.047		.062
White-Black Multi.				.417	***	.040	0.347	***	0.039	.242	***	.041	.182	***	.039
White-Latino Multi.				.490	***	.040	0.452	***	0.039	.282	***	.042	.277	***	.042
Other Multi.				.307	***	.032	0.253	***	0.031	.090	*	.035	.081	*	.034
Gini							3.159	***	.194	2.581	***	.200	1.521	***	.228
× Disadvantage															
× Black															
× Latino															
× Minority															
× White-Black Multi.															
× White-Latino Multi.															
× Other Multi.															
Disadvantage										.189	***	.019	.144	***	.025
Young males													.018	***	.002
Immigration													-.139	***	.019
Renters													.000		.001
Vacant housing (ln)													.150	***	.014
Foreclosure rate (ln)													.093	***	.012
Population													.000	***	.000
Residential loans (ln)													-.155	***	.020
Time	.024	***	.002	.005		.003	.002		.003	.004		.004	.004		.004
Ethno-Racial Nbhd Type															
Black				.075	***	.006	.087	***	.006	.077	***	.009	.061	***	.009
Latino				-.021	*	.009	-.015		.010	-.016		.011	.008		.013
Minority				-.007		.010	.002		.010	-.001		.011	.012		.012
White-Black Multi.				.029	***	.007	.031	****	.007	.024	**	.007	.017	*	.008

White-Latino Multi.	.020	**	.007	.022	**	.007	.019	*	.007	.027	**	.008
Other Multi.	.020	***	.005	.023	***	.006	.022	***	.006	.030	***	.007
Gini				-.087	*	.035	-.004		.037	-.008		.045
× Disadvantage												
× Black												
× Latino												
× Minority												
× White-Black Multi.												
× White-Latino Multi.												
× Other Multi.												
Disadvantage							.001		.003	-.009		.005
Young males										.002	***	.000
Immigration										-.021	***	.004
Renters										.000		.000
Vacant housing (ln)										-.005	*	.003
Foreclosure rate (ln)										.009	***	.002
Population										.000		.000
Residential loans (ln)										-.004		.003
Δ Gini				.101	*	.041	.061		.041	.040		.043
× Δ Disadvantage												
× Black												
× Latino												
× Minority												
× White-Black Multi.												
× White-Latino Multi.												
× Other Multi.												
Δ Disadvantage							.057	***	.005	.044	***	.006
Δ Young males										.001		.000
Δ Immigration										-.011	**	.004
Δ Renters										.001	*	.000
Δ Vacant housing (ln)										.007	***	.002
Δ Foreclosure rate (ln)										.008	***	.002
Δ Population										.000	***	.000
Δ Residential loans (ln)										-.013	***	.003

Time²	-.003	***	.000	-.002	***	.000	-.002	***	.000	-.001	***	.000	-.001	***	.000
Ethno-Racial Nbhd Type															
Black				-.003	***	.000	-.003	***	.000	-.004	***	.001	-.004	***	.001
Latino				.002	**	.001	.002	**	.001	.000		.001	.000		.001
Minority				.002	**	.001	.002	**	.001	.000		.001	.000		.001
White-Black Multi.				-.001	**	.000	-.001	**	.000	-.002	**	.001	-.001	*	.001
White-Latino Multi.				.000		.000	.000		.000	-.001	*	.001	-.001	*	.001
Other Multi.				.000		.000	.000		.000	-.001	**	.000	-.001	*	.000
Gini							-.003		.002	-.009	***	.003	-.007	*	.003
× Disadvantage															
× Black															
× Latino															
× Minority															
× White-Black Multi.															
× White-Latino Multi.															
× Other Multi.															
Disadvantage										.001	***	.000	.001	***	.000
Young males													.000	***	.000
Immigration													.001	**	.000
Renters													.000		.000
Vacant housing (ln)													.000		.000
Foreclosure rate (ln)													-.001	***	.000
Population													.000		.000
Residential loans (ln)													.000		.000
Δ Gini							-.005		.003	-.003		.003	-.002		.003
× Δ Disadvantage															
× Black															
× Latino															
× Minority															
× White-Black Multi.															
× White-Latino Multi.															
× Other Multi.															
Δ Disadvantage										-.002	***	.000	-.002	***	.000

Δ Young males													.000		.000
Δ Immigration													.000		.000
Δ Renters													.000		.000
Δ Vacant housing (ln)													.000	**	.000
Δ Foreclosure rate (ln)													.000	***	.000
Δ Population													.000		.000
Δ Residential loans (ln)													.001	**	.000
Variance (SD)															
Intercept	.429		7.900	.384		5.828	.367		7.136	.359		7.347	.322		5.580
Time	.035	***	.001	.030	***	.001	.030	***	.001	.027	***	.001	.024	***	.001
$Time^2$	.002	***	.000	.002	***	.000	.002	***	.000	.002	***	.000	.002	***	.000

Note. *p < .05, **p < .01, ***p < .001.

Table 4.4 Relative Inequality, Disadvantage, and Controls as Predictors of Latent Growth Curve Models for Burglary Rates (ln), 1999-2013 (Cont.)

	Model 5			Model 6			Model 7			Model 8		
	b		SE	b		SE	b		SE	b		SE
Intercept	1.555	***	.092	1.551	***	.093	1.551	***	.093	1.548	***	.093
Ethno-Racial Nbhd Type												
Black	-.011		.047	.037		.051	.023		.050	.024		.050
Latino	.067		.063	.073		.066	.068		.066	.068		.066
Minority	.024		.061	-.003		.067	-.010		.066	-.010		.066
White-Black Multi.	.157	***	.038	.146	***	.040	.159	***	.039	.159	***	.040
White-Latino Multi.	.244	***	.041	.248	***	.042	.248	***	.042	.248	***	.042
Other Multi.	.069	*	.034	.042		.035	.062		.035	.062		.035
Gini	1.391	***	.226	2.701	***	.329	1.738	***	.367	1.724	***	.367
× Disadvantage	-1.649	***	.168				-1.386	***	.238	-1.400	***	.239
× Black				-3.940	***	.547	-1.374		.705	-1.360		.705
× Latino				-3.015	**	1.145	-.929		1.197	-.909		1.196
× Minority				-2.142	*	1.004	.082		1.070	.111		1.071
× White-Black Multi.				-1.487	*	.581	-.670		.597	-.660		.597
× White-Latino Multi.				-.324		.703	.651		.720	.662		.720
× Other Multi.				-1.167	*	.481	-.361		.498	-.349		.498
Disadvantage	.235	***	.026	.185	***	.025	.234	***	.026	.234	***	.026
Young males	.015	***	.002	.014	***	.002	.015	***	.002	.015	***	.002
Immigration	-.161	***	.019	-.148	***	.019	-.159	***	.019	-.159	***	.019
Renters	.000		.001	.001		.001	.000		.001	.000		.001
Vacant housing (ln)	.141	***	.014	.145	***	.014	.142	***	.014	.142	***	.014
Foreclosure rate (ln)	.069	***	.012	.089	***	.012	.071	***	.012	.071	***	.012
Population	.000	***	.000	.000	***	.000	.000	***	.000	.000	***	.000
Residential loans (ln)	-.130	***	.020	-.149	***	.020	-.131	***	.020	-.131	***	.020
Time	.004		.004	.003		.004	.003		.004	.003		.004
Ethno-Racial Nbhd Type												
Black	.061	***	.009	.054	***	.010	.053	***	.010	.053	***	.010
Latino	.007		.013	.008		.013	.008		.013	.008		.013
Minority	.011		.012	.016		.013	.016		.013	.016		.013
White-Black Multi.	.015	*	.008	.018	*	.008	.019	*	.008	.017	*	.008

White-Latino Multi.	.027	**	.008	.028	**	.008	.028	**	.008	.028	**	.008
Other Multi.	.030	***	.007	.031	***	.007	.033	***	.007	.033	***	.007
Gini	-.013		.045	-.024		.065	-.102		.073	-.110		.073
× Disadvantage	-.019		.034				-.111	*	.048	-.119	*	.048
× Black				.199		.111	.411	**	.144	.414	**	.144
× Latino				.177		.236	.349		.248	.348		.248
× Minority				.082		.202	.265		.216	.284		.217
× White-Black Multi.				-.107		.116	-.038		.121	-.033		.121
× White-Latino Multi.				-.140		.140	-.057		.144	-.050		.144
× Other Multi.				.046		.094	.108		.098	.113		.098
Disadvantage	-.007		.005	-.010	*	.005	-.007		.005	-.007		.005
Young males	.002	***	.000	.002	***	.000	.002	***	.000	.002	***	.000
Immigration	-.022	***	.004	-.021	***	.004	-.022	***	.004	-.022	***	.004
Renters	.000		.000	.000		.000	.000		.000	.000		.000
Vacant housing (ln)	-.006	*	.003	-.005	*	.003	-.006	*	.003	-.006	*	.003
Foreclosure rate (ln)	.009	***	.002	.009	***	.002	.009	***	.002	.008	***	.002
Population	.000		.000	.000		.000	.000		.000	.000		.000
Residential loans (ln)	-.004		.003	-.004		.003	-.003		.003	-.003		.003
Δ Gini	.035		.043	.047		.079	.054		.079	.045		.079
× Δ Disadvantage	.154	*	.074							.151	*	.074
× Black				.040		.118	.024		.118	.029		.118
× Latino				-.092		.204	-.103		.204	-.078		.204
× Minority				.136		.197	.130		.197	.165		.198
× White-Black Multi.				.024		.146	.009		.146	.008		.146
× White-Latino Multi.				-.086		.149	-.094		.149	-.100		.149
× Other Multi.				-.020		.125	-.039		.125	-.025		.126
Δ Disadvantage	.045	***	.006	.044	***	.007	.044	***	.006	.045	***	.007
Δ Young males	.000		.000	.001		.000	.001		.000	.001		.000
Δ Immigration	-.012	**	.004	-.012	**	.004	-.012	**	.004	-.012	**	.004
Δ Renters	.001	*	.000	.001	*	.000	.001	*	.000	.001	*	.000
Δ Vacant housing (ln)	.007	***	.002	.007	***	.002	.007	***	.002	.007	***	.002
Δ Foreclosure rate (ln)	.008	***	.002	.008	***	.002	.007	***	.002	.007	***	.002
Δ Population	.000	***	.000	.000	***	.000	.000	***	.000	.000	***	.000
Δ Residential loans (ln)	-.013	***	.003	-.013	***	.003	-.013	***	.003	-.013	***	.003

Time²	-.002	***	.000	-.001	***	.000	-.001	***	.000	-.001	***	.000
Ethno-Racial Nbhd Type												
Black	-.004	***	.001	-.003	***	.001	-.003	***	.001	-.003	***	.001
Latino	.000		.001	.000		.001	.000		.001	.000		.001
Minority	.000		.001	.000		.001	.000		.001	.000		.001
White-Black Multi.	-.001	*	.001	-.001	*	.001	-.001	**	.001	-.001	*	.001
White-Latino Multi.	-.001		.001	-.001		.001	-.001	*	.001	-.001	*	.001
Other Multi.	-.001	*	.000	-.001	**	.000	-.001	**	.000	-.001	**	.000
Gini	-.007	*	.003	-.006		.005	.000		.005	.001		.005
× Disadvantage	.003		.002				.009	**	.003	.010	**	.003
× Black				-.014		.008	-.032	**	.010	-.032	**	.010
× Latino				-.006		.016	-.021		.017	-.021		.017
× Minority				.000		.014	-.016		.015	-.017		.015
× White-Black Multi.				.002		.008	-.004		.008	-.004		.008
× White-Latino Multi.				.016		.010	.009		.010	.008		.010
× Other Multi.				-.001		.007	-.006		.007	-.007		.007
Disadvantage	.001	**	.000	.001	***	.000	.001	**	.000	.001	**	.000
Young males	.000	***	.000	.000	***	.000	.000	***	.000	.000	***	.000
Immigration	.001	**	.000	.001	**	.000	.001	**	.000	.001	**	.000
Renters	.000		.000	.000		.000	.000		.000	.000		.000
Vacant housing (ln)	.000		.000	.000		.000	.000		.000	.000		.000
Foreclosure rate (ln)	.000	***	.000	-.001	***	.000	.000	***	.000	.000	**	.000
Population	.000		.000	.000		.000	.000		.000	.000		.000
Residential loans (ln)	.000		.000	.000		.000	.000		.000	.000		.000
Δ Gini	-.002		.003	-.004		.006	-.005		.006	-.004		.006
× Δ Disadvantage	-.013	*	.005							-.013	*	.005
× Black				-.003		.008	-.002		.008	-.002		.008
× Latino				.004		.014	.005		.014	.003		.014
× Minority				-.008		.014	-.007		.014	-.010		.014
× White-Black Multi.				.002		.010	.003		.010	.004		.010
× White-Latino Multi.				.009		.010	.010		.010	.010		.010
× Other Multi.				.006		.009	.007		.009	.006		.009
Δ Disadvantage	-.002	***	.000	-.002	***	.000	-.002	***	.000	-.002	***	.000

Δ Young males	.000		.000	.000		.000	.000		.000	.000		.000
Δ Immigration	.000		.000	.000		.000	.000		.000	.000		.000
Δ Renters	.000		.000	.000		.000	.000		.000	.000		.000
Δ Vacant housing (ln)	.000	**	.000	.000	**	.000	.000	**	.000	.000	**	.000
Δ Foreclosure rate (ln)	.000	**	.000	.000	***	.000	.000	**	.000	.000	**	.000
Δ Population	.000		.000	.000		.000	.000		.000	.000		.000
Δ Residential loans (ln)	.001	*	.000	.001	**	.000	.001	*	.000	.001	*	.000
Variance (SD)												
Intercept	.316		4.781	.318		4.970	.315		5.145	.315		5.092
Time	.024	***	.001	.024	***	.001	.024	***	.001	.024	***	.001
$Time^2$	.002	***	.000	.002	***	.000	.002	***	.000	.002	***	.000

Note. *p < .05, **p < .01, ***p < .001.

Burglary. Table 4.4 presents the results of the latent growth curve models for burglary rate trends over 1999-2013. I begin by describing the unconditional model, which contains four parameter estimates: a neighborhood-level intercept, a city-level intercept (omitted from the table), a linear time term, and a quadratic time term (time-squared). The coefficients describing the growth curve are positive for time and negative for time-squared, indicating a curve with an inverse U-shape. Exponentiated predictions shown in Figure 4.1 confirm this shape, where burglary rates rose at a decelerating rate since 1999, reached a maximum level in 2004, and then declined at an accelerating rate through 2013.

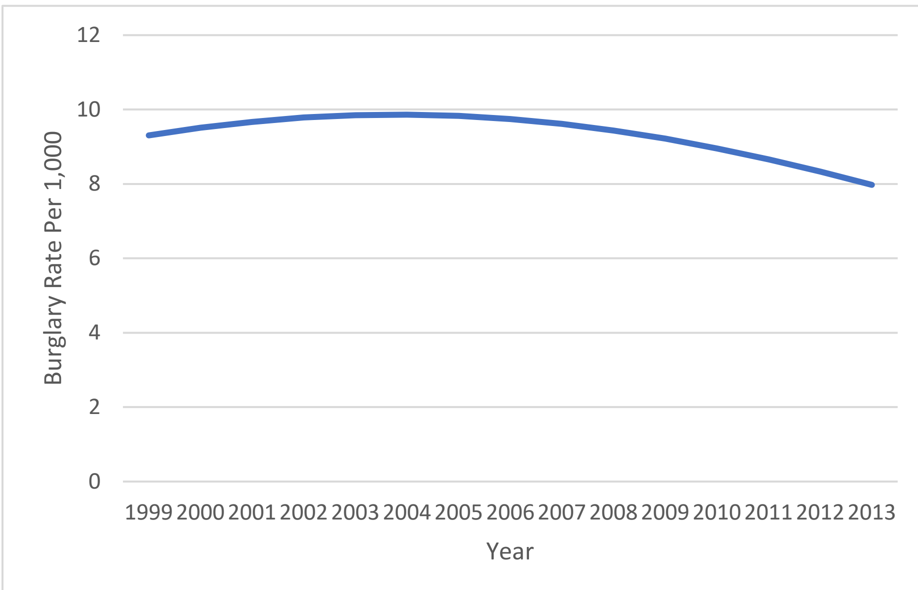

Figure 4.1. Predicted Unadjusted Average Tract Burglary Rates, 1999-2013.

The results from Model 1, the first model with predictor variables, are graphically depicted in Figure 4.2. This figure presents the unadjusted burglary rate growth curves over

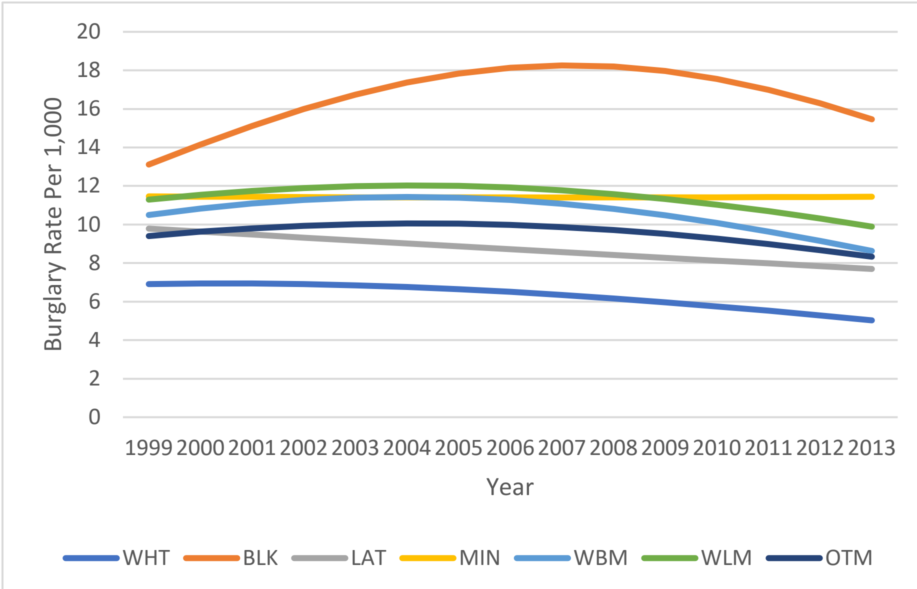

Figure 4.2. Predicted Unadjusted Average Tract Burglary Rates by Ethno-Racial Neighborhood Type, 1999-2013.

1999-2013 separately for each of the seven ethno-racial neighborhood types.[11] All six segregated non-White or multiethnic neighborhoods had higher average burglary rates than did White neighborhoods in 1999, but from there the neighborhood types diverge considerably in the shape of their trajectories. At the start of the period burglary rates were stable in White and Minority neighborhoods but rose gradually in multiethnic neighborhoods and rapidly in Black neighborhoods, while in Latino neighborhoods they slowly declined. During the later years of the period the trends in Minority and Latino neighborhoods remained unchanged, with burglary rates holding steady in the former and declining at a constant pace in the latter, while growth in burglary rates slowed in every other neighborhood type and eventually yielded to falling rates. This reversal is most dramatic in Black neighborhoods, where despite the rapid ascent in burglary levels through 2007, the burglary rate in 2013 is roughly equal to the rate circa 2000.

[11] White neighborhoods are the reference category in Model 1. This and all subsequent models also include the categorical indicators for each city; their coefficients are omitted from Table 4.4.

Models 2-4 sequentially add initial and change levels in relative inequality, disadvantage, and then all controls. Beginning with the results from Models 2 and 3, neighborhoods with initially higher income disparity had an initially higher burglary rate, and Model 3 reveals that high inequality tracts also saw more rapid declines in burglary later in the period. Higher starting levels of disadvantage were associated with an elevated intercept as well, but with a more moderate decline in burglary later in the period. Change in disadvantage was a significant covariate of both time and time-squared; neighborhoods where disadvantage rose saw steeper inclines in burglary during early years and steeper declines during later years. In sum, the models suggest initial levels of relative inequality and growth in disadvantage were associated with more extreme neighborhood growth curves in burglary rates, giving their trend lines steeper rising and falling slopes, whereas areas that started the decade with higher disadvantage benefitted less from the typical decline in burglary since 2004. Turning to Model 4, Figure 4.3 depicts fully adjusted burglary rate growth curves by neighborhood type. The graph clarifies that initial levels and growth in all controls explain much of the variation across neighborhood types in burglary rate intercepts and rates of change, as many of the stark differences

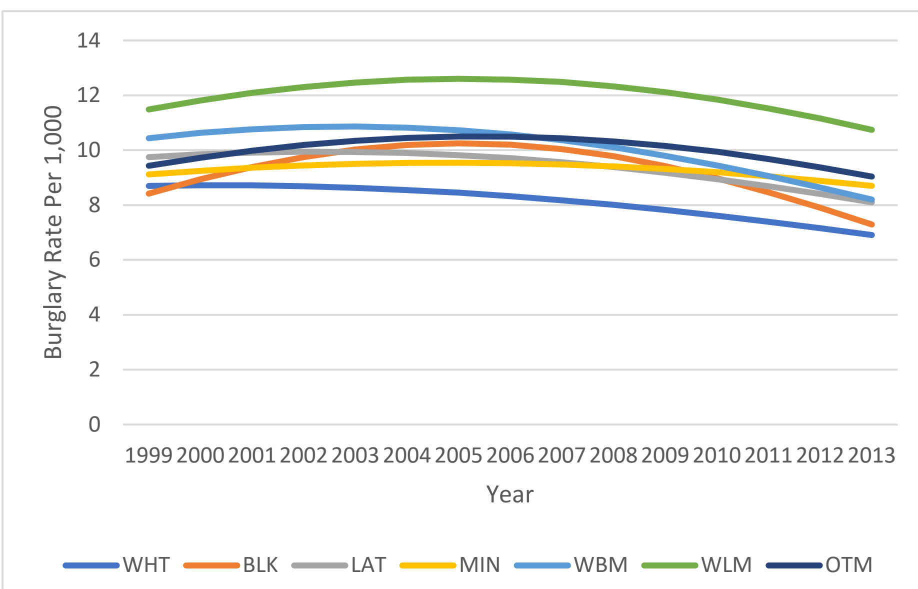

Figure 4.3. Predicted Average Tract Burglary Rates by Ethno-Racial Neighborhood Type, Adjusted for Controls, 1999-2013.

observed in Figure 4.2 are reduced or eliminated. Yet Black and multiethnic neighborhoods continue to have sharper increases in burglary during the early years, and more rapid decreases later, compared with White neighborhoods. Although the coefficients for relative inequality and disadvantage diminish in size, their effects are substantively unchanged.

Model 5 adds in interaction terms between relative inequality and disadvantage. Beginning with their initial levels, the main effects of relative inequality and disadvantage predicting the intercept are again positive, but the term for their interaction is negative and significant. I visualize the impact of this dynamic in Figures 4.4 through 4.6, which present predicted burglary rates over 1999-2013 when initial disadvantage is low (1 standard deviation below the mean value), average, and high (1 standard deviation above the mean value). Within each figure, growth curves are shown for when initial relative inequality

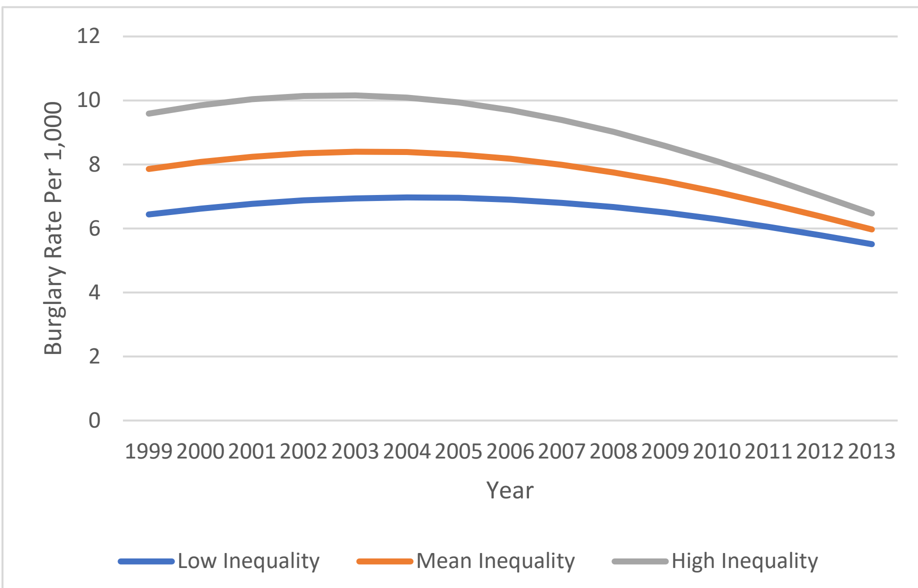

Figure 4.4. Predicted Average Tract Burglary Rates at Low, Average, and High Initial Levels of the Gini Index, When Initial Disadvantage Was Low, 1999-2013.

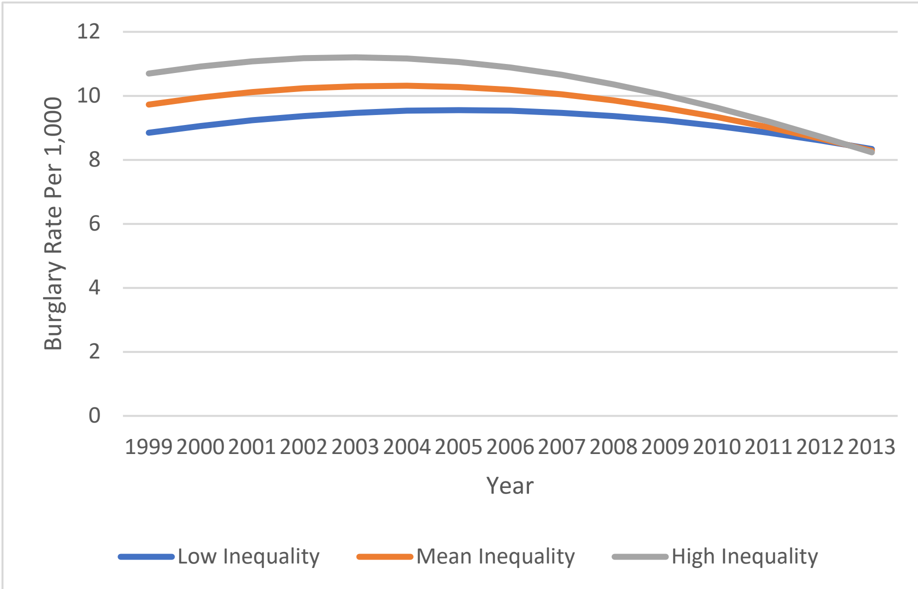

Figure 4.5. Predicted Average Tract Burglary Rates at Low, Average, and High Initial Levels of the Gini Index, When Initial Disadvantage Was Average, 1999-2013.

is low, average, and high (defined the same way as the disadvantage levels); all other variables are held at their means. Two patterns stand out. First, the elevating impact of initially higher relative inequality on the intercept is reduced in neighborhoods that also had more pronounced levels of disadvantage in 1999. Higher relative inequality predicts a greater

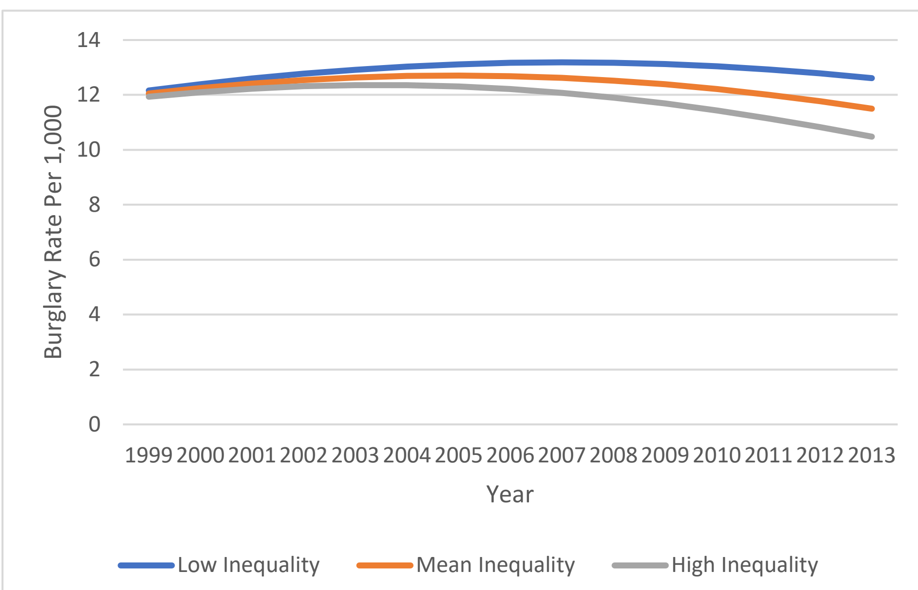

Figure 4.6. Predicted Average Tract Burglary Rates at Low, Average, and High Initial Levels of the Gini Index, When Initial Disadvantage Was High, 1999-2013.

burglary rate intercept where disadvantage is low, but the difference in intercept levels increasingly narrows in tracts with increasingly higher disadvantage levels. Second, higher relative inequality provides a protective effect against burglary later in the period in the most disadvantaged neighborhoods. Although neighborhoods with high inequality have the highest burglary rates in any year where disadvantage is low, where disadvantage is at its mean neighborhoods with high inequality are predicted to have lower burglary rates than other neighborhoods by 2013, and where disadvantage is high neighborhoods with high inequality are predicted to have lower burglary rates than elsewhere over the entire timeframe.

Neither of the initial relative inequality by disadvantage interaction terms predicting time or time-squared are significant, so now I turn to discussing the interactions between their change versions. The interaction effect is positive for the linear time term and negative for the time-squared term. I visualize these effects jointly in Figures 4.7 through 4.9, which present growth curves by low, average, and high disadvantage change scores within the Figures and by low, average, and high Gini index change scores across them

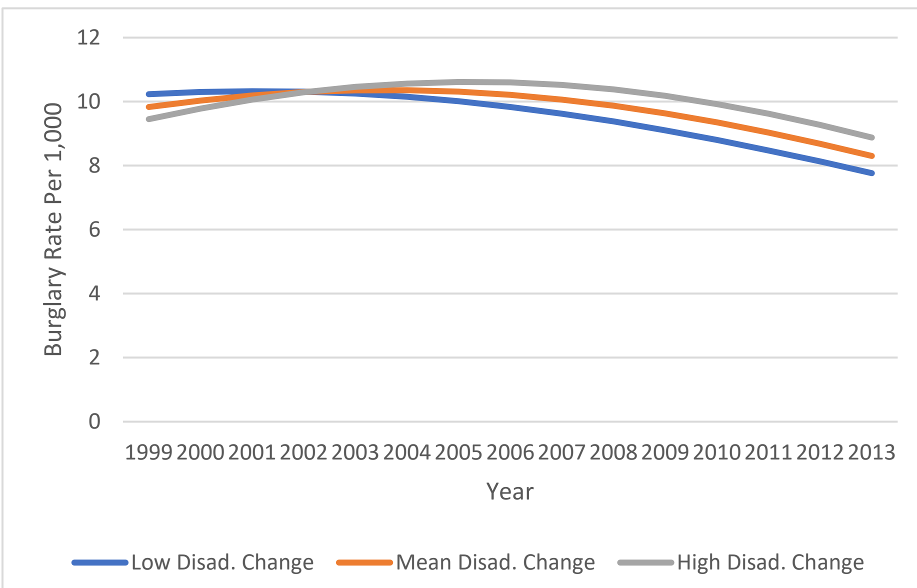

Figure 4.7. Predicted Average Tract Burglary Rates at Low, Average, and High Levels of Change in Disadvantage, When Gini Index Change Was Low (i.e., Relative Inequality Decreased), 1999-2013.

(“low,” average, and “high” scores are defined the same way as the initial levels were).

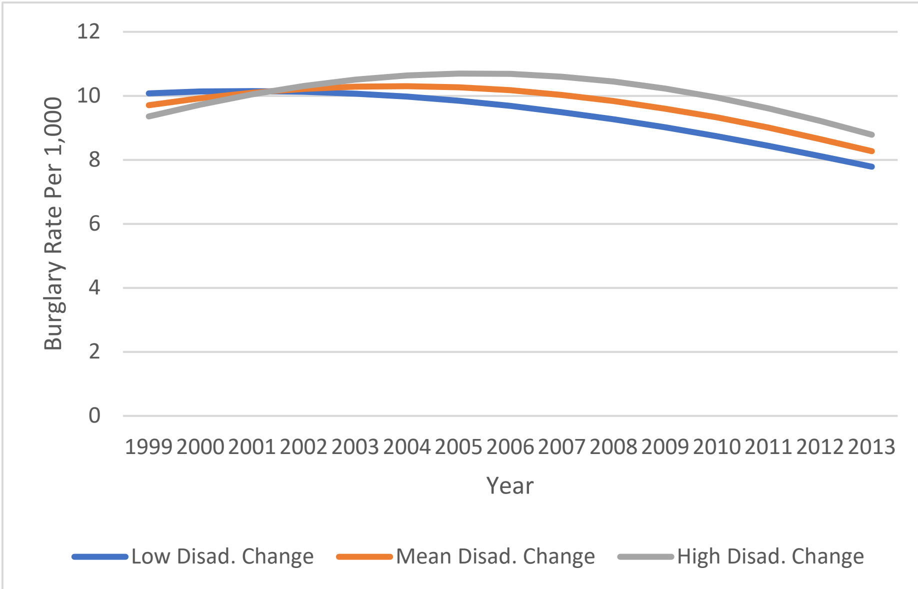

Figure 4.8. Predicted Average Tract Burglary Rates at Low, Average, and High Levels of Change in Disadvantage, When Gini Index Change Was Average (i.e., Relative Inequality Increased Modestly), 1999-2013.

Comparing trend lines within any of the figures, in neighborhoods where disadvantage rose in greater quantities, burglary levels ascended more quickly at the start of the period but their growth also more swiftly slowed and reversed direction. Comparing across figures, in accordance with the interaction terms, the rapid rise and fall of burglary rates in tracts where disadvantage rose was even more pronounced in tracts where relative inequality also rose. Despite the significant

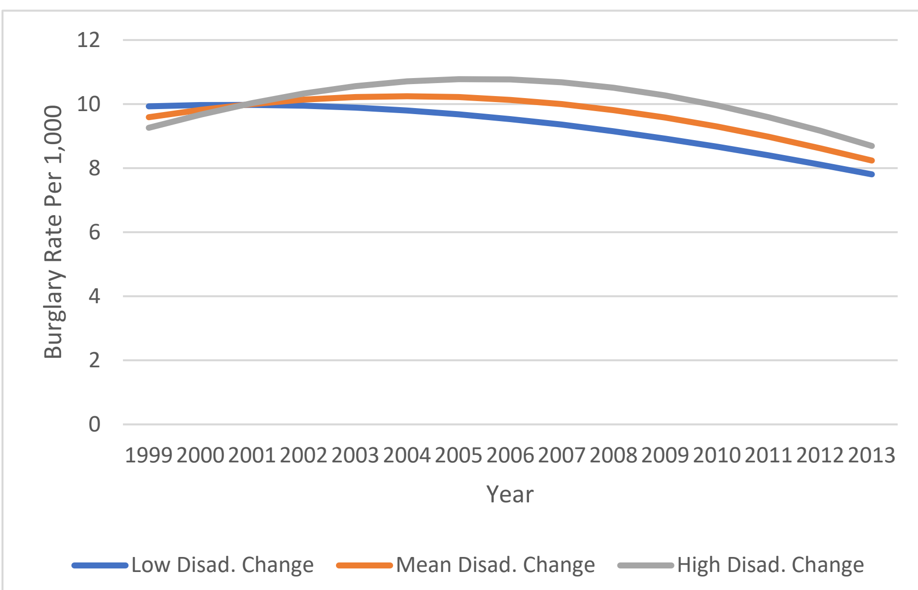

Figure 4.9. Predicted Average Tract Burglary Rates at Low, Average, and High Levels of Change in Disadvantage, When Gini Index Change Was High (i.e., Relative Inequality Increased Greatly), 1999-2013.

interaction terms, however, change in disadvantage was much more substantively important for the ultimate shape of the burglary rate trends than was change in the Gini index.

I temporarily withdraw the interactions involving disadvantage to focus on interactions between relative inequality and ethno-racial neighborhood type, which I present in Model 6. The coefficients for the interaction terms between neighborhood type and relative inequality predicting the intercept are, except for White-Latino Multiethnic neighborhoods, negative and significant. This indicates that the elevating effect of initially higher levels of the Gini index on the intercept is lesser in most other neighborhood types compared with White neighborhoods, and is in fact so much lower in predominantly Black or Latino neighborhoods that relative inequality is associated with lower average initial burglary rates there. None of the initial level or change values for the main effect of the Gini or its interactions with the neighborhood types are significant among the coefficients predicting time or time-squared, so the differences in burglary rate trajectories between each neighborhood type and White neighborhoods in the current model remain substantively unchanged from those in Model 4.

In the final two models I sequentially add back in the interaction effects initially estimated in Model 5, first those between initial relative inequality and disadvantage in Model 7 and then those between their change score versions in Model 8. Their results are similar, so I focus my discussion on the last model. As in Model 5, the interaction predicting the intercept shows that relative inequality effects on burglary at the start of the period were weaker where disadvantage was higher, and the interaction between the change scores of these variables on time and time-squared indicate that where relative inequality and disadvantage levels rose by greater amounts, burglary rate growth curves tended to have steeper upward slopes that more quickly decelerate and reverse direction into steeper downward trends. There is a key difference however: although the main effects of initial levels of the Gini and disadvantage indices are not significant in predicting time or time-squared, their interaction terms are significant. The negative sign of the interaction for linear time and positive sign for time-squared imply that greater initial levels of these factors had the opposite effect on the burglary rate growth curve than did greater change: they tended to result in more moderate curves with a more gradual ascent and decline over the period.

Finally, I consider how the relative inequality by neighborhood type interaction terms initially estimated in Model 6 are affected by the inclusion of the relative inequality by disadvantage interactions. Recall from Model 6 that initial relative inequality had a diminished intercept-raising effect in most segregated and multiethnic neighborhoods compared with White neighborhoods, but none of the other initial level or change score relative inequality by neighborhood type terms were significant. In Model 8, all the initial relative inequality by neighborhood type interaction terms predicting the intercept are non-significant. Thus, upon the inclusion of the interaction between relative inequality and disadvantage, the intercept-raising effect of initial relative inequality is similar across the different ethno-racial neighborhood categories. There is another difference from Model 6: the initial relative inequality by Black neighborhood interaction term predicting linear time is

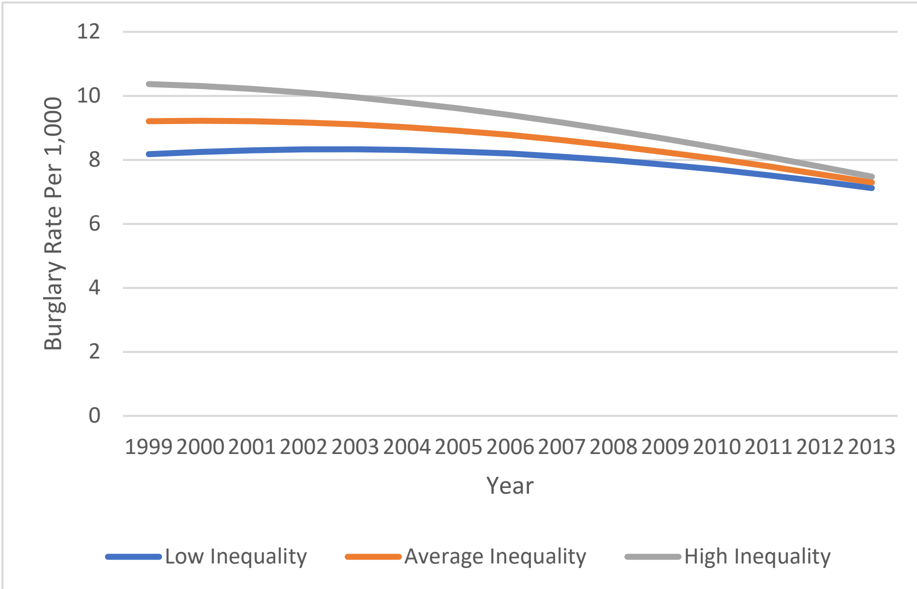

Figure 4.10. Predicted Average Tract Burglary Rates at Low, Average, and High Initial Levels of the Gini Index in White Neighborhoods, Adjusted for the Interactions Between Initial Levels and Changes in Relative Inequality and Disadvantage, 1999-2013.

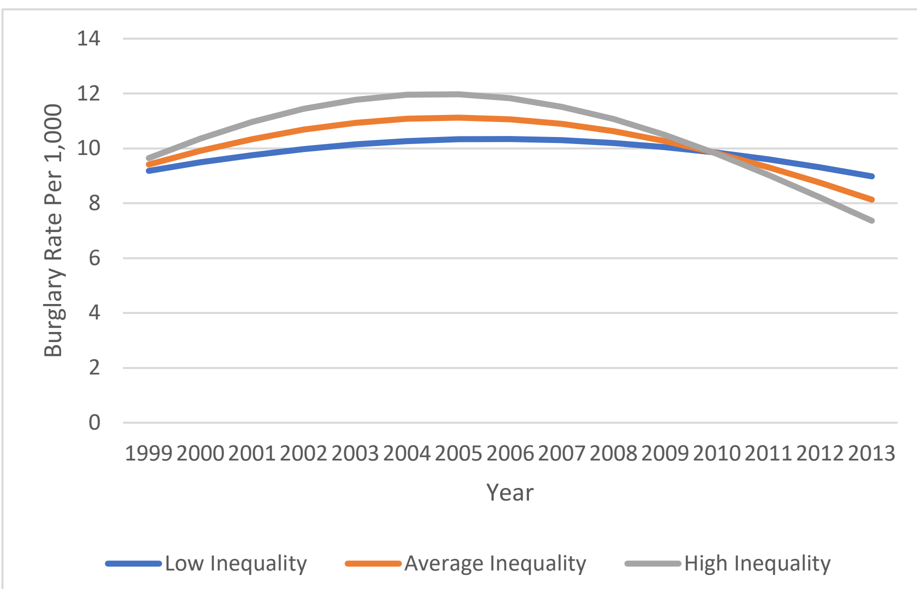

Figure 4.11. Predicted Average Tract Burglary Rates at Low, Average, and High Initial Levels of the Gini Index in Black Neighborhoods, Adjusted for the Interactions Between Initial Levels and Changes in Relative Inequality and Disadvantage, 1999-2013.

positive, and the interaction term between these variables predicting time-squared is negative. That is, in Black neighborhoods where relative inequality was high at the start of the period, the burglary rate growth curve had a more extreme shape, rising more quickly at first and then slowing its ascent and reversing direction more quickly to steeper downward trend, compared with White neighborhoods. This disparity can be seen by

Table 4.5 Relative Inequality, Disadvantage, and Controls as Predictors of Latent Growth Curve Models for Violent Crime Rates (ln), 1999-2013

	Unconditional			Model 1			Model 2			Model 3			Model 4		
	b		SE	b		SE	b		SE	b		SE	b		SE
Intercept	-.572	*	.222	-1.562	***	.191	-1.19	***	0.178	-0.27		0.178	.017		.166
Ethno-Racial Nbhd Type															
Black				2.110	***	.068	1.493	***	0.069	.581	***	.090	.489	***	.089
Latino				1.827	***	.105	1.725	***	0.099	.754	***	.114	.571	***	.120
Minority				1.894	***	.114	1.562	***	0.108	.576	***	.122	.490	***	.115
White-Black Multi.				1.522	***	.080	1.308	***	0.075	.964	***	.077	.791	***	.072
White-Latino Multi.				1.411	***	.079	1.292	***	0.075	.783	***	.079	.561	***	.077
Other Multi.				1.192	***	.064	1.028	***	0.06	.551	***	.065	.365	***	.064
Gini							9.474	***	0.373	8.206	***	.377	4.213	***	.426
× Disadvantage															
× Black															
× Latino															
× Minority															
× White-Black Multi.															
× White-Latino Multi.															
× Other Multi.															
Disadvantage										.561	***	.037	.238	***	.046
Young males													.034	***	.005
Immigration													-.141	***	.035
Renters													.008	***	.001
Vacant housing (ln)													.177	***	.026
Foreclosure rate (ln)													.124	***	.021
Population													.000	*	.000
Residential loans (ln)													-.477	***	.037
Time	.063	***	.004	.075	***	.007	0.059	***	0.007	.060	***	.008	.058	***	.009
Ethno-Racial Nbhd Type															
Black				-.019		.012	.033	*	.013	.027		.017	.021		.018
Latino				-.085	***	.019	-.066	***	.019	-.061	**	.022	-.033		.025
Minority				-.028		.019	.005		.020	.008		.022	.006		.023
White-Black Multi.				-.029	*	.014	-.015		.014	-.020		.015	-.028		.015

White-Latino Multi.	-.001		.014	.010		.014	.009		.015	.019		.016
Other Multi.	-.001		.011	.011		.011	.013		.012	.017		.013
Gini				-0.58	***	0.07	-.456	***	.074	-.292	**	.092
× Disadvantage												
× Black												
× Latino												
× Minority												
× White-Black Multi.												
× White-Latino Multi.												
× Other Multi.												
Disadvantage							-.003		.007	-.010		.009
Young males										.002	*	.001
Immigration										-.011		.007
Renters										.000		.000
Vacant housing (ln)										-.005		.005
Foreclosure rate (ln)										.019	***	.003
Population										.000	*	.000
Residential loans (ln)										.008		.007
Δ Gini				0.062		0.083	.016		.083	.055		.086
× Δ Disadvantage												
× Black												
× Latino												
× Minority												
× White-Black Multi.												
× White-Latino Multi.												
× Other Multi.												
Δ Disadvantage							.076	***	.011	.043	**	.013
Δ Young males										.000		.001
Δ Immigration										.019	*	.009
Δ Renters										.003	***	.000
Δ Vacant housing (ln)										-.007	*	.003
Δ Foreclosure rate (ln)										.021	***	.004
Δ Population										.000		.000
Δ Residential loans (ln)										-.010		.006

Time²	-.006	***	.000	-.007	***	.000	-.006	***	.000	-.006	***	.001	-.005	***	.001
Ethno-Racial Nbhd Type															
Black				.003	***	.001	.000		.001	-.001		.001	-.001		.001
Latino				.005	***	.001	.004	**	.001	.002		.001	.001		.002
Minority				.003	*	.001	.002		.001	.000		.002	.000		.002
White-Black Multi.				.002	*	.001	.002		.001	.001		.001	.001		.001
White-Latino Multi.				.001		.001	.000		.001	-.001		.001	-.001		.001
Other Multi.				.001		.001	.001		.001	.000		.001	-.001		.001
Gini							.026	***	.005	.019	***	.005	.009		.006
× Disadvantage															
× Black															
× Latino															
× Minority															
× White-Black Multi.															
× White-Latino Multi.															
× Other Multi.															
Disadvantage										.001	**	.000	.002	*	.001
Young males													.000	**	.000
Immigration													.000		.000
Renters													.000		.000
Vacant housing (ln)													.000		.000
Foreclosure rate (ln)													-.001	***	.000
Population													.000	*	.000
Residential loans (ln)													.000		.000
Δ Gini							-.001		.006	.001		.006	-.001		.006
× Δ Disadvantage															
× Black															
× Latino															
× Minority															
× White-Black Multi.															
× White-Latino Multi.															
× Other Multi.															
Δ Disadvantage										-.003	***	.001	-.002		.001

Δ Young males													.000		.000
Δ Immigration													-.001		.001
Δ Renters													.000	***	.000
Δ Vacant housing (ln)													.000	*	.000
Δ Foreclosure rate (ln)													-.001	***	.000
Δ Population													.000		.000
Δ Residential loans (ln)													.000		.000
Variance (SD)															
Intercept	.916	***	.023	.756		#####	.695		n/a	.661		7.418	.578		8.043
Time	.053	***	.001	.046	***	.003	.046	***	.003	.041	***	.003	.036	***	.003
$Time^2$	.000	***	.000	.001	***	.000	.001	***	.000	.001	***	.000	.002	***	.000

Note. *p < .05, **p < .01, ***p < .001.

Table 4.5 Relative Inequality, Disadvantage, and Controls as Predictors of Latent Growth Curve Models for Violent Crime Rates (ln), 1999-2013 (Cont.)

	Model 5			Model 6			Model 7			Model 8		
	b		SE	b		SE	b		SE	b		SE
Intercept	.121		.163	.113		.166	.122		.164	.115		.164
Ethno-Racial Nbhd Type												
Black	.556	***	.088	.599	***	.094	.557	***	.094	.559	***	.094
Latino	.460	***	.118	.492	***	.123	.485	***	.122	.485	***	.122
Minority	.438	***	.113	.434	***	.124	.418	**	.123	.418	**	.123
White-Black Multi.	.731	***	.071	.706	***	.074	.750	***	.073	.752	***	.073
White-Latino Multi.	.479	***	.077	.481	***	.079	.490	***	.078	.490	***	.078
Other Multi.	.340	***	.063	.280	***	.066	.354	***	.065	.355	***	.065
Gini	3.875	***	.421	6.573	***	.615	3.463	***	.684	3.453	***	.685
× Disadvantage	-4.173	***	.313				-4.475	***	.444	-4.486	***	.445
× Black				-7.753	***	1.024	.668		1.317	.689		1.317
× Latino				-6.115	**	2.141	.780		2.233	.820		2.233
× Minority				-5.258	**	1.872	1.996		1.992	2.015		1.993
× White-Black Multi.				-4.263	***	1.085	-1.481		1.111	-1.478		1.111
× White-Latino Multi.				-.697		1.312	2.524		1.341	2.531		1.341
× Other Multi.				-1.616		.896	.990		.926	1.001		.926
Disadvantage	.454	***	.048	.321	***	.047	.460	***	.048	.459	***	.048
Young males	.029	***	.004	.028	***	.005	.028	***	.005	.028	***	.005
Immigration	-.193	***	.035	-.160	***	.035	-.195	***	.035	-.194	***	.035
Renters	.008	***	.001	.009	***	.001	.008	***	.001	.008	***	.001
Vacant housing (ln)	.156	***	.025	.166	***	.025	.153	***	.025	.153	***	.025
Foreclosure rate (ln)	.067	**	.021	.116	***	.021	.065	**	.022	.065	**	.022
Population	.000	*	.000	.000	*	.000	.000	*	.000	.000	*	.000
Residential loans (ln)	-.418	***	.037	-.468	***	.037	-.416	***	.037	-.417	***	.037
Time	.047	***	.009	.051	***	.009	.050	***	.009	.049	***	.009
Ethno-Racial Nbhd Type												
Black	.012		.018	.009		.020	.013		.020	.013		.020
Latino	-.027		.026	-.029		.026	-.030		.026	-.031		.026
Minority	.009		.023	.018		.026	.018		.026	.018		.026
White-Black Multi.	-.026		.015	-.024		.016	-.028		.016	-.031	*	.016

White-Latino Multi.	.025		.016	.022		.017	.020		.017	.021		.017
Other Multi.	.017		.013	.023		.014	.014		.014	.014		.014
Gini	-.267	**	.092	-.389	**	.134	-.097		.150	-.114		.151
× Disadvantage	.342	***	.068				.419	***	.098	.401	***	.098
× Black				.492	*	.228	-.321		.296	-.319		.296
× Latino				.846		.466	.169		.491	.167		.491
× Minority				.031		.402	-.660		.433	-.618		.433
× White-Black Multi.				.538	*	.238	.251		.246	.262		.246
× White-Latino Multi.				-.291		.280	-.605	*	.289	-.589	*	.289
× Other Multi.				-.088		.192	-.332		.199	-.319		.199
Disadvantage	-.023	*	.010	-.016		.010	-.026	*	.010	-.024	*	.010
Young males	.003	**	.001	.003	**	.001	.003	**	.001	.003	**	.001
Immigration	-.008		.007	-.009		.007	-.006		.007	-.007		.007
Renters	.000		.000	.000		.000	.000		.000	.000		.000
Vacant housing (ln)	-.004		.005	-.004		.005	-.003		.005	-.003		.005
Foreclosure rate (ln)	.023	***	.004	.019	***	.003	.023	***	.004	.022	***	.004
Population	.000	*	.000	.000	*	.000	.000	*	.000	.000	*	.000
Residential loans (ln)	.004		.007	.007		.007	.004		.007	.004		.007
Δ Gini	.087		.086	.247		.162	.222		.162	.204		.162
× Δ Disadvantage	.375	*	.149							.354	*	.150
× Black				-.260		.239	-.216		.239	-.207		.239
× Latino				-.173		.402	-.133		.402	-.076		.403
× Minority				-.139		.392	-.112		.392	-.031		.394
× White-Black Multi.				.270		.296	.300		.296	.302		.296
× White-Latino Multi.				-.335		.298	-.301		.298	-.318		.298
× Other Multi.				-.469		.252	-.395		.253	-.359		.253
Δ Disadvantage	.049	***	.013	.044	**	.013	.043	**	.013	.046	***	.013
Δ Young males	.001		.001	.001		.001	.001		.001	.001		.001
Δ Immigration	.017	*	.009	.017	*	.009	.017		.009	.016		.009
Δ Renters	.003	***	.000	.003	***	.000	.003	***	.000	.003	***	.000
Δ Vacant housing (ln)	-.005		.003	-.006		.003	-.005		.003	-.005		.003
Δ Foreclosure rate (ln)	.024	***	.004	.021	***	.004	.024	***	.004	.024	***	.004
Δ Population	.000		.000	.000		.000	.000		.000	.000		.000
Δ Residential loans (ln)	-.012		.006	-.012		.007	-.014	*	.007	-.014	*	.007

Time²	-.005	***	.001	-.005	***	.001	-.005	***	.001	-.005	***	.001
Ethno-Racial Nbhd Type												
Black	-.001		.001	.000		.001	.000		.001	.000		.001
Latino	.000		.002	.001		.002	.001		.002	.001		.002
Minority	.000		.002	-.001		.002	-.001		.002	-.001		.002
White-Black Multi.	.001		.001	.001		.001	.001		.001	.002		.001
White-Latino Multi.	-.002		.001	-.001		.001	-.001		.001	-.001		.001
Other Multi.	-.001		.001	-.001		.001	.000		.001	.000		.001
Gini	.008		.006	.013		.009	-.005		.010	-.004		.010
× Disadvantage	-.020	***	.005				-.025	***	.007	-.024	***	.007
× Black				-.034	*	.015	.015		.020	.015		.020
× Latino				-.044		.031	-.004		.033	-.004		.033
× Minority				.017		.028	.058		.030	.055		.030
× White-Black Multi.				-.031		.016	-.014		.017	-.015		.017
× White-Latino Multi.				.021		.019	.040	*	.020	.039	*	.020
× Other Multi.				.012		.013	.026		.014	.026		.014
Disadvantage	.002	**	.001	.002	**	.001	.002	***	.001	.002	**	.001
Young males	.000	**	.000	.000	**	.000	.000	**	.000	.000	**	.000
Immigration	.000		.001	.000		.001	.000		.001	.000		.001
Renters	.000		.000	.000		.000	.000		.000	.000		.000
Vacant housing (ln)	.000		.000	.000		.000	.000		.000	.000		.000
Foreclosure rate (ln)	-.001	***	.000	-.001	***	.000	-.001	***	.000	-.001	***	.000
Population	.000	*	.000	.000	*	.000	.000	*	.000	.000	*	.000
Residential loans (ln)	.000		.000	.000		.000	.000		.000	.000		.000
Δ Gini	-.003		.006	-.008		.011	-.006		.011	-.005		.011
× Δ Disadvantage	-.023	*	.010							-.021	*	.010
× Black				.006		.016	.004		.016	.003		.016
× Latino				.005		.027	.002		.027	-.001		.027
× Minority				.001		.027	-.001		.027	-.005		.027
× White-Black Multi.				-.022		.020	-.024		.020	-.024		.020
× White-Latino Multi.				.005		.020	.003		.020	.004		.020
× Other Multi.				.029		.017	.025		.017	.023		.017
Δ Disadvantage	-.002	*	.001	-.001		.001	-.001		.001	-.002		.001

Δ Young males	.000		.000		.000		.000		.000		.000		.000		.000	
Δ Immigration	-.001		.001		-.001		.001		-.001		.001		-.001		.001	
Δ Renters	.000	***	.000		.000	***	.000		.000	***	.000		.000	***	.000	
Δ Vacant housing (ln)	.000		.000		.000		.000		.000		.000		.000		.000	
Δ Foreclosure rate (ln)	-.001	***	.000		-.001	***	.000		-.001	***	.000		-.001	***	.000	
Δ Population	.000		.000		.000		.000		.000		.000		.000		.000	
Δ Residential loans (ln)	.000		.000		.000		.000		.000		.000		.000		.000	
Variance (SD)																
Intercept	0.564		n/a		.571		#####		.563		9.442		.563		3.220	
Time	.036	***	.003		.036	***	.003		.036	***	.003		.036	***	.003	
$Time^2$	.002	***	.000		.002	***	.000		.002	***	.000		.002	***	.000	

Note. *p < .05, **p < .01, ***p < .001.

comparing Figures 4.10 and 4.11, which present predicted burglary rates over 1999-2013 when initial relative inequality is at low, average, and high values within White neighborhoods and Black neighborhoods, respectively.

Violence. In this section, I refit all the models estimated for burglary in the previous section using the combined homicide and robbery rate as the dependent variable. The results are similar, so in what follows I devote most of my attention to areas where there are notable differences. I encourage curious readers to carefully review Table 4.5, which presents the results of the latent growth curve models for homicide and robbery rates, and Figures 4.12 through 4.22, whose contents are described below.

Figure 4.12 presents exponentiated predictions of homicide and robbery rates over 1999-2013 estimated from the unconditional model. Like the burglary rate trend, homicide and robbery rates rose at a slowing pace from 1999 through 2005 and then declined at a growing pace through 2013. In Figure 4.13, which presents unadjusted violent crime rate trajectories by ethno-racial neighborhood type, all six non-White neighborhood categories had a higher average violent crime rate intercept than did White neighborhoods. Compared with the trend in White areas, homicide and robbery rates

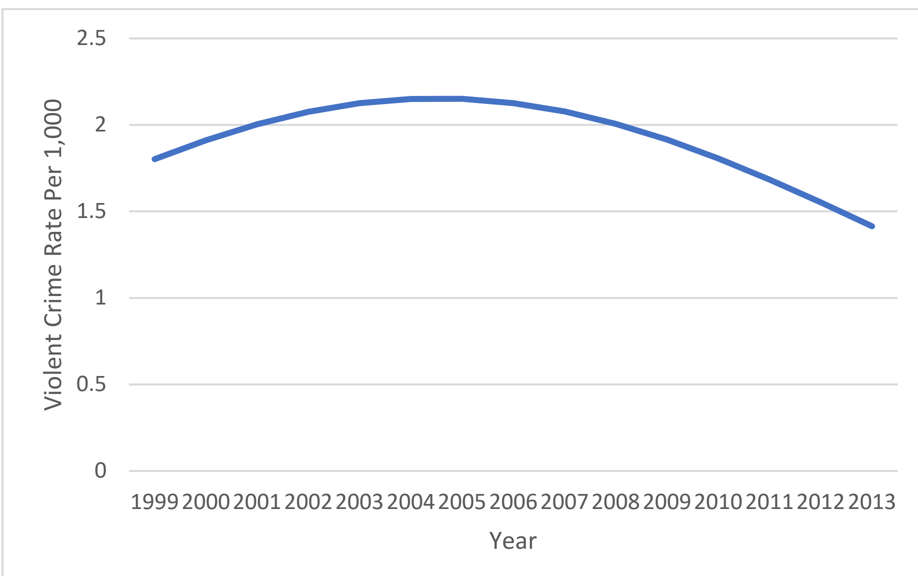

Figure 4.12. Predicted Unadjusted Average Tract Violent Crime Rates, 1999-2013.

in White-Black multiethnic neighborhoods rose more gradually at the period start while in Latino neighborhoods violent crime rates declined; and during the later years of the period most areas saw slower declines in homicide and robbery than did White neighborhoods.

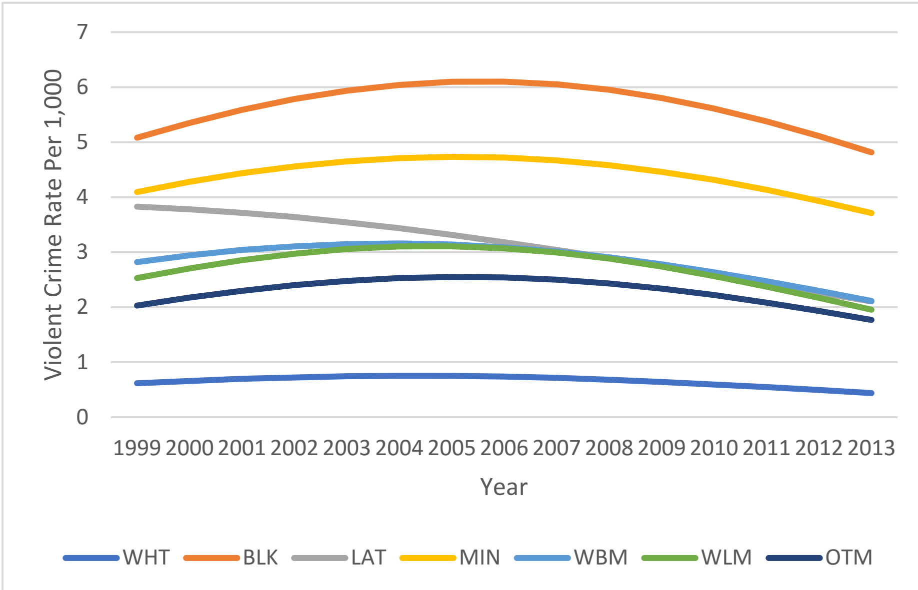

Figure 4.13. Predicted Unadjusted Average Tract Violent Crime Rates by Ethno-Racial Neighborhood Type, 1999-2013.

Net of all key independent and control variables, the effects of initial levels and changes in relative inequality and disadvantage on violent crime trends are similar to those for burglary, with one exception. The starting level of the Gini index was associated with a more rapid crime decline during the later years of the period for

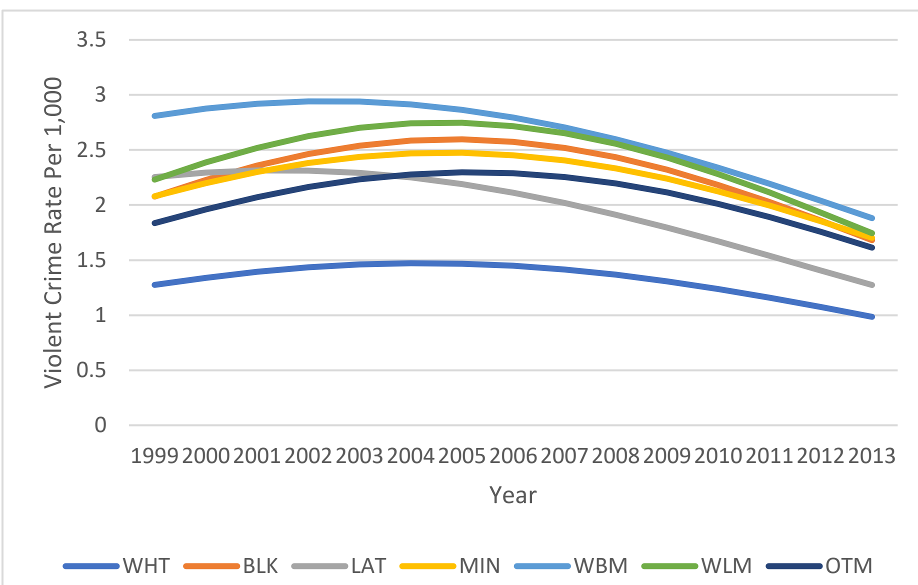

Figure 4.14. Predicted Average Tract Violent Crime Rates by Ethno-Racial Neighborhood Type, Adjusted for Controls, 1999-2013.

burglary, but for homicide and robbery higher initial relative inequality predicted slower growth in violence at the period start. Reexamining differences in growth curves by neighborhood ethno-racial composition, the multiethnic and segregated non-White neighborhoods still have higher average violent crime intercepts than White neighborhoods, but the differences in the shape of their growth curves are modest in the sample and no longer statistically different from 0 (see Figure 4.14).

I now consider the interactions between relative inequality and disadvantage, assessing first the interactions between initial values. Unlike with the burglary rate curves, where only the starting level was affected by the interaction effect, with the homicide and robbery rate the intercept, time and time-squared terms are all significantly impacted.

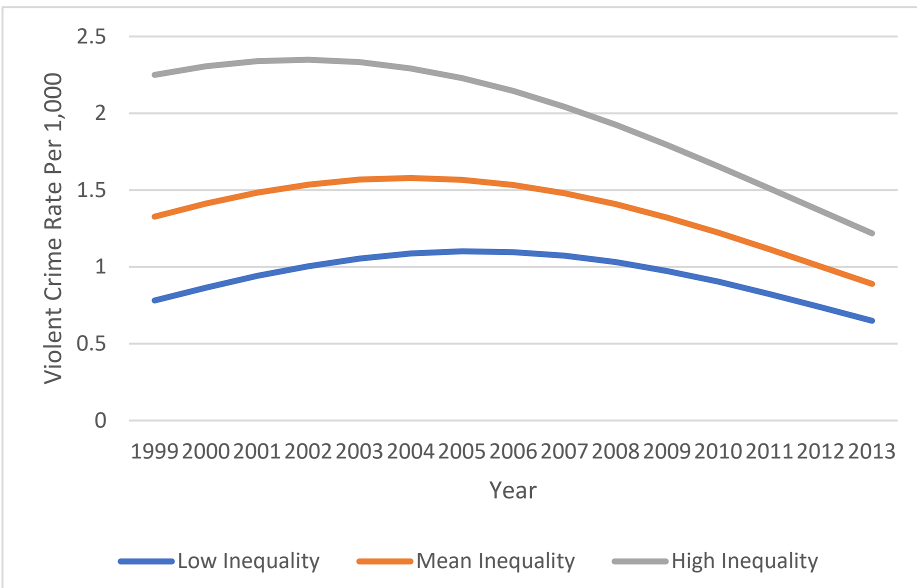

Figure 4.15. Predicted Average Tract Violent Crime Rates at Low, Average, and High Initial Levels of the Gini Index, When Initial Disadvantage Was Low, 1999-2013.

This dynamic is illustrated in Figures 4.15 through 4.17, which present predicted homicide and robbery rates over 1999-2013 when the initial disadvantage level is low, average, and high across figures and when initial relative inequality is low, average, and high within figures. Comparing trends within and between figures reveals that the impacts of income inequality on the growth curve's starting value and initial ascent rate diminish as

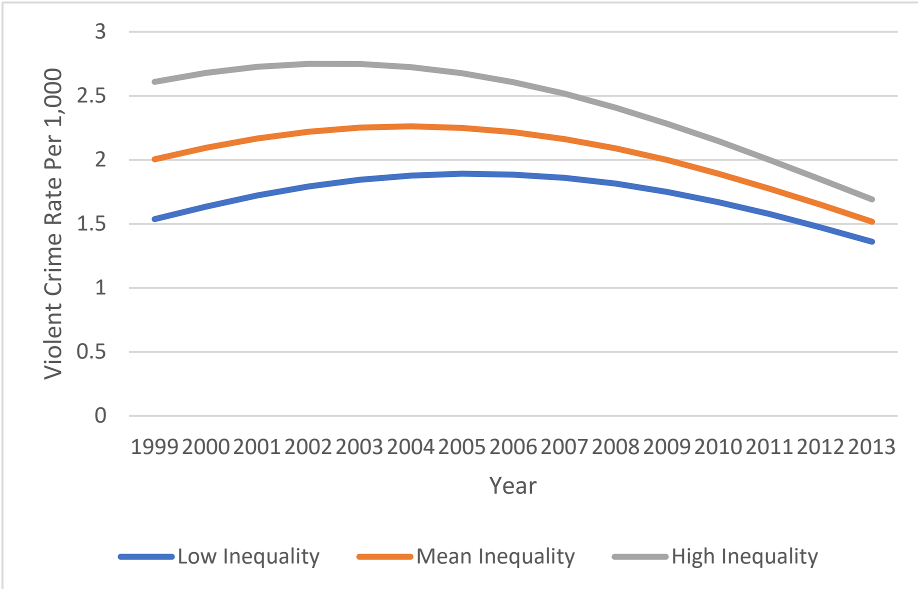

Figure 4.16. Predicted Average Tract Violent Crime Rates at Low, Average, and High Initial Levels of the Gini Index, When Initial Disadvantage Was Average, 1999-2013.

disadvantage rises; in fact, in areas with above-average initial disadvantage the growth curves across different inequality levels have nearly identical intercepts and linear slopes. They differ most in their curvilinear rate of decline, which is much faster in areas where relative inequality was already high at the start of the period. Turning to the change score interactions next, the dynamic can be observed by comparing trend lines in any of Figures 4.18 through 4.20, which present growth curves by low, average, and high disadvantage change scores within the Figures and by low, average, and high Gini index

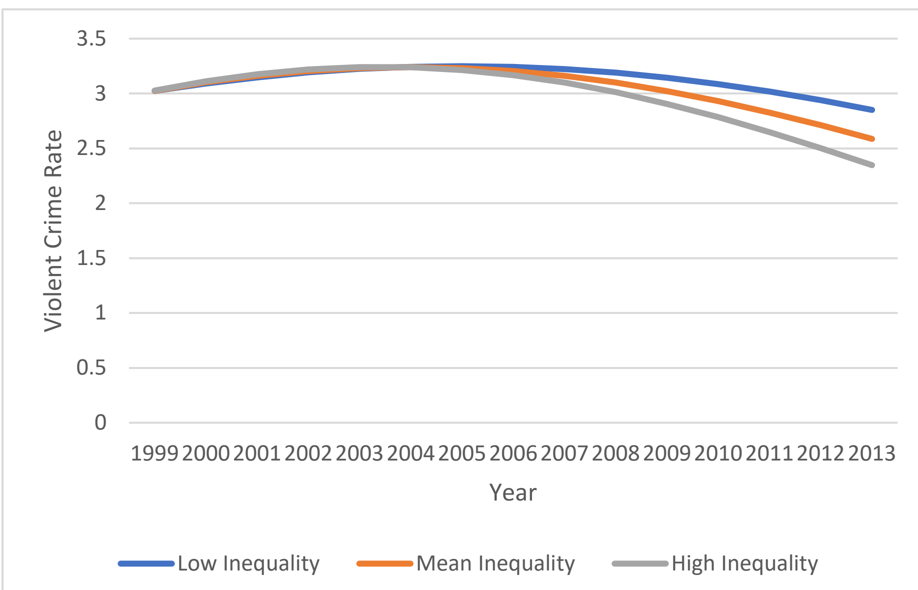

Figure 4.17. Predicted Average Tract Violent Crime Rates at Low, Average, and High Initial Levels of the Gini Index, When Initial Disadvantage Was High, 1999-2013.

change scores across them. Like the corresponding results for burglary, neighborhoods where disadvantage rose by at least the average quantity of change had crime rates that ascended and descended more quickly than in neighborhoods where disadvantage decreased.

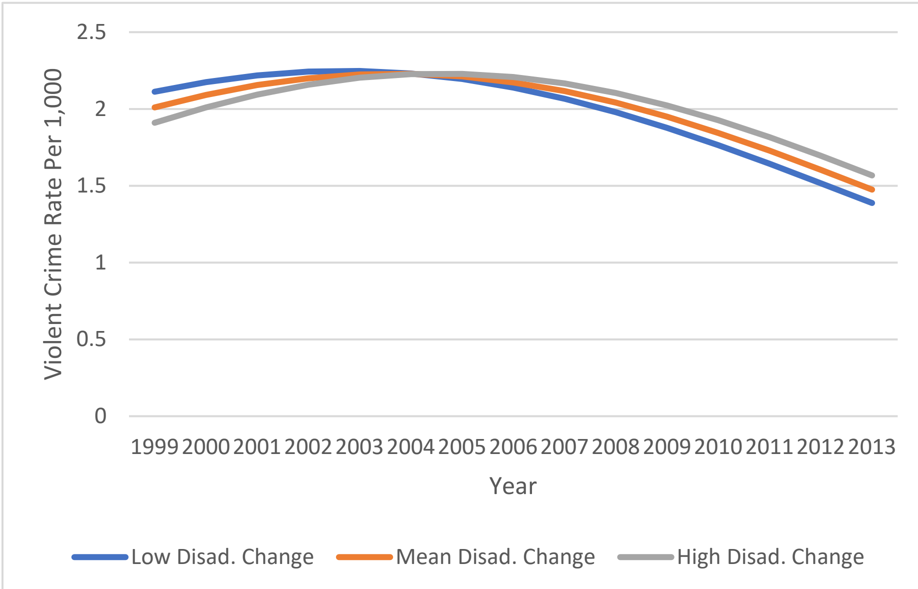

Figure 4.18. Predicted Average Tract Violent Crime Rates at Low, Average, and High Levels of Change in Disadvantage, When Gini Index Change Was Low (i.e., Relative Inequality Decreased), 1999-2013.

Examining the interactions between relative inequality and ethno-racial neighborhood type next, I again find that the elevating effect of initially higher levels of the Gini index on the intercept is lesser in most communities compared with

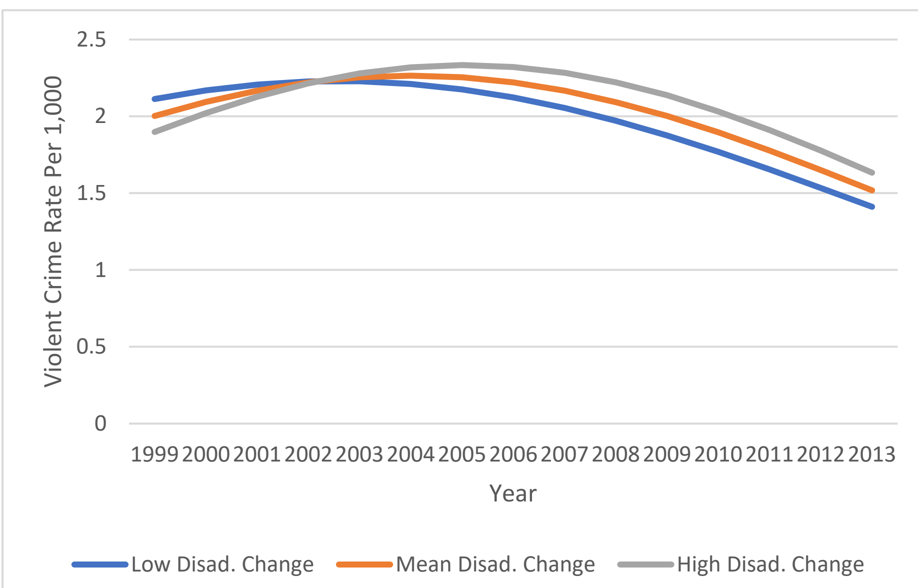

Figure 4.19. Predicted Average Tract Violent Crime Rates at Low, Average, and High Levels of Change in Disadvantage, When Gini Index Change Was Average (i.e., Relative Inequality Increased Modestly), 1999-2013.

White neighborhoods (in fact, associated with a lower average intercept in predominantly

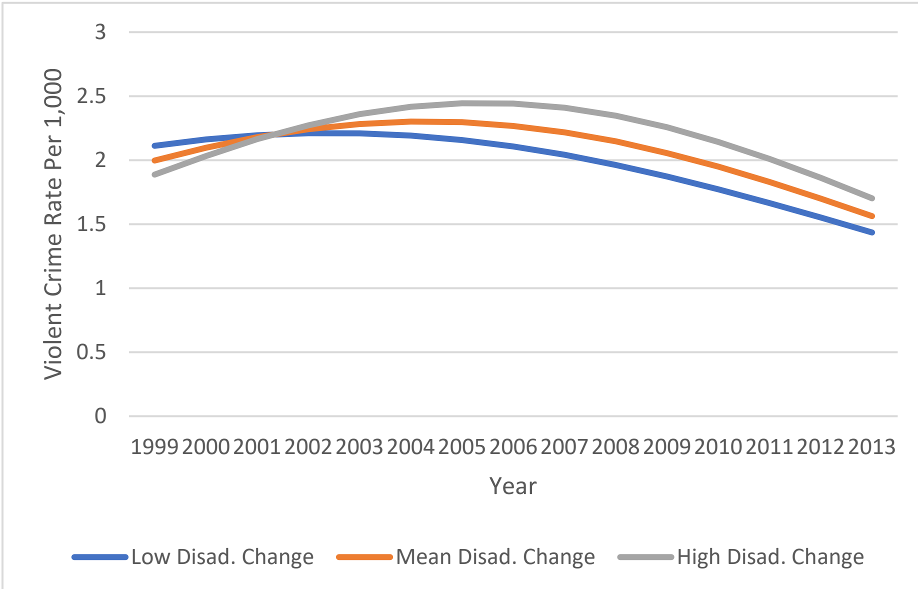

Figure 4.20. Predicted Average Tract Violent Crime Rates at Low, Average, and High Levels of Change in Disadvantage, When Gini Index Change Was High (i.e., Relative Inequality Increased Greatly), 1999-2013.

Black neighborhoods). Unique to the violent crime rate growth curves, three other interactions merit attention. While a higher level of initial relative inequality predicted a more gradual ascent in homicide and robbery rates in White neighborhoods at the start of the period, the opposite was true in segregated Black and White-Black multiethnic neighborhoods, where a greater starting level of income disparity was associated with a steeper ascent in violence. Moreover, in Black neighborhoods that began the period with greater relative inequality, the deceleration of growth and reversal to falling violent crime rates that characterized all neighborhoods occurred at an even faster rate.

Finally, when I include the Gini index by disadvantage interactions in the last model, all of the aforementioned differences in the impact of relative inequality by neighborhood type are rendered null. The elevating effect of initial income inequality on the violent crime rate intercept is comparable across neighborhood types and its impact on the linear time and time-squared parameters is similar between White neighborhoods and Black or White-Black multiethnic neighborhoods. However, there is now a significant difference for White-Latino multiethnic neighborhoods. The coefficients suggest that compared with White neighborhoods, a higher starting level of relative inequality is associated with a more modest initial ascent of homicide and robbery that more gradually slows and reverses direction in White-Latino multiethnic neighborhoods. This difference can be observed in Figures 4.21 and 4.22, which depict predicted homicide and robbery rate growth curves

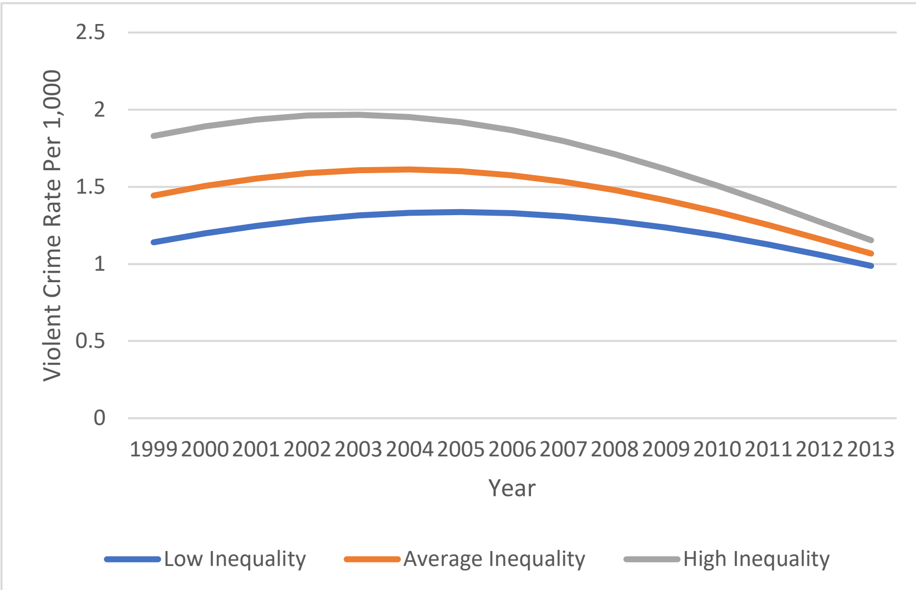

Figure 4.21. Predicted Average Tract Violent Crime Rates at Low, Average, and High Initial Levels of the Gini Index in White Neighborhoods, Adjusted for the Interactions Between Initial Levels and Changes in Relative Inequality and Disadvantage, 1999-2013.

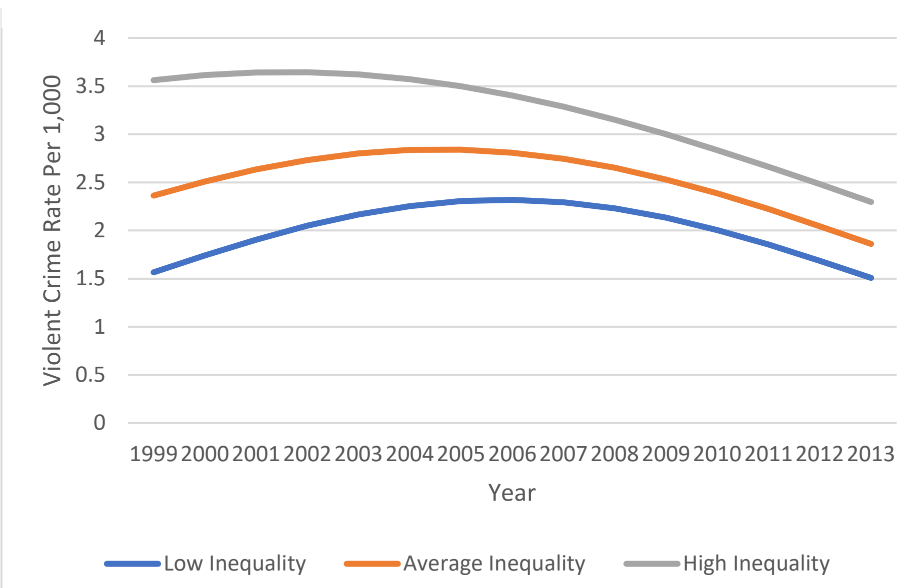

Figure 4.22. Predicted Average Tract Violent Crime Rates at Low, Average, and High Initial Levels of the Gini Index in White-Latino Multiethnic Neighborhoods, Adjusted for the Interactions Between Initial Levels and Changes in Relative Inequality and Disadvantage, 1999-2013.

when initial relative inequality is at low, average, and high levels in White and White-Latino multiethnic neighborhoods, respectively.

Conclusion

Did initial and changing levels of relative inequality differentially affect crime trends across neighborhoods of different colors during the 2000s decade? And if so, were these uneven effects the result of varying distributions of initial and changing levels of disadvantage—that is, does the inequality-disadvantage interaction matter over time? Past work has considered how changes in economic inequality have affected race- or ethnicity-specific changes in crime rates (LaFree & Drass, 1996; Light & Ulmer, 2016; Messner et al., 2001) and analyzed longitudinal impacts at the neighborhood level during the 2000s (Hipp & Kubrin, 2017), but to my knowledge no prior study has documented variation in the impact of initial or changing levels of relative inequality on crime trajectories between neighborhoods of different ethno-racial compositions or explored sources of this variation. The current chapter contributes to this gap by extending my arguments from Chapter 3 to a longitudinal framework.

Specifically, I maintained that high or increasing levels of both relative inequality and structural disadvantage may accelerate the pace of rising crime trends (or decelerate declining trends) by raising the prevalence of unfavorable social comparison, depleting forms of social capital essential to warding off crime, or drawing together motivated offenders and suitable targets into more regular proximity. If so, then initial and changing levels of relative inequality may have had lesser impacts on crime trends in communities that already began the decade with high levels of disadvantage or saw their levels sharply rise. Since neighborhoods with larger shares of Black and Latino residents were more likely to experience these conditions during the 2000s, such a dynamic could potentially account for weaker effects of relative inequality on crime trends in those areas. I tested my hypotheses by analyzing longitudinal data from the NNCS2-P, which permitted estimating the effects of initial and changing levels of the Gini and disadvantage indices on latent growth curves of property and violent crime rates over 1999-2013 in 28 cities and 2,757 census tracts. The results can be summarized in four sets of findings.

First, although I expected that initial and change values of relative inequality would be positively associated with crime change, the results were more complicated. My first hypothesis was based on what prior longitudinal research has found on the impact of disadvantage on neighborhood crime change, but in fact only initial levels of relative inequality and change in disadvantage were associated with a more rapid ascent in crime during the early 2000s, while initial disadvantage levels predicted a slower rise in crime. Moreover, during the later years of the period when crime rates were falling, initial levels of relative inequality and change in disadvantage accelerated this decline, while starting levels of disadvantage tempered it. In short, for both property and violent crime rates, initial relative inequality and change in disadvantage led to more *extreme* (taller, narrower) growth curves, and initial disadvantage led to more *moderate* (shorter, wider) growth curves. It is possible some neighborhoods that began the period high in disadvantage already had high crime levels that were less likely to either rise or fall by large amounts compared with other areas, and thus had crime trajectories characterized more by stability than change over the decade (Krivo et al., 2018). Notably, changes in relative inequality were not associated with changes in either property or violent crime trends, possibly because of the modest amount of change in the Gini index observed in my sample during the 2000s decade (see Table 4.2).

My second hypothesis, that the positive association of initial or changing levels of relative inequality with crime change would be diminished in neighborhoods that had high or increasing levels of disadvantage, was also only partially supported. For example, I found that in neighborhoods with initially high disadvantage, areas with different initial relative inequality levels had nearly overlapping violent crime growth curves, trends that diverged only during the later years of period when the homicide and robbery rate began to decline. Other patterns, however, suggest relative inequality amplified the main effects of disadvantage rather than attenuating them. For the burglary rate, the effect of initial levels of disadvantage in making the growth curve shorter and wider was somewhat greater in neighborhoods where initial levels of relative inequality were also high; and for both violent and property crime rates, the effect of rising disadvantage on making growth curves taller and narrower was slightly increased in areas where relative inequality also rose. Taken together with their main effects, it appears that initial and changing levels of relative inequality, and changes in disadvantage, tended to contribute to greater *volatility* in crime rates over the 2000s decade, raising the likelihood that neighborhoods experienced more rapid ascents in crime during the earlier years before seeing these trends quickly reverse direction and fall more sharply downward. Conversely, higher initial levels of disadvantage appeared to predict greater *stability* in crime trends that were resistant to effects of initial or changing levels of relative inequality.

My remaining hypotheses proposed that the influence of initial and changing levels of relative inequality on crime change would be lesser in segregated non-White neighborhoods compared with White neighborhoods, but that the interaction terms indicating this difference would reduce to non-significance after controlling for the interactions between initial and changing levels of relative inequality and disadvantage. In this case, the results departed from my expectations considerably. Before adjusting for the inequality-disadvantage interactions, the only difference I detected was for initial levels of relative inequality on the homicide and robbery rate growth curve in Black and White-Black multiethnic neighborhoods – and the direction of the sign for the interactions indicated relative inequality was associated with more, not less, extreme violent crime rate growth curves in those areas. After adjusting for the inequality-disadvantage interactions, the significant interaction terms for Black and White-Black multiethnic neighborhoods vanished, replaced by significant interaction terms in White-Latino multiethnic neighborhoods indicating that initial relative inequality was associated with a more moderate growth curve. What's more, for the burglary rate, the initial relative inequality by Black neighborhoods interaction terms in the final model suggest that Black neighborhoods that started the period with higher relative inequality had taller, narrower growth curves than did White neighborhoods. The more modest trends in neighborhoods with higher shares of Latinos aligns with some extant perspectives (e.g., Burchfield & Silver, 2013; Wright et al., 2016), but the shaper impact of initial relative inequality in Black neighborhoods is surprising, and I return to this point in this dissertation's concluding chapter.

Finally, there were several secondary findings that corroborate my findings from Chapter 3. To this point I have focused on the associations of initial and changing levels of relative inequality and disadvantage on crime change, captured by the linear time and time-squared parameter estimates of the growth curve models. Turning now to the consequences of initial relative inequality for the violent and property crime model intercepts, I found that relative inequality elevated the intercept to a lesser degree in segregated non-White and in some multiethnic neighborhoods than in predominantly White neighborhoods, but net of the inequality-disadvantage interaction term (itself negative in direction), these associations reduced to non-significance. Thus, I uncovered a pattern of findings identical to those reported in Chapter 3, even when using a slightly different sample and analytic strategy. Moreover, in the previous chapter I found that relative inequality sometimes has a protective effect (e.g., having a negative association with crime in Black neighborhoods before adjusting for the inequality-disadvantage interaction). This protective effect occasionally reappears in the present chapter. For instance, the taller, narrower burglary rate growth curves resulting from higher initial relative inequality in Black neighborhoods meant that Black neighborhoods that had above-average relative inequality in 1999 had *lower* burglary rates post-2010 than did Black neighborhoods that started the period with average or below-average relative inequality (see Figure 4.11). Additionally, I observed that areas with above-average initial relative inequality and disadvantage had *lower* property and violent crime rates during at least some years of the 1999-2013 timeframe than did areas that began the period with similarly high levels of disadvantage but with average or below-average initial levels of relative inequality (see Figures 4.6 and 4.17).

The present study thus aligns with the conclusion from past work that how structural factors contribute to disparities in neighborhood crime change depend on the factors, time periods, and offense types under consideration (Busik & Webb, 1982; Kikuchi & Desmond, 2010; Kubrin & Herting, 2003; Krivo et al., 2018). This emphasis holds for the relative inequality-disadvantage interaction as well. Jointly considering their main and interactive effects, initial and changing levels of relative inequality and changing levels of disadvantage contributed to more volatility in neighborhood crime change during the 2000s decade, pressuring crime trends into sharper upswings and downswings, whereas higher initial levels of disadvantage tended to "pin" neighborhoods down at high and stable levels of crime. Starting levels of relative inequality also sometimes had uneven effects on crime trends between neighborhoods of different colors, but not in a straightforward manner. My findings point to the importance of analyzing the racial structure of neighborhood criminal inequality and its factors dynamically, as how urban communities have changed or held steady over a specific period plays a significant role in upholding the racial hierarchy in power and resources and, therefore, exposure to crime and violence (Lyons et al., 2022). They also demonstrate the complexities of interactions of relative inequality with other structural features of the urban landscape in shaping neighborhood crime. Is it possible that relative inequality interacts not only with neighborhood disadvantage, but also with economic, political, and civic life dimensions at higher levels of aggregation (Burraston et al., 2018; Wenger, 2019) – at the city level, in particular? I turn to this final question of my dissertation in the next chapter.

5. ARE RELATIVE INEQUALITY EFFECTS ON NEIGHBORHOOD CRIME STRONGER IN SOME CITIES THAN OTHERS?

In the previous two chapters, I have explored whether disadvantage moderates the relative inequality and neighborhood crime relationship and whether this dynamic accounts for apparent variation in the effect of inequality by neighborhoods of different colors. I have shown that structural disadvantage dampens the impact of relative inequality on neighborhood crime at a single time point, and I find mixed evidence that this interaction also shapes trajectories of crime change over time. So far, I have neglected the possible conditioning effects of city-level factors on neighborhood relative inequality, treating urban area characteristics strictly as controls. Yet prior work with the NNCS reveals that features of the broader urban context can shape relationships between local area conditions and crime in ways that are important for understanding neighborhood criminal inequality (Krivo et al., 2009; Lyons et al., 2013; Vélez et al., 2015). Several extant studies document that income inequality's effects on crime vary by other markers of socioeconomic composition, including income segregation at the city level (Hipp, 2011) and disadvantage at the county level (Burraston et al., 2018), and one multilevel assessment found that income disparity at more highly aggregated levels (e.g., the census tract or city) moderates income disparity effects on crime at lower levels of aggregation (e.g., the census block group) (Wenger, 2019). To date, however, there remains minimal investigation into whether a wider set of urban structural characteristics conditions the impact of relative inequality on neighborhood crime.

In this chapter, I develop hypotheses around three city-level constructs I suspect moderate the relative inequality and neighborhood crime relationship: racial residential segregation, minority political empowerment, and community organizational capacity. In short, I argue that residential segregation and the prevalence of community-oriented nonprofits render economic inequality within neighborhoods less salient to their social organization, while minority political empowerment enhances neighborhood residents' willingness and ability to work collectively to address mutual problems even in the presence of income disparities. I assess these propositions by analyzing a cross-sectional sample of the 2010-2013 NNCS2 data supplemented with information on Black and Latino city elected officials drawn in part from the National Association of Latino Elected Officials (NALEO), Black and Latino sworn police officers from the Law Enforcement Management and Administrative Statistics (LEMAS) database, and community nonprofit organizations from the National Center for Charitable Statistics (NCCS). In what follows, I provide a brief overview of the literature on each city characteristic before elaborating on why I think that factor will decrease the impact of relative inequality on neighborhood crime.

Racial Residential Segregation

Urban sociologists have long recognized a connection between racial residential segregation and elevated levels of crime and disorder in minority neighborhoods (Du Bois, [1889] 1973; Park & Burgess, [1925] 2019; Shaw & McKay, 1942; Wilson, 1987). This relationship occurs because, despite ubiquitous colorblind frames that posit segregation as natural and innocuous in the post-civil rights period (Bonilla-Silva, 2014), racial residential segregation is a fundamental driver of unequal neighborhood conditions (Massey & Denton, 1993; Sampson, 2012). Housing segregation locates the highest quality and most desirable goods, services, jobs, and public amenities disproportionately in predominantly White neighborhoods; lures the bulk of investment into already affluent areas; concentrates racial inequalities produced across other institutions into racially distinct communities of (dis)privilege; and impedes the mobility of residents of color into the most frequently visited urban hubs (Krivo et al., 2009; Peterson & Krivo, 2010a; Sampson & Levy, 2020). Moreover, residential segregation is persistent. Although some urban neighborhoods have diversified over the last few decades, this pattern has been uneven—with cities with large Black and Latino populations being the least likely to diversify—and stalled in the wake of the global financial crisis as foreclosures forced many minority homeowners to become renters in more segregated neighborhoods (Hall et al., 2016, 2018).

Yet despite its criminogenic nature, racial residential segregation may temper the positive association between neighborhood-level relative inequality and crime. Residential segregation draws together people of the same racial or ethnic groups irrespective of other status characteristics, including income (Firebaugh & Acciai, 2016; Fry & Taylor, 2012), and in this way may reduce the salience of class divisions compared with other axes of social demarcation. A lowered significance placed on income disparity may, in turn, alter community social ties in ways that reduce unfavorable social comparisons, boost social organization, or reconfigure routine activities to guard against crime. Patillo-McCoy's (1999) ethnography of the Chicago neighborhood of Groveland illustrates one example of this dynamic. As she observes, not only do middle class Black areas of segregated cities often serve as a "buffer" between affluent White neighborhoods and poor Black neighborhoods (thus co-locating lower- and higher-income Black residents in some areas), but residents within Black middle class neighborhoods sometimes cooperate with their neighbors involved in organized crime to maintain social order according to a "negotiated coexistence" model (Browning, 2009). For Blacks or Latinos living in areas with greater shares of poor or working-class residents, their concentration in structurally disadvantaged neighborhoods and related experiences of discrimination may trigger perceptions of linked fate (Gay, 2004; Sanchez & Masuoka, 2010), further eroding the status gap argued to account for the relationship between localized income disparity and crime (Chamberlain & Hipp, 2015; Hipp & Kubrin, 2017).

Importantly, my argument does not require that social capital within segregated neighborhoods necessarily be oriented against crime, as strong ties between neighbors of different class backgrounds may in fact work against the elimination of all crime in a community (Browning, 2009; Patillo, 1998). Rather, I only hypothesize that these ties will reduce the salience of local income inequality, leading to a diminished effect on crime. Thus, my first hypothesis is as follows:

> H1: The cross-level interaction effect between city-level racial residential segregation and neighborhood relative inequality will be negative, such that relative inequality has smaller effects on crime in cities that are more highly segregated by race or ethnicity.

Minority Political Empowerment

Minority political empowerment is the achievement of representation and influence in political decision making by a minority racial or ethnic group (Bobo & Gilliam, 1990; Merolla et al., 2013). Prior research on minority political empowerment can be divided broadly into two bodies of work. The first centers *descriptive representation*, or the extent to which the racial makeup of an elected position or body reflects its constituency, and explores how the representation of non-White groups affects minority political attitudes, behavior, or outcomes. In a landmark study, Bobo and Gilliam (1990) found that African Americans were more politically active in cities with a Black mayor and suggested that having a co-racial representative signified likely policy responsiveness to Blacks' concerns, elevating their belief that they could participate meaningfully in the institutionalized political process. A sizeable body of work has supported Bobo and Gilliam's thesis, finding that descriptive representation of Blacks among elected officials is associated with increased Black political participation (Gay, 2001; Uhlaner & Scola, 2016; Whitby, 2007) or political efficacy attitudes (Gleason & Stout, 2014; Merolla et al., 2013). Other work suggests descriptive representation extends to Latinos, with the presence of Latino mayors and legislators found to elevate Latino voter turnout and decrease political alienation (Barreto, 2007; Pantoja & Segura, 2003; Schildkraut, 2013). Extant scholarship also finds that empowerment effects tend to be stronger at more local levels (Hayes et al., 2022) and can fade over time if minority constituents become disillusioned with the ability of descriptive representatives to address the concerns of their group (Gilliam & Kaufmann, 1998; Spence et al., 2009).

A related line of research argues that beyond merely symbolizing policy responsiveness, descriptive representatives can provide substantive benefits to co-racial or co-ethnic constituents (Preuhs, 2006; Marschall & Ruhil, 2007; Jeong, 2013). As examples, Marschall and Ruhil (2007) reported that greater representation by Blacks in city hall and on school boards was associated with more positive assessments of neighborhood conditions and public services by Black residents, and Jeong (2013) noted the greater political engagement by Latinos in states with more pro-immigrant policies (e.g., the presence of Limited English Proficiency programs, level of welfare benefits provided to legal immigrants, and coverage for immigrants under state-sponsored healthcare programs). Scholars are careful to emphasize, however, that substantive representation of minority interests does not automatically follow the election of descriptive representatives. Exploring their motivations for pursuing the substantive policy interests of key groups, scholars have found that minority elected officials often have shared experiences of discrimination and feel a sense of responsibility toward co-racial or co-ethnic constituents (Broockman, 2013; Sobolewska et al., 2018). Yet they are also motivated to win over and retain minority voters, a goal that declines in significance as descriptive representatives advance in their careers, gaining credibility and becoming more interested in other policy or legislative priorities (Bailer et al., 2022).

The second body of work centers *bureaucratic incorporation*, or the incorporation of racial or ethnic minority concerns by civil service agencies. This line of work has shown that in many suburban and rural areas, where immigrant populations are smaller and hold less political capital, public service bureaucrats have taken the lead in responding to immigrants' needs, motivated by a professional ethos that stresses collaboration with clients in the improvement of service delivery (Jones-Correa, 2008; Marrow, 2009). Even in large urban areas, bureaucrats may be pressured into more inclusive service delivery by immigrant advocacy organizations and demographically diverse local legislatures (de Graauw & Vermeulen, 2022). While studies in this vein have focused on several different service agencies, including school districts and public health departments (Jones-Correa, 2008; Lanesskog et al., 2021), the bulk of the work has examined minority bureaucratic incorporation in police departments. This focus is due to the high level of discretion policing enjoys compared to other bureaucratic agencies, the relative independence of police departments from control by elected officials, and the regular and conspicuous contact police officers have with the public (Lewis & Ramakrishnan, 2007). Indeed, most studies that explore Black bureaucratic incorporation consider law enforcements' responsiveness to African Americans' concerns about policing (Pickett et al., 2024; Sharp, 2014; Theobald & Haider-Markel, 2008), often by assessing the impact of Black representation on police forces. In a recent set of survey-embedded experiments, for example, Pickett et al. (2024) found that many Black Americans fear police mistreatment but are less afraid when hypothetical police encounters involve Black or Latino officers instead of White officers.

Why would I expect minority political empowerment to weaken the impact of relative inequality on crime? If localized income inequality raises social distance between residents and thereby lowers neighborhood social organization, descriptive representation and bureaucratic incorporation may offset this effect. As described above and in extant work, minority elected officials and civil service staff can work to provide higher quality and more culturally appropriate services, improve relationships between constituents and city officials, and invest a more equitable share of city funds into public projects or contracts with vendors located in segregated neighborhoods of color (Velez et al., 2015). These actions can elevate social organization against crime even in contexts with weak or infrequent ties among residents by, for example, generating partnerships between businesses and police, creating spaces for discussion and mobilization against shared problems, and promoting the involvement of youth in prosocial activities (Bellair, 1997; Sharkey, 2018). Minority political empowerment may dampen localized income inequality effects on crime even where the impact is mostly symbolic. As Marschall and Ruhil (2007) found, merely having descriptive representatives in city hall and on school boards predicted greater satisfaction with neighborhood conditions and public services among African Americans, and these attitudes are themselves associated with a greater willingness to participate in informal social control behaviors (Silver & Miller, 2004).

I therefore expect the following:

H2: The cross-level interaction effect between city-level descriptive representation and neighborhood relative inequality will be negative, such that relative inequality has smaller effects on crime in cities with elected officials that are more representative of the population's Black and Latino composition.

H3: The cross-level interaction effect between city-level bureaucratic incorporation by police departments and neighborhood relative inequality will be negative, such that relative inequality has smaller effects on crime in cities with police forces that are more representative of the population's Black and Latino composition.

Community Organizational Capacity

The final construct I expect to condition the neighborhood relative inequality and crime relationship is a city's rate of community organizations. My focus on this potential moderator is drawn from the prominent role of local institutions in social disorganization theory. Local institutions have long been thought to mediate the relationship between community conditions and crime by structuring the regular interaction patterns of residents (Peterson et al., 2000). Institutions that are prevalent, well-resourced, and integrated with mainstream urban life may help keep crime rates low by socializing residents to participation in conventional activities like work or school, providing legitimate routes to valued goals, and offering oversight over resident conduct (Bursik & Grasmick, 1993; Kornhauser, 1978; Wilson, 1987). They may also foster foundational levels of social cohesion that underlie mutual expectations for participation in informal social control, serve as forums from which to address shared problems, and "bridge" residents to extra-local resources that can shore up neighborhood social organization (Kubrin et al., 2011; Lee & Ousey, 2005; Morenoff et al., 2001).

However, empirical evidence for the suspected negative association between local institutional capacity and crime is mixed. The relationship appears to be conditional, notably by organization type and neighborhood context. As an example of the former, religious institutions may diminish homicide rates in rural areas (Lee, 2006), and recreation centers appear to buffer the impact of structural disadvantage on violence (Peterson et al., 2000). Meanwhile, crime levels tend to be higher in areas with a greater prevalence of drinking establishments, subway stations, drug treatment centers, and predatory financial institutions such as payday lenders and pawn shops (Groff & Lockwood, 2014; Kubrin et al., 2011; Lee et al., 2014). Regarding context, Slocum et al. (2013) found that several types of community organizations, including those serving at-risk populations and charitable organizations, only had negative associations with violence in neighborhoods with more extensive commercial land use and lower structural disadvantage.

These nuanced findings have led some scholars to focus on voluntary organizations, or nonprofits that provide services, activities, or events in their local communities, because the prevalence of these institutions is thought to imply a capacity for civic engagement not captured by neighborhood organizations in general. Yet here, too, the relationship with crime generally varies with community and organization features. Nonprofits located in neighborhoods with higher levels of social organization, and that are at a more mature stage of their organizational life course, appear to be most effective (Slocum et al., 2013; Wo et al., 2016). An assessment with more consistent effects is Sharkey et al.'s (2017) investigation into the contribution of voluntary organizations to the U.S. crime drop. Focusing narrowly on nonprofits dedicated to strengthening community life or reducing crime, which they refer to collectively as "community organizations," Sharkey and colleagues found that cities with higher rates of these institutions experienced sharper decreases in violent and property crime during the 1990s and 2000s.

In this chapter I extend the work of Sharkey et al. (2017) by exploring whether community organizational capacity at the city level attenuates the neighborhood-level relative inequality and crime relationship. I assess the conditioning impact of the same five types of nonprofits considered by Sharkey et al., as these organizations may have the most reliable inverse relationships with crime *and* be most likely to temper the inequality-crime association. Nonprofit organizations focused on enhancing social vitality and preventing crime may bring together residents of different income backgrounds in service of addressing mutual challenges to community life, thereby narrowing the social distance thought to be generated by relative inequality. Beyond the specific impact of Sharkey et al.'s particular conception of community organizations, assessing my expectation by considering multiple organization types across a large sample of urban areas also serves to mitigate a concern of many prior studies of voluntary organizations and crime. That is, the crime-reducing effects of a single organization type in a single area may be offset if that institution additionally serves as a crime generator or attractor by drawing together many potential crime victims and offenders into the same location (Brantingham & Brantingham, 1995; McCord et al., 2007). Formally, my final hypothesis is the following:

H4: The cross-level interaction effect between city-level community organizations and neighborhood relative inequality will be negative, such that relative inequality has smaller effects on crime in cities with a higher rate of community organizations.

Data

I assess my hypotheses in this chapter by analyzing a subset of the cross-sectional second wave of the NNCS2 dataset. I merged the dataset used in Chapter 3 with 2010 NALEO Latino elected officials data, Black elected officials data I collected manually, 2013 LEMAS sworn police officer data, and NCCS community organization data. The information I gathered on Black mayors and city councilors was either for 2010 or the earliest year available after 2010 (ranging from 2011-2014), and the community organization data include all nonprofits that fall within one of the five categories identified by Sharkey et al. (2017) and that were active for at least one year between 2008 and 2016 (refer to Chapter 2 for further detail). My analytic sample for the present chapter comprises 7,830 tracts nested within 66 cities, a slightly smaller analytic sample than used in Chapter 3 because some NNCS2 cities are not represented in the LEMAS data. My dependent variables are the rates of violent crimes (homicides and robberies) and property crimes (burglaries) per 1,000 tract residents averaged over 2010-2013, logged in my regression models to adjust for skew.

Descriptive statistics for the variables in my analyses are presented in Table 5.1. The figures approximate those presented in Chapter 3 because my variable selection and sample are similar, so I focus my discussion on the city-level measures relevant to this chapter. As prior research with the NNCS data show, large urban areas in the U.S. are characterized by considerable levels of racial residential segregation. The mean White-Black index of dissimilarity value is 45.652, indicating that more than two of every five White (or Black)

Table 5.1 Descriptive Statistics

	Mean	SD
Tract-Level (N = 7,830)		
Violent crime rate	3.390	4.174
Burglary rate	10.159	8.381
Ethno-Racial Nbhd. Type		
White	.270	
Black	.121	
Latino	.097	
Minority	.051	
White-Black Multi.	.079	
White-Latino Multi.	.125	
Other Multi.	.258	
Gini	.424	.062
Disadvantage	.010	.847
Young males (%)	15.950	6.009
Residential instability	.000	.880
Immigration	.018	.927
Residential loans	30139.660	44551.750
Vacant housing (%)	11.374	8.455
Foreclosure rate	15.054	19.330
Sp. Lag (Burglary rate)	10.178	6.950
Sp. Lag (Homicide/robbery rate)	3.403	3.194
City-Level (N = 66)		
White-Black Index of Diss.	45.652	16.677
White-Hispanic Index of Diss.	39.376	13.784
Disadvantage	.006	.942
Manufacturing (%)	9.510	3.851
Population	460,306	597,867
Black (%)	18.530	14.539
Recent movers (%)	18.852	4.536
Foreign-born (%)	17.041	11.129
Young males (%)	15.815	2.232
South	.333	
West	.288	
Minority (Black or Latino) mayor	.152	
Minority (Black or Latino) city councilor rate	1.609	1.758
Minority (Black or Latino) police representation	.538	.212
Crime prev. nonprofit rate	5.990	3.842
Nbhd. dev. nonprofit rate	23.384	17.354
Sub. abuse prev. nonprofit rate	4.374	2.480
Workforce dev. nonprofit rate	2.614	1.892
Youth prgrm. nonprofit rate	26.496	13.490
Total community organizations rate	62.857	35.544

residents would have to move to a different neighborhood to achieve an even residential distribution; the corresponding value for the White-Hispanic index is slightly lower at 39.376. Just over 15% of cities in the sample had a minority (Black or Latino) mayor. The average city had about 1.6 minority city councilors per 100,000 minority residents and a share of minority police officers roughly half that of the share of minority residents making up the urban population. The typical city also had about 63 community organizations of any kind per 100,000 residents, ranging from a rate of roughly 3 workforce development nonprofits per 100,000 to 26 youth program nonprofits per 100,000.

As in the previous two chapters, I describe the results from my regression models separately for property crime (burglary rates) and for violent crime (homicide and robbery rates). As in Chapter 4, I use a violent crime rate rather than an incident count because my data analysis software does not allow estimation of categorical outcome variables with my particular model specification—namely, my treating the tract-level Gini index and neighborhood ethno-racial composition type variables as random effects. For each outcome I begin by discussing the results of a baseline model with no interaction effects, highlighting the size and direction of the relative inequality coefficient and the quantity of between-city variation around its random slope. I then estimate cross-level interaction terms between relative inequality and my hypothesized city-level moderators, with one interaction per model, and note the extent to which the significant product terms account variation around the random slope of the Gini index.

Results

Burglary. Table 5.2 presents the results of the multilevel models regressing the logged burglary rate on tract-level relative inequality, my hypothesized city-level moderators, and

Table 5.2 Multilevel OLS Regression of Burglary Rate (ln) on Gini Index and City-Level Moderators

	Model 1			Model 2			Model 3			Model 4		
Tract-Level	b		SE	b		SE	b		SE	b		SE
Black nbhd	.194	***	.043	.196	***	.043	.192	***	.043	.194	***	.043
Latino nbhd	.130		.078	.130		.077	.128		.077	.130		.077
Minority nbhd	.139	*	.060	.141	*	.060	.138	*	.060	.140	*	.060
White-Black Multi. nbhd	.209	***	.035	.212	***	.035	.208	***	.035	.209	***	.035
White-Latino Multi. nbhd	.198	***	.040	.200	***	.040	.199	***	.040	.198	***	.040
Other Multi. nbhd	.138	***	.029	.139	***	.029	.139	***	.029	.139	***	.029
Gini	1.140	***	.247	1.285	***	.231	1.229	***	.244	1.334	***	.264
City-Level Moderators												
× W-B Index of Diss.				-.046	**	.014						
× W-L Index of Diss.							-.042	*	.017			
× Minority mayor										-1.141		.608
× Minority city councilor rate												
× Minority police representation												
× Crime prev. nonprofit rate												
× Nbhd. dev. nonprofit rate												
× Sub. abuse prev. nonprofit rate												
× Workforce dev. nonprofit rate												
× Youth prgrm. nonprofit rate												
× Total community orgs. rate												
Disadvantage	.208	***	.015	.207	***	.015	.208	***	.015	.207	***	.015
Young males	.003	*	.001	.003	*	.001	.003	*	.001	.003	*	.001
Residential instability	.062	***	.011	.062	***	.011	.062	***	.011	.062	***	.011
Immigration	-.172	***	.011	-.173	***	.011	-.172	***	.011	-.172	***	.011
Residential loans (ln)	-.024	***	.006	-.024	***	.006	-.024	***	.006	-.024	***	.006
Vacant housing (ln)	.040	***	.005	.040	***	.005	.040	***	.005	.040	***	.005
Foreclosure rate (ln)	.095	***	.008	.095	***	.008	.095	***	.008	.095	***	.008
Burglary rate spatial lag	.035	***	.002	.035	***	.002	.035	***	.002	.035	***	.002
City-Level												
White-Black Index of Diss.	.003		.008	.003		.008	.003		.008	.003		.008
White-Latino Index of Diss.	.010		.006	.010		.006	.010		.006	.010		.006
Disadvantage	.032		.105	.028		.105	.029		.105	.036		.105

Manufacturing jobs	-.030		.019	-.030		.019	-.031		.019	-.031		.019
Population	.000		.000	.000		.000	.000		.000	.000		.000
Percent Black	.002		.008	.002		.008	.002		.008	.002		.008
Recent movers	.005		.024	.006		.024	.005		.024	.005		.024
Foreign-born	-.011		.007	-.010		.007	-.010		.007	-.011		.007
Young males	.020		.040	.018		.040	.019		.040	.020		.040
South	.184		.159	.181		.159	.182		.159	.183		.159
West	.080		.188	.078		.188	.080		.188	.077		.188
Minority mayor	-.092		.190	-.087		.190	-.091		.190	-.094		.191
Minority city councilor rate	-.026		.033	-.026		.033	-.026		.033	-.027		.033
Minority police representation	.396		.341	.391		.341	.395		.340	.401		.341
Crime prev. nonprofit rate												
Nbhd. dev. nonprofit rate												
Sub. abuse prev. nonprofit rate												
Workforce dev. nonprofit rate												
Youth prgrm. nonprofit rate												
Total community orgs. rate	-.081		.149	-.086		.149	-.085		.149	-.080		.150
Intercept	1.785	***	.114	1.792	***	.114	1.789	***	.114	1.788	***	.114
Variance (SD)												
Intercept	.442	***	.040	.442	***	.040	.442	***	.040	.444	***	.040
Gini	1.611	***	.228	1.384	***	.226	1.548	***	.221	1.539	***	.226
Variance Explained in Gini Index				*26%*			*8%*					

Note. *p < .05, **p < .01, ***p < .001. Standard deviations around the ethno-racial neighborhood type random effects are omitted.

Table 5.2 Multilevel OLS Regression of Burglary Rate (ln) on Gini Index and City-Level Moderators (Cont.)

	Model 5			Model 6			Model 7			Model 8		
Tract-Level	b		SE	b		SE	b		SE	b		SE
Black nbhd	.196	***	.043	.194	***	.043	.194	***	.043	.197	***	.043
Latino nbhd	.131		.077	.128		.077	.130		.077	.130		.077
Minority nbhd	.140	*	.060	.139	*	.060	.139	*	.060	.142	*	.060
White-Black Multi. nbhd	.212	***	.036	.209	***	.035	.210	***	.035	.213	***	.035
White-Latino Multi. nbhd	.200	***	.040	.199	***	.040	.199	***	.040	.199	***	.040
Other Multi. nbhd	.139	***	.029	.138	***	.029	.139	***	.029	.140	***	.029
Gini	1.245	***	.237	1.232	***	.238	1.159	***	.248	1.252	***	.237
City-Level Moderators												
× W-B Index of Diss.												
× W-L Index of Diss.												
× Minority mayor												
× Minority city councilor rate	-.328	**	.104									
× Minority police representation				-3.102	**	1.114						
× Crime prev. nonprofit rate							-.160		.220			
× Nbhd. dev. nonprofit rate										-.843	**	.298
× Sub. abuse prev. nonprofit rate												
× Workforce dev. nonprofit rate												
× Youth prgrm. nonprofit rate												
× Total community orgs. rate												
Disadvantage	.208	***	.015	.207	***	.015	.208	***	.015	.207	***	.015
Young males	.003	*	.001	.003	*	.001	.003	*	.001	.003	*	.001
Residential instability	.062	***	.011	.063	***	.011	.063	***	.011	.062	***	.011
Immigration	-.173	***	.011	-.172	***	.011	-.172	***	.011	-.173	***	.011
Residential loans (ln)	-.024	***	.006	-.024	***	.006	-.024	***	.006	-.024	***	.006
Vacant housing (ln)	.040	***	.005	.040	***	.005	.040	***	.005	.040	***	.005
Foreclosure rate (ln)	.095	***	.008	.096	***	.008	.095	***	.008	.095	***	.008
Burglary rate spatial lag	.035	***	.002	.035	***	.002	.035	***	.002	.035	***	.002
City-Level												
White-Black Index of Diss.	.003		.008	.003		.008	.001		.008	.004		.008
White-Latino Index of Diss.	.010		.006	.010		.006	.010		.006	.010		.006
Disadvantage	.031		.105	.029		.105	.049		.107	.037		.101

Manufacturing jobs	-.030		.019	-.030		.019	-.030		.020	-.033		.020
Population	.000		.000	.000		.000	.000		.000	.000		.000
Percent Black	.002		.008	.002		.008	.001		.008	.002		.008
Recent movers	.005		.024	.005		.024	.001		.023	.006		.023
Foreign-born	-.010		.007	-.010		.007	-.010		.007	-.011		.007
Young males	.019		.040	.020		.040	.024		.039	.021		.039
South	.181		.159	.189		.159	.200		.157	.157		.164
West	.074		.188	.084		.188	.077		.189	.058		.189
Minority mayor	-.090		.190	-.085		.191	-.115		.192	-.073		.191
Minority city councilor rate	-.031		.033	-.027		.033	-.027		.033	-.025		.033
Minority police representation	.391		.341	.363		.342	.394		.343	.392		.341
Crime prev. nonprofit rate							-.002		.059			
Nbhd. dev. nonprofit rate										-.111		.129
Sub. abuse prev. nonprofit rate												
Workforce dev. nonprofit rate												
Youth prgrm. nonprofit rate												
Total community orgs. rate	-.086		.150	-.083		.150						
Intercept	1.792	***	.114	1.785	***	.114	1.785	***	.115	1.803	***	.115
Variance (SD)												
Intercept	.443	***	.040	.444	***	.040	.443	***	.040	.443	***	.040
Gini	1.476	***	.216	1.497	***	.221	1.609	***	.228	1.465	***	.224
Variance Explained in Gini Index	*16%*			*14%*						*17%*		

Note. *p < .05, **p < .01, ***p < .001. Standard deviations around the ethno-racial neighborhood type random effects are omitted.

Table 5.2 Multilevel OLS Regression of Burglary Rate (ln) on Gini Index and City-Level Moderators (Cont.)

	Model 9			Model 10			Model 11			Model 12		
Tract-Level	b		SE	b		SE	b		SE	b		SE
Black nbhd	.194	***	.043	.194	***	.043	.194	***	.043	.196	***	.043
Latino nbhd	.128		.077	.130		.077	.130		.077	.130		.077
Minority nbhd	.139	*	.060	.139	*	.060	.139	*	.060	.140	*	.060
White-Black Multi. nbhd	.210	***	.035	.210	***	.035	.210	***	.035	.211	***	.035
White-Latino Multi. nbhd	.198	***	.040	.199	***	.040	.198	***	.040	.199	***	.040
Other Multi. nbhd	.139	***	.029	.139	***	.029	.139	***	.029	.139	***	.029
Gini	1.180	***	.245	1.173	***	.248	1.150	***	.248	1.196	***	.244
City-Level Moderators												
× W-B Index of Diss.												
× W-L Index of Diss.												
× Minority mayor												
× Minority city councilor rate												
× Minority police representation												
× Crime prev. nonprofit rate												
× Nbhd. dev. nonprofit rate												
× Sub. abuse prev. nonprofit rate	-.421		.354									
× Workforce dev. nonprofit rate				-.183		.198						
× Youth prgrm. nonprofit rate							-.218		.464			
× Total community orgs. rate										-.711		.413
Disadvantage	.207	***	.015	.208	***	.015	.208	***	.015	.207	***	.015
Young males	.003	*	.001	.003	*	.001	.003	*	.001	.003	*	.001
Residential instability	.063	***	.011	.063	***	.011	.062	***	.011	.063	***	.011
Immigration	-.172	***	.011	-.172	***	.011	-.172	***	.011	-.172	***	.011
Residential loans (ln)	-.024	***	.006	-.024	***	.006	-.024	***	.006	-.024	***	.006
Vacant housing (ln)	.040	***	.005	.040	***	.005	.040	***	.005	.040	***	.005
Foreclosure rate (ln)	.096	***	.008	.095	***	.008	.095	***	.008	.095	***	.008
Burglary rate spatial lag	.035	***	.002	.035	***	.002	.035	***	.002	.035	***	.002
City-Level												
White-Black Index of Diss.	.006		.009	.000		.008	.002		.008	.003		.008
White-Latino Index of Diss.	.010		.006	.010		.006	.010		.006	.010		.006
Disadvantage	.021		.102	.057		.101	.035		.106	.032		.105

Manufacturing jobs	-.027		.019	-.031		.019	-.030		.019	-.030		.019
Population	.000		.000	.000		.000	.000		.000	.000		.000
Percent Black	.000		.007	.001		.007	.002		.008	.002		.008
Recent movers	.004		.023	-.001		.023	.004		.024	.005		.024
Foreign-born	-.011		.007	-.010		.008	-.010		.007	-.010		.007
Young males	.022		.039	.024		.039	.020		.040	.019		.040
South	.173		.157	.206		.157	.199		.156	.183		.159
West	.128		.193	.080		.188	.085		.189	.080		.188
Minority mayor	-.059		.192	-.123		.186	-.107		.186	-.090		.190
Minority city councilor rate	-.023		.033	-.026		.033	-.027		.033	-.027		.033
Minority police representation	.354		.341	.377		.343	.399		.341	.394		.341
Crime prev. nonprofit rate												
Nbhd. dev. nonprofit rate												
Sub. abuse prev. nonprofit rate	-.119		.109									
Workforce dev. nonprofit rate				.019		.052						
Youth prgrm. nonprofit rate							-.058		.136			
Total community orgs. rate										-.088		.150
Intercept	1.773	***	.114	1.784	***	.114	1.782	***	.114	1.788	***	.114
Variance (SD)												
Intercept	.440	***	.039	.443	***	.040	.443	***	.040	.443	***	.040
Gini	1.559	***	.230	1.586	***	.230	1.609	***	.228	1.555	***	.227
Variance Explained in Gini Index												

Note. *p < .05, **p < .01, ***p < .001. Standard deviations around the ethno-racial neighborhood type random effects are omitted.

my tract- and city-level controls. In Model 1, which presents baseline parameter estimates with no interaction terms, the positive and significant coefficient for the Gini index (b = 1.140) indicates that localized income inequality is associated with higher neighborhood burglary rates on average, consistent with the findings discussed in Chapter 3. (The main effect for relative inequality will also remain positive and significant in all subsequent

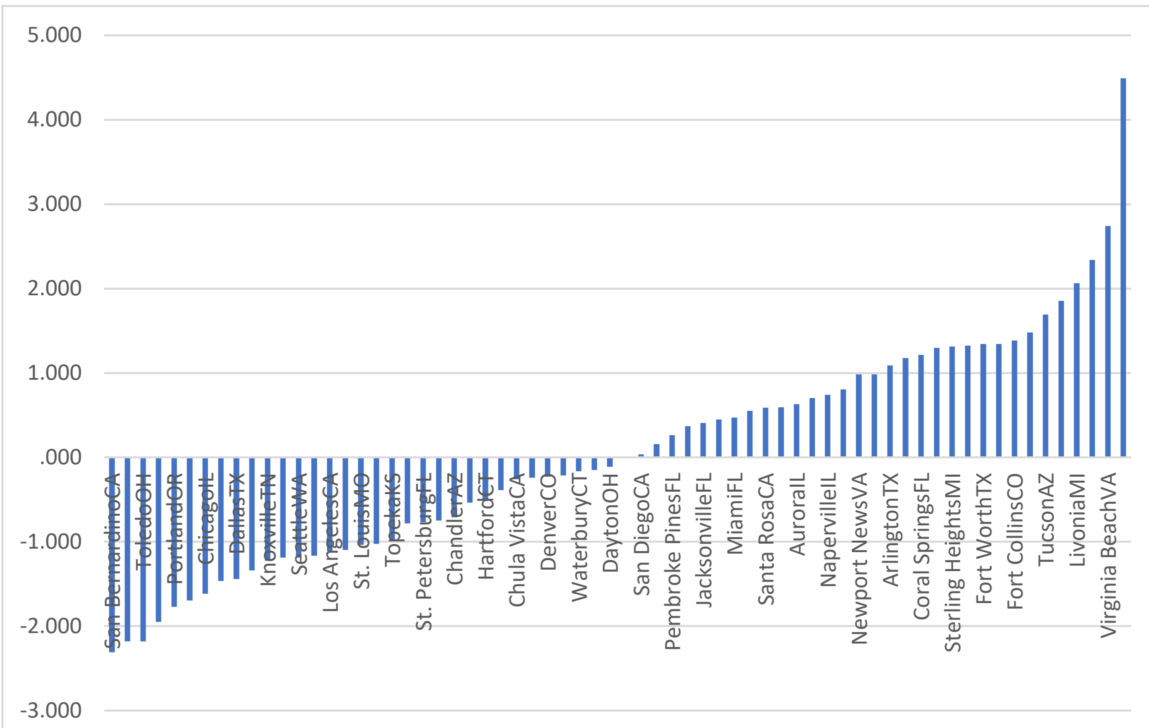

Figure 5.1. Predicted Linear Slope Terms for the Tract-Level Relative Inequality-Burglary Rate Association, by NNCS2-P City, 2010-2013.

burglary rate models.) However, in the Table 5.2 models relative inequality is specified as a random effect, and the variance component around the slope term is sizeable (SD = 1.611). This variation is evident in Figure 5.1, which graphs the predicted value of the relative inequality slope for each city in my sample (only some cities are labeled in the figure due to space constraints). Many cities have estimated slopes that are considerably greater than the global average, and approximately half have slopes in the negative range. Having established that the size and direction of the relative inequality effect on burglary varies across cities, my next aim is to explore the extent to which this variation is attributable to the city-level characteristics that are the subject of this chapter.

Models 2 and 3 assess whether an urban area's level of racial residential segregation conditions the impact of income inequality on burglary rates within that city's neighborhoods. The interaction terms with the White-Black index of dissimilarity in Model 2 and the with the White-Hispanic index of dissimilarity in Model 3 are both negative and significant. Figures 5.2 and 5.3 visualize these interaction effects for White-Black segregation and White-Hispanic segregation, respectively, and chart the predicted burglary rate per 1,000 residents at different percentiles of the Gini index when the level of residential segregation is low (1 standard deviation below the mean), average (the mean segregation value), and high (1 standard deviation above the mean), with the values for all other model predictors held at their means.[12] Both figures show

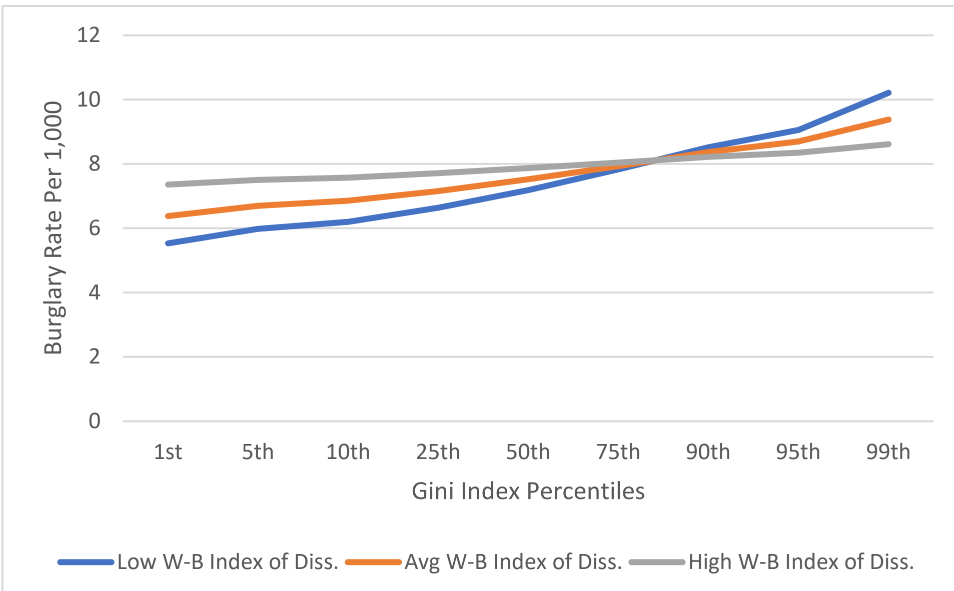

Figure 5.2. Predicted Average Tract Burglary Rate by Gini Index Percentiles at Low, Average, and High White-Black Residential Segregation, 2010-2013.

[12] For the sake of brevity, I do not repeat these specifications in my descriptions of subsequent figures illustrating interaction effects. However, except for Figure 5.8 described below, all figures in this chapter define low, average, and high levels of city-level moderating variables the same way, and hold all other variables not depicted in the figures at their means.

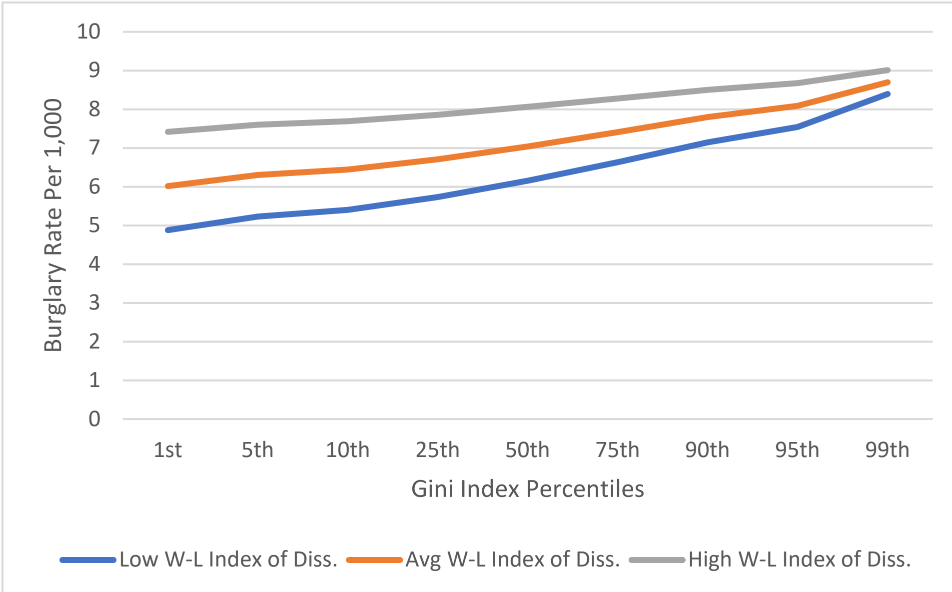

Figure 5.3. Predicted Average Tract Burglary Rate by Gini Index Percentiles at Low, Average, and High White-Hispanic Residential Segregation, 2010-2013.

that burglary rates climb with relative inequality values at a more modest pace in high-segregation cities than in average- or low-segregation places, consistent with my expectations. In fact, Figure 5.2 reveals that for neighborhoods with the highest income disparities (at or above the 90th percentile), burglary rates are *lower* in cities with high White-Black residential segregation than in cities with average or low segregation. Moreover, White-Black segregation accounts for more of the between-city variation in the relative inequality effect than does White-Hispanic segregation; the variance around the Gini index slope is reduced by 26% in Model 2, compared to a reduction of 8% in Model 3.

Models 4-6 assess the moderating potential on relative inequality of minority political empowerment. Of my two measures of descriptive representation, the minority mayor and minority city councilor rate, only the latter is significant and in the hypothesized negative direction in Model 5. Figure 5.4 illustrates this interaction, showing that the burglary rate ascends more slowly with income inequality in cities with high rates of Black or Latino city councilors than in cities with average or low rates of these elected officials. Turning next to my indicator of bureaucratic incorporation, I find that the Gini index by minority police representation interaction term is also negative and significant. As Figure 5.5 depicts, the larger the share of Black and Latino officers on a city's police force relative to the share of Black and Latino residents in the total urban population, the more gradual is the positive slope summarizing the impact of neighborhood income inequality on burglary. Like the effect of White-Black residential segregation in Figure 5.2, Figure 5.5 indicates that at the highest

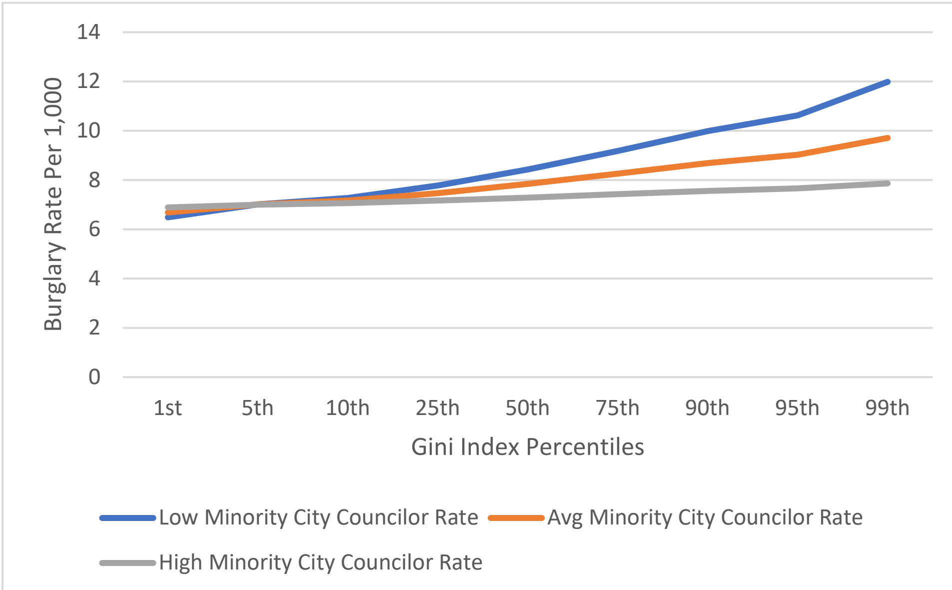

Figure 5.4. Predicted Average Tract Burglary Rate by Gini Index Percentiles at Low, Average, and High Minority City Councilor Rate, 2010-2013.

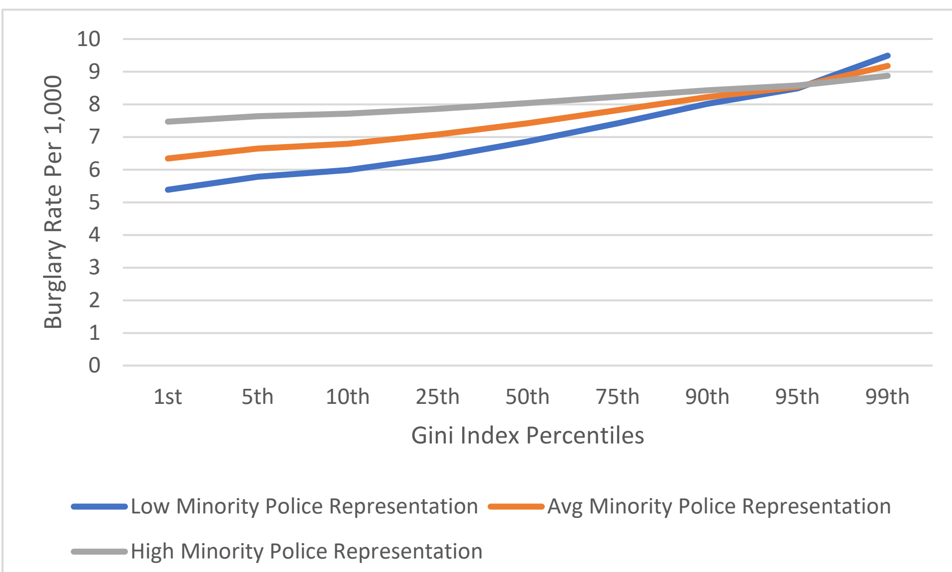

Figure 5.5. Predicted Average Tract Burglary Rate by Gini Index Percentiles at Low, Average, and High Minority Police Representation, 2010-2013.

levels of income disparity, Model 6 predicts that burglary rates will be lower in cities with above-average rates of minority police representation than in cities with mean or below-average rates. The minority city councilor rate and police representation variables explain similar shares of the inter-city variation in the Gini index slope (16% and 14%, respectively).

I now consider the conditioning influence on relative inequality of community organizational capacity in Models 7-12. In contrast to my expectations, most types of community organization do not temper the influence of the Gini index on burglary, and the rate of all five community organization types summed together is also not a significant moderator. The exception is the rate of neighborhood development nonprofits, for which the interaction term with neighborhood relative inequality is negative and significant. As illustrated in Figure 5.6, the magnitude of association of the Gini index with burglary is conditional on the rate of neighborhood development organizations in a similar manner as the other city-level moderators considered in this chapter: the burglary rate ascends more gradually in cities where more of these institutions are active. The proportion of inter-city variance in the relative inequality slope explained by this interaction,

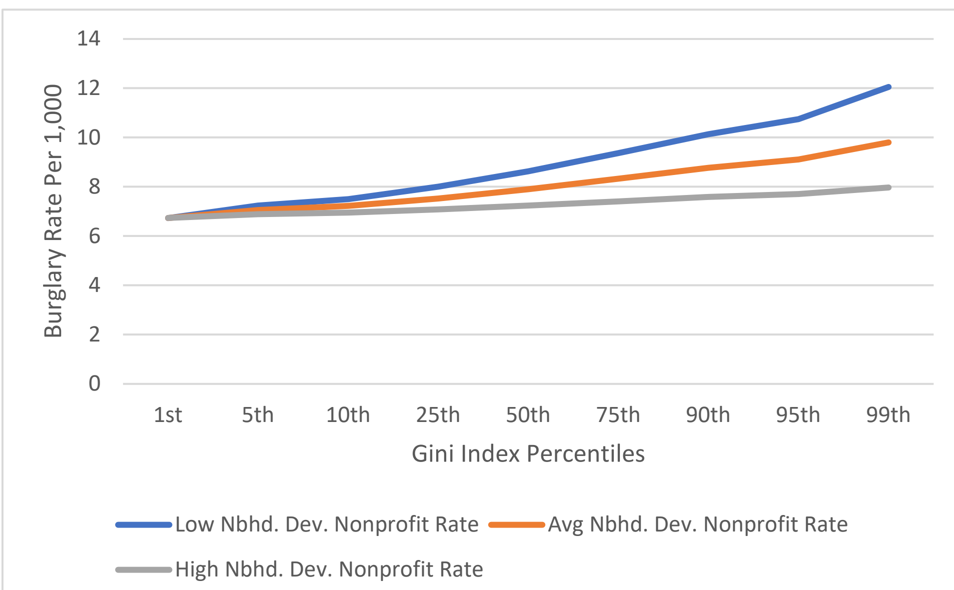

Figure 5.6. Predicted Average Tract Burglary Rate by Gini Index Percentiles at Low, Average, and High Neighborhood Development Nonprofit Rate, 2010-2013.

17%, is comparable to the shares accounted for by the minority political empowerment variables.

Violence. Table 5.3 presents the results from a similar set of models as the ones described above for the combined homicide and robbery rate. Model 1 shows that although the average effect of relative inequality is positive (b = 2.227), there is again considerable between-city variation in the size and direction of the slope (SD = 2.023). (As in Table 5.2, the average main effect for the Gini index remains positive and significant across all models in Table 5.3.) Figure 5.7 illustrates this variation by plotting predicted values of the relative inequality slope for each city, and just as with the burglary results, the predicted slopes in some cities are far greater than the average and fall below 0 in others.

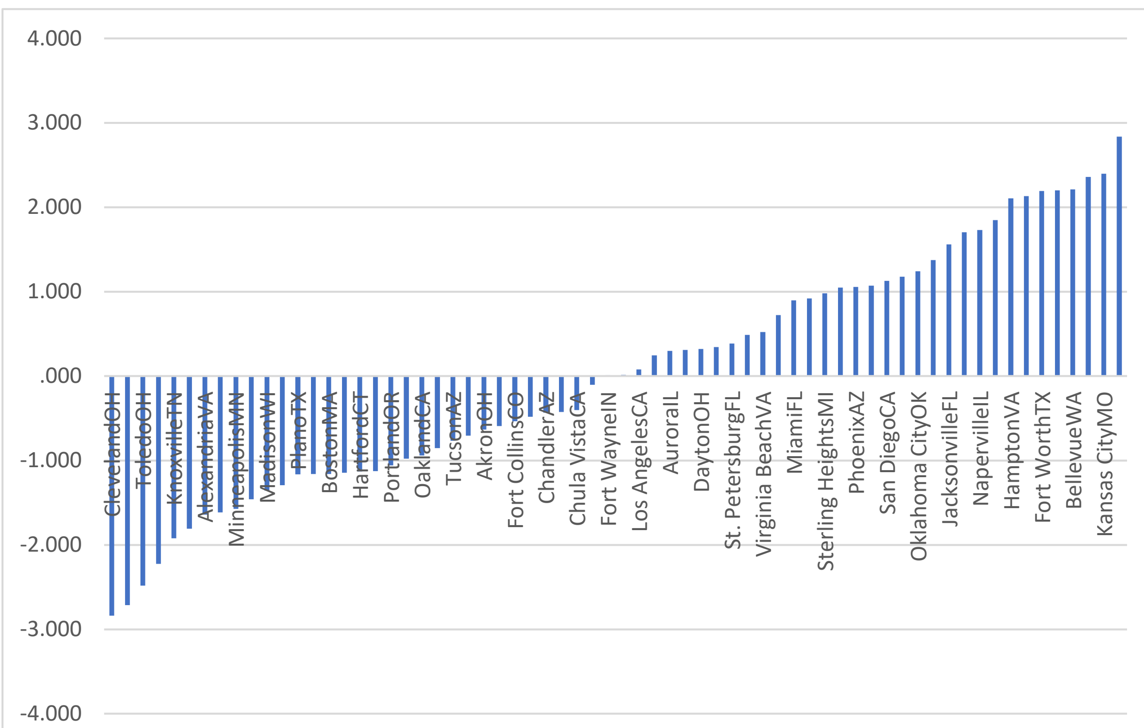

Figure 5.7. Predicted Linear Slope Terms for the Tract-Level Relative Inequality-Violent Crime Rate Association, by NNCS2-P City, 2010-2013.

Neither of the coefficients for the interaction effects involving the racial residential segregation variables are significant in Models 2 or 3, so I turn directly to the interactions

Table 5.3 Multilevel OLS Regression of Rate of Violent Crime Rate (ln) on Gini Index and City-Level Moderators

	Model 1			Model 2			Model 3			Model 4		
Tract-Level	b		SE									
Black nbhd	.466	***	.064	.469	***	.064	.465	***	.064	.467	***	.063
Latino nbhd	.304	***	.086	.305	***	.086	.303	***	.086	.305	***	.085
Minority nbhd	.431	***	.077	.433	***	.077	.431	***	.077	.433	***	.077
White-Black Multi. nbhd	.398	***	.047	.400	***	.048	.397	***	.047	.398	***	.047
White-Latino Multi. nbhd	.349	***	.056	.350	***	.056	.349	***	.056	.350	***	.055
Other Multi. nbhd	.269	***	.040	.270	***	.040	.269	***	.040	.269	***	.040
Gini	2.227	***	.351	2.370	***	.358	2.314	***	.360	2.545	***	.374
City-Level Moderators												
× W-B Index of Diss.				-.030		.021						
× W-L Index of Diss.							-.027		.025			
× Minority mayor										-1.771	*	.831
× Minority city councilor rate												
× Minority police representation												
× Crime prev. nonprofit rate												
× Nbhd. dev. nonprofit rate												
× Sub. abuse prev. nonprofit rate												
× Workforce dev. nonprofit rate												
× Youth prgrm. nonprofit rate												
× Total community orgs. rate												
Disadvantage	.462	***	.025	.461	***	.025	.462	***	.025	.461	***	.025
Young males	.010	***	.002	.010	***	.002	.010	***	.002	.010	***	.002
Residential instability	.312	***	.018	.312	***	.018	.312	***	.018	.311	***	.018
Immigration	-.010		.019	-.010		.019	-.010		.019	-.009		.019
Residential loans (ln)	-.036	***	.010	-.036	***	.010	-.036	***	.010	-.036	***	.010
Vacant housing (ln)	.069	***	.009	.069	***	.009	.069	***	.009	.069	***	.009
Foreclosure rate (ln)	.086	***	.012	.086	***	.012	.086	***	.012	.086	***	.012
Homicide + robbery rate spatial lag	.081	***	.005	.082	***	.005	.082	***	.005	.082	***	.005
City-Level												
White-Black Index of Diss.	.007		.008	.007		.008	.007		.008	.007		.008
White-Latino Index of Diss.	.012	*	.006	.012	*	.006	.012	*	.006	.012	*	.006
Disadvantage	.041		.098	.038		.098	.038		.098	.049		.098

Manufacturing jobs	-.065	***	.018	-.065	***	.018	-.066	***	.018	-.066	***	.018
Population	.000		.000	.000		.000	.000		.000	.000		.000
Percent Black	.011		.007	.011		.007	.011		.007	.011		.007
Recent movers	-.026		.022	-.026		.022	-.027		.022	-.027		.022
Foreign-born	-.016	*	.007	-.016	*	.007	-.016	*	.007	-.016	*	.007
Young males	.033		.037	.032		.037	.033		.037	.033		.037
South	.000		.147	-.002		.147	-.001		.147	-.001		.147
West	.194		.175	.192		.175	.193		.175	.187		.175
Minority mayor	-.048		.176	-.045		.176	-.047		.176	-.048		.176
Minority city councilor rate	.017		.030	.016		.030	.016		.030	.015		.030
Minority police representation	.238		.319	.234		.319	.237		.319	.249		.319
Crime prev. nonprofit rate												
Nbhd. dev. nonprofit rate												
Sub. abuse prev. nonprofit rate												
Workforce dev. nonprofit rate												
Youth prgrm. nonprofit rate												
Total community orgs. rate	-.046		.139	-.051		.139	-.050		.139	-.045		.139
Intercept	-.033		.108	-.026		.108	-.029		.108	-.027		.108
Variance (SD)												
Intercept	.396	***	.038	.396	***	.038	.396	***	.038	.397	***	.038
Gini	2.023	***	.351	1.927	***	.354	2.018	***	.349	1.891	***	.341
Variance Explained in Gini Index										*13%*		

Note. *p < .05, **p < .01, ***p < .001. Standard deviations around the ethno-racial neighborhood type random effects are omitted.

Table 5.3 Multilevel OLS Regression of Rate of Violent Crime Rate (ln) on Gini Index and City-Level Moderators (Cont.)

	Model 5			Model 6			Model 7			Model 8		
Tract-Level												
Black nbhd	.469	***	.064	.466	***	.064	.467	***	.063	.472	***	.063
Latino nbhd	.308	***	.086	.304	***	.086	.305	***	.086	.305	***	.085
Minority nbhd	.434	***	.077	.431	***	.077	.432	***	.077	.435	***	.077
White-Black Multi. nbhd	.401	***	.047	.398	***	.047	.399	***	.047	.402	***	.048
White-Latino Multi. nbhd	.352	***	.055	.349	***	.056	.349	***	.056	.351	***	.056
Other Multi. nbhd	.271	***	.040	.269	***	.040	.269	***	.040	.272	***	.040
Gini	2.401	***	.346	2.240	***	.358	2.258	***	.355	2.400	***	.342
City-Level Moderators												
× W-B Index of Diss.												
× W-L Index of Diss.												
× Minority mayor												
× Minority city councilor rate	-.407	**	.156									
× Minority police representation				-.317		1.670						
× Crime prev. nonprofit rate							-.197		.327			
× Nbhd. dev. nonprofit rate										-.994	*	.433
× Sub. abuse prev. nonprofit rate												
× Workforce dev. nonprofit rate												
× Youth prgrm. nonprofit rate												
× Total community orgs. rate												
Disadvantage	.461	***	.025	.462	***	.025	.462	***	.025	.460	***	.025
Young males	.010	***	.002	.010	***	.002	.010	***	.002	.010	***	.002
Residential instability	.312	***	.018	.312	***	.018	.312	***	.018	.312	***	.018
Immigration	-.011		.019	-.010		.019	-.010		.019	-.010		.019
Residential loans (ln)	-.036	***	.010	-.036	***	.010	-.036	***	.010	-.036	***	.010
Vacant housing (ln)	.069	***	.009	.069	***	.009	.069	***	.009	.069	***	.009
Foreclosure rate (ln)	.086	***	.012	.086	***	.012	.086	***	.012	.086	***	.012
Homicide + robbery rate spatial lag	.082	***	.005	.081	***	.005	.082	***	.005	.082	***	.005
City-Level												
White-Black Index of Diss.	.007		.008	.007		.008	.006		.007	.006		.008
White-Latino Index of Diss.	.012	*	.006	.012	*	.006	.012	*	.006	.012	*	.006
Disadvantage	.041		.098	.040		.098	.051		.100	.054		.094

Manufacturing jobs	-.066	***	.018	-.065	***	.018	-.065	***	.019	-.064	***	.018
Population	.000		.000	.000		.000	.000		.000	.000		.000
Percent Black	.011		.007	.011		.007	.011		.007	.011		.007
Recent movers	-.026		.022	-.026		.022	-.029		.021	-.029		.022
Foreign-born	-.016	*	.007	-.016	*	.007	-.016	*	.007	-.015	*	.007
Young males	.031		.037	.033		.037	.035		.036	.035		.036
South	-.005		.147	.001		.147	.010		.145	.010		.152
West	.184		.175	.194		.175	.192		.176	.190		.177
Minority mayor	-.046		.175	-.048		.176	-.062		.177	-.061		.178
Minority city councilor rate	.009		.030	.016		.030	.016		.031	.015		.031
Minority police representation	.234		.318	.234		.320	.237		.320	.233		.319
Crime prev. nonprofit rate							-.003		.055			
Nbhd. dev. nonprofit rate										.000		.121
Sub. abuse prev. nonprofit rate												
Workforce dev. nonprofit rate												
Youth prgrm. nonprofit rate												
Total community orgs. rate	-.053		.138	-.046		.139						
Intercept	-.020		.108	-.033		.108	-.032		.109	-.023		.109
Variance (SD)												
Intercept	.395	***	.038	.397	***	.038	.397	***	.038	.398	***	.038
Gini	1.889	***	.336	2.019	***	.352	2.015	***	.351	1.798	***	.354
Variance Explained in Gini Index	*13%*									*21%*		

Note. *p < .05, **p < .01, ***p < .001. Standard deviations around the ethno-racial neighborhood type random effects are omitted.

Table 5.3 Multilevel OLS Regression of Rate of Violent Crime Rate (ln) on Gini Index and City-Level Moderators (Cont.)

	Model 9			Model 10			Model 11			Model 12		
Tract-Level												
Black nbhd	.465	***	.063	.466	***	.063	.466	***	.064	.469	***	.064
Latino nbhd	.300	***	.085	.306	***	.086	.304	***	.086	.304	***	.086
Minority nbhd	.430	***	.077	.432	***	.077	.431	***	.077	.433	***	.077
White-Black Multi. nbhd	.398	***	.048	.398	***	.047	.398	***	.047	.400	***	.048
White-Latino Multi. nbhd	.345	***	.056	.350	***	.056	.348	***	.056	.349	***	.056
Other Multi. nbhd	.267	***	.040	.270	***	.040	.269	***	.040	.270	***	.040
Gini	2.256	***	.357	2.247	***	.360	2.232	***	.354	2.305	***	.350
City-Level Moderators												
× W-B Index of Diss.												
× W-L Index of Diss.												
× Minority mayor												
× Minority city councilor rate												
× Minority police representation												
× Crime prev. nonprofit rate												
× Nbhd. dev. nonprofit rate												
× Sub. abuse prev. nonprofit rate	-.143		.525									
× Workforce dev. nonprofit rate				-.095		.301						
× Youth prgrm. nonprofit rate							-.050		.666			
× Total community orgs. rate										-.774		.595
Disadvantage	.461	***	.025	.462	***	.025	.462	***	.025	.461	***	.025
Young males	.010	***	.002	.010	***	.002	.010	***	.002	.010	***	.002
Residential instability	.313	***	.018	.312	***	.018	.312	***	.018	.312	***	.018
Immigration	-.009		.019	-.010		.019	-.010		.019	-.010		.019
Residential loans (ln)	-.036	***	.010	-.036	***	.010	-.036	***	.010	-.035	***	.010
Vacant housing (ln)	.069	***	.009	.069	***	.009	.069	***	.009	.069	***	.009
Foreclosure rate (ln)	.088	***	.012	.086	***	.012	.086	***	.012	.086	***	.012
Homicide + robbery rate spatial lag	.082	***	.005	.081	***	.005	.081	***	.005	.082	***	.005
City-Level												
White-Black Index of Diss.	.014		.008	.005		.007	.008		.007	.007		.008
White-Latino Index of Diss.	.011	*	.006	.012	*	.006	.012	*	.006	.012	*	.006
Disadvantage	.010		.095	.060		.094	.026		.098	.041		.098

Manufacturing jobs	-.060	**	.018	-.066	***	.018	-.065	***	.018	-.065	***	.018
Population	.000		.000	.000		.000	.000		.000	.000		.000
Percent Black	.009		.007	.011		.007	.012		.007	.011		.007
Recent movers	-.024		.021	-.031		.021	-.023		.023	-.026		.022
Foreign-born	-.016	*	.007	-.015	*	.007	-.016	*	.007	-.016	*	.007
Young males	.032		.036	.035		.036	.029		.037	.032		.037
South	-.027		.144	.017		.145	.008		.144	-.001		.147
West	.263		.177	.194		.175	.204		.175	.193		.175
Minority mayor	.019		.175	-.071		.172	-.048		.171	-.046		.176
Minority city councilor rate	.022		.030	.017		.030	.016		.030	.016		.030
Minority police representation	.181		.316	.215		.321	.245		.318	.237		.319
Crime prev. nonprofit rate												
Nbhd. dev. nonprofit rate												
Sub. abuse prev. nonprofit rate	-.170		.101									
Workforce dev. nonprofit rate				.026		.050						
Youth prgrm. nonprofit rate							-.096		.126			
Total community orgs. rate										-.055		.139
Intercept	-.050		.107	-.034		.108	-.038		.108	-.028		.108
Variance (SD)												
Intercept	.389	***	.038	.396	***	.038	.395	***	.038	.397	***	.038
Gini	1.993	***	.354	2.012	***	.356	2.022	***	.351	1.932	***	.354
Variance Explained in Gini Index												

Note. *p < .05, **p < .01, ***p < .001. Standard deviations around the ethno-racial neighborhood type random effects are omitted.

with the minority political empowerment variables in Models 4-6. In Model 4 the cross-level interaction between the Gini index and minority mayor indicator is negative and significant, suggesting that the relative inequality effect on violence is tempered in cities with a Black or Latino mayor. This conditional effect is depicted in Figure 5.8, which graphs predicted values of the combined homicide and robbery rate at varying percentiles of the Gini index separately for cities with and without a minority mayor, with all other model variables held constant. The figure reveals that although tracts with a Black or Latino mayor have higher violent crime rates when the Gini index is below the 25th percentile, the

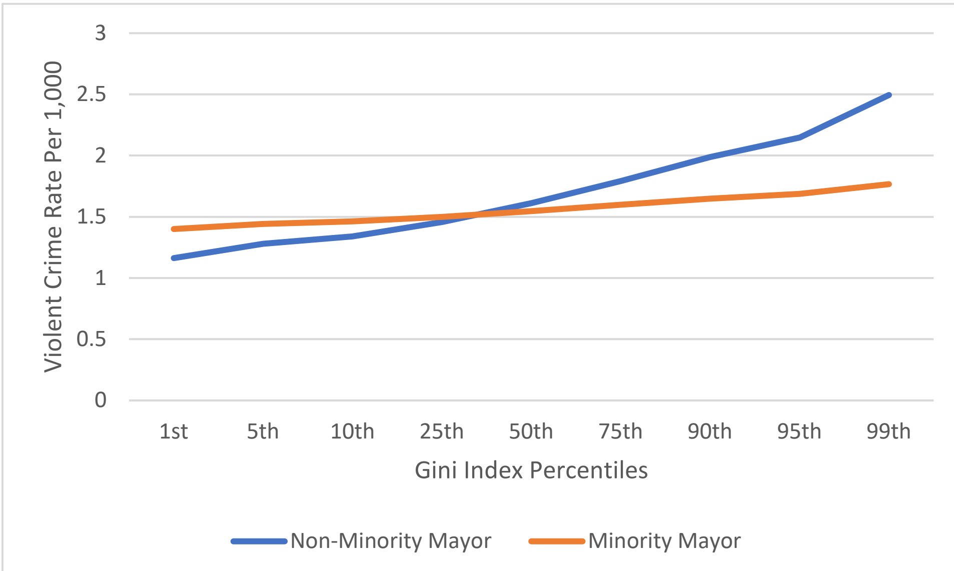

Figure 5.8. Predicted Average Tract Violent Crime Rate by Gini Index Percentiles in Cities with a Minority Mayor or Non-Minority Mayor, 2010-2013.

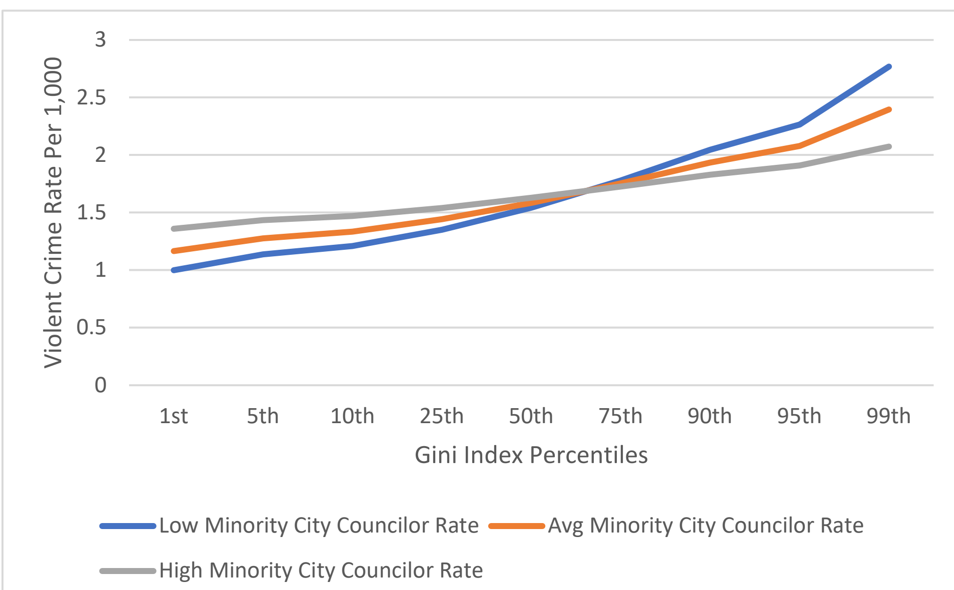

Figure 5.9. Predicted Average Tract Violent Crime Rate by Gini Index Percentiles at Low, Average, and High Minority City Councilor Rate, 2010-2013.

crime rate rises more gradually with neighborhood income inequality in these cities, so that at or above the 50th percentile of the Gini index the violent crime rate is greater in cities with a non-minority mayor. Like the burglary results, the interaction term involving the minority city councilor rate in Model 5 is also negative and significant, and this dynamic is charted in Figure 5.9. The now-familiar pattern in this line graph shows that the violent crime rate rises more slowly with percentiles of the Gini index in cities where the rate of Black and Latino city councilors more closely matches the share of Black and Latino city residents. Both the mayor and city councilor interactions with the Gini index account for approximately 13% of the inter-city variation around its slope.

Finally, in Models 7-12 I estimate the moderating effects of the rates of the five community organizations and their total rate. Identical to my findings for burglary, only the interaction term between neighborhood development nonprofits and the Gini index is significant and is negative in direction. I illustrate this interaction in Figure 5.10, where I once again observe that the rate of homicides and

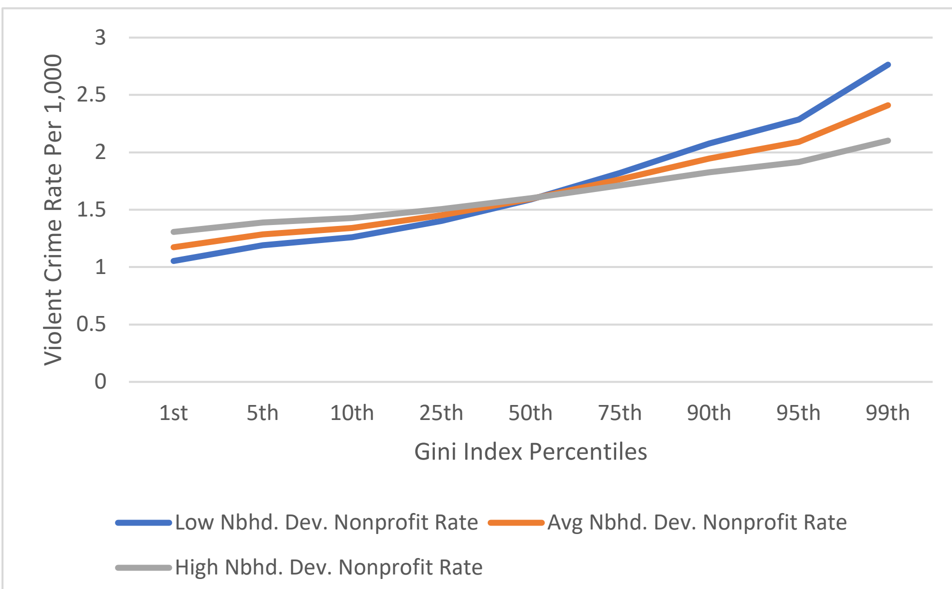

Figure 5.10. Predicted Average Tract Violent Crime Rate by Gini Index Percentiles at Low, Average, and High Neighborhood Development Nonprofit Rate, 2010-2013.

robberies rises at a slower pace with ascending percentiles of income inequality in cities with above-average rates of neighborhood development organizations.

Supplemental Analysis. Does the magnitude of the Gini index by minority political empowerment variables vary by neighborhood ethno-racial composition? In the preceding discussion I have presumed that these interaction effects are constant across all sample tracts, but it is conceivable that Black or Latino empowerment is more important in neighborhoods with larger shares of Black or Latino residents. I explore this possibility in Table 5.4, which summarizes the results of models similar to Models 4-6 of Table 5.2 and 5.3 but with two differences: (1) I now estimate three-way interaction terms involving neighborhood ethno-racial composition, the Gini index and the minority political empowerment variables; (2) and rather than collapsing Black and Latino representation into single combined “minority” empowerment variables, I assess the impact of Black and Latino empowerment separately (refer to Panels A and B of Table 5.4). For each combination of political empowerment variable and neighborhood type, the direction of the three-way interaction with the Gini index is presented if significant at the .05 level, or “n/a” is shown if not significant (White neighborhoods are the reference category; model coefficients available upon request).

Considering Black political empowerment first, these variables do not appear to have uniform effects in neighborhoods with higher shares of Black residents. A Black mayor is associated with an elevated relative inequality-crime slope in Black neighborhoods for the homicide and robbery rate, but the two remaining significant interactions in Panel A occur only in Other Multiethnic neighborhoods for either crime type. A somewhat more consistent pattern emerges for Latino political empowerment in Panel B. For the burglary rate, a Latino mayor and a police force with a higher share of Latino officers significantly predicts a higher

Table 5.4 Summary of Gini Index by City Moderator by Neighborhood Type Interactions

	Panel A: Black Political Empowerment					
	Burglary			Homicide + Robbery		
Nbhd. Type	**Blk. Mayor**	**Blk. C.C.s**	**Blk. Police**	**Blk. Mayor**	**Blk. C.C.s**	**Blk. Police**
White	n/a	n/a	n/a	n/a	n/a	n/a
Black	n/a	n/a	n/a	+	n/a	n/a
Latino	n/a	n/a	n/a	n/a	n/a	n/a
Minority	n/a	n/a	n/a	n/a	n/a	n/a
White-Black Multi.	n/a	n/a	n/a	n/a	n/a	n/a
White-Latino Multi.	n/a	n/a	n/a	n/a	n/a	n/a
Other Multi.	n/a	n/a	-	n/a	n/a	-
	Panel B: Latino Political Empowerment					
	Burglary			Homicide + Robbery		
Nbhd. Type	**Lat. Mayor**	**Lat. C.C.s**	**Lat. Police**	**Lat. Mayor**	**Lat. C.C.s**	**Lat. Police**
White	-	-	-	+	-	n/a
Black	n/a	n/a	n/a	-	n/a	n/a
Latino	+	n/a	+	-	n/a	n/a
Minority	+	n/a	+	-	n/a	+
White-Black Multi.	n/a	n/a	n/a	n/a	n/a	n/a
White-Latino Multi.	+	n/a	n/a	-	n/a	n/a
Other Multi.	n/a	n/a	n/a	-	n/a	n/a

Note. The direction of the three-way interaction effect between the Gini index, the political empowerment variable in the table column, and the neighborhood type in the table row is shown if significant at the .05 level (+ or -) or "n/a" is presented if not significant. White neighborhoods are the reference group for the ethno-racial neighborhood type variable.

positive relative inequality-crime slope in at least two of six non-White neighborhoods for each empowerment variable, including Latino and White-Latino Multiethnic neighborhoods, relative to White neighborhoods. (The interaction terms in White neighborhoods themselves are negative for all three minority empowerment variables, suggesting they offset the positive terms noted above.) However, for the homicide and robbery rate, this pattern reverses for the impact of a Latino mayor: the interaction terms are negative for nearly all neighborhood types except White neighborhoods, for which the term is positive. It is therefore possible that within neighborhoods with higher shares of Latino residents, the impact of Latino political empowerment on the relative-inequality crime relationship varies by crime type, amplifying the association for burglary while attenuating it for criminal violence.

Conclusion

Prior research finds that structural factors of neighborhood criminal inequality do not operate independently of their host cities, that their impacts may be conditioned by features of the broader urban context (Chamberlain & Hipp, 2015; Lyons et al., 2013; Vélez et al., 2015). Extant studies on income inequality-crime associations report moderated effects at the city and county levels (Burraston et al., 2018; Hip, 2011) and some evidence of interaction across levels (Wenger, 2019), but there is little research on how relative inequality effects on crime vary by a wider set of urban characteristics. In the present chapter, I sought a preliminary answer to this question by investigating the potential for city-level racial residential segregation, minority political empowerment, and community organizational capacity to moderate the neighborhood-level income inequality and crime relationship. I argued that indicators of all three constructs would soften relative inequality's impact on crime either by reducing the importance of class divisions to neighbors' social capital (for residential segregation and community organizations) or by strengthening neighborhood social organization against crime (for minority political empowerment). To assess my hypotheses, I supplemented cross-sectional data from the 2010-2013 NNCS2 with data on my key constructs from the NALEO, LEMAS, and NCCS databases, as well as primary data on Black and/or African American mayors and city councilors that I collected for this project.

Beginning with residential segregation, I found that both White-Black and White-Hispanic segregation tempered the impact of the Gini index on burglary, but neither did so for violence. Racial segregation is distinct from my other hypothesized moderators in that it is a central factor in the persistence of racial and ethnic differences in levels of neighborhood crime, and especially violence (Peterson & Krivo, 2010a; Krivo et al., 2009). Why then did segregation fail to dampen within-neighborhood economic inequality effects for violence? Part of the answer may lie in the crime types examined. Burglary is highly sensitive to situation-specific features, with its commission driven by the availability of suitable targets in or near offenders' home neighborhoods and the presence of crime generators and attractors (Brantingham & Brantingham, 2011; Shover, 1991). By contrast, homicide tends to occur between people who know one another in the context of ongoing relationships (Hipp, 2007; Papachristos et al., 2012). Robbery has aspects in common with both offenses, as it involves the threat or use of force but is dependent on opportunities created by offenders' social and environmental context (Bernasco & Block, 2009; Hipp & Kim, 2019). Thus, it is possible that while residential segregation renders relative inequality less consequential to property crimes, income divisions may continue to break down social relationships in ways conducive to violence, possibly in a highly regulated manner characteristic of the negotiated coexistence model in some neighborhoods (Browning, 2009; Patillo-McCoy, 1999).

The results were more consistent with my expectations regarding minority political empowerment. A more representative police force in terms of Black and Latino officers weakened the relative inequality impact for burglary, as did having a minority mayor for violence, and a higher rate of Black and Latino city council members was associated with a reduced relative inequality effect for both outcomes. As hypothesized in this chapter and suggested in prior work, minority elected and civil service officials may provide substantive benefits to residents of segregated neighborhoods, such as more appropriate and higher quality services, relationships, and investments, that enhance their capacity to coordinate crime control activities regardless of differences in their economic backgrounds (Silver & Miller, 2004; Velez et al., 2015). Lastly, I found that the rate of neighborhood development nonprofits moderated the relative inequality and crime relationship for both burglary and violence, but no other community organization subcategory did so. Given their operational definition, it is possible that these institutions both narrow the social distance between neighbors of different income levels *and* generate improvements to neighborhood conditions (e.g., greater access to housing, economic support for new businesses, and improvements to the built environment) that bolster social organization, a unique combination benefits that the other organizations I consider may simply be unable to provide.

Thus, while offering some insights on city characteristics that shape the size of relative inequality effects, my findings evoke several areas of inquiry for future research. One such area might involve seeking a better understanding of how Latino descriptive representation interacts with localized income inequality in predominantly Latino neighborhoods. As my supplemental analysis revealed, in neighborhoods with higher shares of Latino residents, Latino political empowerment may strengthen the inequality-crime relationship for burglary rather than weakening it. Economic inequality effects on crime that differ for Latinos compared with other groups are not unheard of (Wright et al., 2016), and I reflect on this finding further in this dissertation's conclusion. Additionally, my assessment of the moderating potential of community organizational capacity is subject to an important limitation: I am not able to adjust for endogeneity in the relationship between community organizations and neighborhood crime, a critical element of past work given that neighborhood development nonprofits are likely founded and placed in areas where crime and inequality are already high (Slocum et al., 2013; Wo et al., 2016). Although an instrumental variable correlated with community organization formation yet unrelated to urban crime rates is available in the NCCS data (Sharkey et al., 2017), a traditional instrumental variable analysis does not apply in my case, because I investigate the organization-crime relationship in the context of a cross-level interaction with the Gini index. Untangling the community organization-inequality-crime relationship is therefore a complex matter outside the scope of this chapter, but one I encourage future research to investigate.

Combined with the findings from the last two chapters, my findings here suggest that relative inequality can best be understood as a factor that interacts with other neighborhood and city-level factors in shaping crime rates. Curiously, although I find relative inequality to exert similar effects on crime by neighborhood ethno-racial composition net of the relative inequality by disadvantage interaction in Chapters 3 and 4, the present chapter further indicates that relative inequality may have effects that vary with neighborhood ethno-racial composition in its interactions with city-level moderators. It is with these considerations in mind that I turn to my concluding chapter.

6. CONCLUSION

If U.S. urban neighborhoods were the suspect of a murder mystery novel, markedly unequal living conditions and criminal victimization risk across communities segregated by race and class could serve as a metaphorical fingerprint, betraying a uniquely American identity. Extant scholarship demonstrates that the bulk of this “racial-spatial divide” is attributable to facets of the social context within and around neighborhoods, especially structural disadvantage, rather than distinct characteristics of racial or ethnic groups themselves (Krivo et al., 2021; Peterson & Krivo, 2010a; Sampson et al., 2005; Wilson, 1987). The uneven distribution of disadvantage leaves Black, Latino, and multiethnic neighborhoods with less of the economic resources, social capital, and political leverage needed to maintain public spaces generally free from crime and disorder, a condition I referred to as absolute neighborhood inequality. But what role does *relative* neighborhood inequality, or economic disparity *within* neighborhoods, play in upholding the U.S. racial structure and ethno-racial criminal inequality? Intra-neighborhood inequality does not vary by neighborhood racial makeup to the same degree as disadvantage, but recent studies confirm its reliability as an antecedent of crime (McNulty et al., 2023; Torres, 2020; Wenger, 2019), and the economic inequality and crime relationship more broadly has long been linked to perspectives that suggest that its impact may vary by race/ethnicity or area ethno-racial composition (Agnew, 1999; Merton, 1968; Smith et al., 2012).

In this dissertation, I took up the question of whether relative inequality has effects on neighborhood crime that are stronger in some communities than others in general, and for neighborhoods of some ethno-racial compositions in particular. I sought an answer by drawing on cross-sectional and longitudinal subsamples of the NNCS2-P, a nationally representative panel dataset of 8,856 census tracts nested within 81 cities for approximately 2000 and 2010, to approach the question from three angles. First, are there differences in the impact of relative inequality on crime by neighborhood ethno-racial composition, and does the interaction between relative inequality and disadvantage account for these differences? Second, do starting levels and growth in relative inequality contribute to ethno-racial variation in trajectories of neighborhood crime change, and do their interactions with disadvantage similarly account for this variation? And finally, are the consequences of relative inequality for neighborhood crime more severe in some cities than others, and what characteristics of urban areas help explain where they are weaker or stronger? In what follows, I provide a summary of the answers I uncovered to these questions and address their harmony with prior work. I then discuss limitations of my analyses and directions for future research on relative inequality and neighborhood crime before concluding.

Overview of Findings

In Chapter 3, I explored an approach to account for apparent ethno-racial differences in the impact of relative inequality on crime. Building on the legacy of Blau and Blau's (1982) seminal work, much prior research draws on a variant of relative deprivation theory to hypothesize an inequality-crime connection and, upon uncovering differential impacts by race, suggests that meanings attributed to economic inequality also vary by race (Cernkovich et al., 2000; Harer & Steffensmeier, 1992; Stolzenberg et al., 2006). This body of work has come under fire for drawing conclusions about racial group differences without measuring the central construct—cognitive appraisals of unfair deprivation relative to others—and recent work that has operationalized perceived inequality finds no association with crime (Rogers & Pridemore, 2022).

Thus, rather than rely on unsupported assumptions about group-level subjective experiences of inequality, I drew attention to the similarities between how neighborhood crime scholars explain the impact on crime of relative inequality and disadvantage. Drawing on relative deprivation, social disorganization, and opportunity theories, researchers have argued that both factors are disruptive to the social fabric in ways that raise motivations to commit crime and weaken foundations of effective crime control (Chamberlain & Hipp, 2015; Hipp, 2007; Wang & Arnold, 2008; Wenger, 2019). If relative inequality and disadvantage affect crime through similar mechanisms, but average disadvantage levels are higher in segregated neighborhoods of color, then relative inequality may have diminished effects on crime in these areas where incremental differences in income disparity are substantively less meaningful to resident social interactions. In other words, the interaction between relative inequality and disadvantage may account for apparent differences in the impact of inequality by neighborhood ethno-racial makeup. My findings supported this expectation: although relative inequality initially elevated crime rates to a lesser extent (and, in some cases, reduced them) in neighborhoods with higher shares of Blacks and Latinos compared with predominantly White areas, net of the interaction between relative inequality and disadvantage, these differences in effect size were either nullified or substantially reduced. A major takeaway is that the impact of localized income inequality on crime rates across neighborhoods of different colors cannot be fully understood without adjusting for inequality's diminished impact in areas of high disadvantage.

If relative inequality and disadvantage operate in tandem to shape neighborhood social organization and influence crime levels similarly by neighborhood ethno-racial makeup at a single point in time, do these dynamics also hold longitudinally? I tackled this second question in Chapter 4 by exploring how initial and changing levels of relative inequality and disadvantage affected variation in violent and property crime rate trajectories during 1999-2013. During this period trends in the typical neighborhood had an “inverse-U” shape where crime rates rose during the early 2000s, slowed their ascent and plateaued in the mid-2000s, and then declined through the early 2010s (Baumer et al., 2018; Krivo et al., 2018). I hypothesized that initial levels and growth in my central predictors would positively associate with crime change and that their interaction would account for observed differences in their impact on growth curves by neighborhood ethno-racial makeup, but my results were more nuanced. I found that starting levels of relative inequality and growth in disadvantage tended to result in more extreme trajectories of crime change (i.e., more rapid ascents in crime at the start of the period and declines at the end), while initial levels of disadvantage tended to “lock in” neighborhoods at high but more stable levels of crime. When I considered how these dynamics varied by neighborhood composition, after controlling for the initial level and change versions of the relative inequality by disadvantage interactions, initial relative inequality predicted a more modest growth curve in violence for White-Latino multiethnic neighborhoods, but a more extreme trajectory in property crime for Black neighborhoods, compared with predominantly White neighborhoods. This chapter therefore uncovered some racial variation in the impact of starting levels of localized income inequality on trajectories in neighborhood crime during the 2000s and early 2010s.

In my last empirical chapter, I investigated whether variation in the size of relative inequality effects on crime across neighborhoods in general (i.e., irrespective of their ethno-racial composition) may be attributable to features of the broader urban areas in which neighborhoods are embedded. Prior research on large cities and counties suggests that the impact of income inequality on crime varies by a variety of other markers of socioeconomic composition (Burraston et al., 2018; Chamberlain & Hipp, 2015; Hipp, 2011), but there remains little consideration of a wider set of potential urban moderators of the localized income inequality and crime relationship. In Chapter 5, I maintained that three city-level constructs would blunt relative inequality's impact: racial residential segregation, minority political empowerment, and community organizational capacity. My analyses revealed that the impact of relative inequality significantly varied in size and direction across the cities in the NNCS2-P sample and that a considerable share, up to more than a quarter, of this variation is attributable to my hypothesized city-level moderators. Specifically, the relative inequality effect on property crime was attenuated in cities with greater racial residential segregation, and the effect on both property and violent crime was tempered in cities with greater Black and Latino descriptive representation, Black and Latino bureaucratic incorporation, and neighborhood development organizational capacity. Additionally, my supplemental analyses indicated that in Latino and White-Latino multiethnic neighborhoods, Latino minority empowerment amplified the impact of relative inequality on property crime.

Harmony with Prior Work

Racial (In)variance. While this dissertation extends past research on race, relative inequality, and neighborhood crime by employing a nationally representative sample of urban neighborhoods and incorporating the interactive nature of inequality and disadvantage, its findings largely accord with that body of work in yielding mixed evidence for the alignment of relative inequality with the racial invariance thesis (McNulty et al., 2023; Messner & Tardiff, 1986; Torres, 2020; Wright et al., 2016). When limited to neighborhood-level homicide and robbery for a single point in time, I found that relative inequality uniformly elevates neighborhood violence regardless of racial makeup and differences in effect sizes are negligible. Yet relative inequality was less consistent with the thesis for property crime, ethno-racial differences in neighborhood crime trajectories, and variation in the extent to which city-level factors offset its impact. As recent commentary speculates, the assumption of racially similar processes may apply less cleanly for factors of crime besides disadvantage, for non-violent offenses, and in mixed race neighborhoods (Hernandez et al., 2018). Additionally, extant literature cautions that stringent assumptions of racial invariance may require relaxation under certain conditions. The scope of the thesis may not extend to the interactive effect of disadvantage with other factors on crime, for example, which may vary by race (Berthelot et al., 2016; Sampson et al., 2018). Thus, like disadvantage, neighborhood relative inequality may have racially variant effects on crime in its interactions with other structural features of neighborhoods or the larger urban area. As I discovered in the supplemental analyses of Chapter 5, whether minority political empowerment raised or lowered relative inequality's effect may vary by ethno-racial neighborhood composition and crime type.

Moreover, the discordant findings for Latino and White-Latino multiethnic neighborhoods I observed in Chapters 4 and 5 are broadly consistent with the Latino Paradox, a perspective that is sometimes viewed as at odds with the application of the racial invariance thesis to Hispanic or Latino offenders (Painter-Davis & Harris, 2016; Wright et al., 2016; but see Vélez, 2006). The Latino Paradox refers the observation that communities with high shares of recent Latino immigrants or Spanish language speakers have "paradoxically" low rates of crime given their average levels of disadvantage (Saenz & Morales, 2012). Researchers have suggested that social and cultural features particular to these communities, including dense social networks, high labor market participation, and family-oriented norms, work to integrate youth into conventional institutions and strengthen their attachments to law-abiding friends and family even in disadvantaged areas (Burchfield & Silver, 2013; Feldmeyer et al., 2016; Portes & Rumbaut, 2014). On the one hand, given my overarching argument that relative inequality elevates crime through similar processes as does disadvantage, it is possible that the Latino Paradox contributes to my finding that relative inequality was associated with more modest violent crime growth in White-Latino multiethnic neighborhoods and that Latino political empowerment did not further attenuate the relative inequality effect in Latino and White-Latino multiethnic neighborhoods. Such a pattern would be consistent with a recent study that detected significantly smaller positive effects of relative inequality on recidivism by Latino youth than White or Black youth (Wright et al., 2016). On the other hand, it should be noted that I did not observe cross-sectional levels of relative inequality to have distinctly lesser impacts on crime in Latino or White-Latino multiethnic neighborhoods in Chapters 3 and 4.

Trajectories of Neighborhood Crime Change. Past research on neighborhood crime change largely concurs that initial levels and growth in disadvantage, vacant or foreclosed housing, and wider urban economic inequality are associated with growth in crime (Hipp & Kubrin, 2017; Kikuchi & Desmond, 2010; Kubrin & Herting, 2003; Krivo et al., 2018; Lyons et al., 2022). My observation in Chapter 4 that initial relative inequality and growth in disadvantage accelerated rising crime levels at the start of the 1999-2013 period is consistent with this work, but my finding that initial disadvantage was associated with a more stable crime trend and that growth in relative inequality was unrelated to crime trends at all was unexpected. It is possible that many neighborhoods in my sample had high enough starting levels of disadvantage that their crime levels were unlikely to shift by very much over the ensuing decade, thus leading initial disadvantage levels to predict more modest crime trajectories (Krivo et al., 2018). As I noted in Chapter 4, the consistent lack of any effect from growth in relative inequality on crime trends may partially result from how little the tract-level Gini index changed in my sample during my chosen timeframe. This is in stark contrast with rapid increases in the Gini index at the national level in previous decades, which have raised levels of income segregation and possibly made within-neighborhood increases in income inequality less likely (Fry & Taylor, 2012; Horowitz et al., 2020; Reardon & Bischoff, 2011).

When I adjusted my analyses for the interactions between initial and changing levels of relative inequality and disadvantage, the results appeared to vary somewhat by crime type. I found some evidence that the impact of initial relative inequality on violent crime rate growth curves was offset by initial levels of disadvantage, consistent with the cross-sectional findings for the interaction between relative inequality and disadvantage observed in Chapter 3. For property crime trends, however, I found that the effect of initial disadvantage in making crime curves more modest was amplified in areas where initial relative inequality was higher. In sum, I noted in Chapter 4 that the impacts of structural factors on crime trajectories documented in prior research vary by period and crime type, and those qualifiers apply to the analyses of this chapter as well. My findings may also be somewhat unique to my sample and analytic strategy, as at least one study has found increases in focal neighborhood and spatial inequality to associate with growth in crime during the 2000s (Hipp & Kubrin, 2017).

Moderators of Relative Inequality. The findings from this dissertation are largely in accord with prior work in finding that relative inequality is best conceptualized as a predictor of crime whose impact varies with other critical features of the social milieu, whether solely at the neighborhood level or encompassing the wider urban context. My principal contribution in Chapter 5 was to consider city-level moderators of relative inequality beyond those of the economic domain, which have been the primary focus of prior work (Burraston et al., 2018; Chamberlain & Hipp, 2015; Hipp, 2011; Wenger, 2019). Nevertheless, a pattern that is strikingly consistent with most past findings is that the interaction terms involving relative inequality are universally *negative* in direction. Substantively, this means that relative inequality tends to have reduced consequences for crime in neighborhoods that are more disadvantaged, more segregated, represented by minority elected officials and bureaucrats, and enmeshed in cities with more organizations dedicated to strengthening community life and public safety. It would be rather incredible if it were mere coincidence that all these features are to some degree more present in communities with higher shares of people of color with fewer social, economic, and political resources than their White neighbors. More likely is that relative inequality is a feature of neighborhoods that systematically has its strongest impacts on crime only when other traditional structural determinants of crime are less severe or ubiquitous (see Burraston et al., 2018, for a similar argument). If so, it may represent an additional obstacle to crime-free public spaces for those predominantly Black, Latino, or multiethnic neighborhoods that are able to attain greater social, economic, and political empowerment, a barrier not similarly shared by many White neighborhoods that have low levels of both relative inequality and disadvantage.

Limitations and Directions for Future Research

Despite the considerable advantages of the NNCS2-P and my supplemental city-level data, my analyses are subject to several limitations. First, my focus on the consequences of intra-neighborhood economic inequality within census tracts potentially elucidates only a small portion of the full relationship between relative inequality and neighborhood crime. As I noted in Chapter 2, if census tracts underestimate the amount of inequality neighborhood residents are exposed to, my findings may represent a conservative estimate of the true impact of relative inequality and differences in the magnitude or direction of its effects. Moreover, considering intra-neighborhood inequality alone obscures important spatial dynamics. Levels of crime and disadvantage in the areas surrounding neighborhoods have long been known to elevate crime and widen ethno-racial criminal disparities above and beyond the impact of focal area conditions (Peterson & Krivo, 2010a; Mears & Bhati, 2006; Morenoff et al., 2001). There is mounting evidence that spatial proximity to economic inequality, too, is independently associated with higher crime levels and growth in crime over time (Chamberlain & Hipp, 2015; Hipp & Kubrin, 2017; Stucky et al., 2016). But does spatial inequality differentially affect crime by neighborhood ethno-racial composition, cross-sectionally or longitudinally? Are the effects of spatial inequality on crime also moderated by spatial disadvantage? And what is the most appropriate unit or units of analysis for answering these questions? I invite future research to build on my findings by experimenting with different operationalizations of relative inequality and neighborhoods, especially by using non-government-defined geographic areas as neighborhood proxies where possible, and by including measures of spatial inequality.

Second, I encourage future research to carry out similar analyses but with different samples, time periods, and methods of longitudinal analysis. A recent cross-sectional example is McNulty et al.'s (2023) study of Atlanta block groups, which found that the Gini index had similar positive effects on violence by neighborhood racial composition even without controlling for the inequality by disadvantage interaction, though their sample of neighborhoods was for only one city. Regarding my analyses in Chapter 5, my findings for the effects of growth in relative inequality have limited generalizability because of how little the Gini index changed during the 2000s, and the complexity of my LGC model approach hampers a more parsimonious account of how intra-neighborhood inequality and crime changed over time. Additionally, my longitudinal analyses held neighborhoods constant at their ethno-racial compositions in 2000, but in fact the demographic characteristics of some census tracts changed dramatically from 2000 to 2010 (Lyons et al., 2022). My analyses did not consider how different patterns of ethno-racial stability or change interact with changes in disadvantage or relative inequality. It is possible that relative inequality had a more pronounced influence on crime trajectories in neighborhoods that became more racially or ethnically diverse and experienced reductions in disadvantage over time, and this may be a fruitful line of inquiry for later work.

Third, I recommend that future research continue to investigate the sources of my racially variant findings. A major limitation of the current study is that although I frame my analyses using extant arguments about how relative inequality raises crime rates through relative deprivation, social disorganization, and opportunity theory processes, I am not able to measure these processes directly. Future work that concretely operationalizes the connections between relative inequality, social capital, and crime for neighborhoods of varying ethno-racial compositions will aid our understanding of why relative inequality occasionally exhibits racially variant effects. Additionally, because crime and sociodemographic data for a large sample of neighborhoods at multiple time points have until recently been unavailable, there is a particular need for more longitudinal research on the sources of racial variation in changes in crime over time. The findings from this dissertation suggest that initial levels of relative inequality shape subsequent trajectories of crime differently across neighborhoods of different colors, but future studies should corroborate this finding and identify explanations for this variation. Finally, scholars can also attempt to discover other city-level moderators of relative inequality beyond my three core constructs, which may aid in explaining why relative inequality effects were more strongly moderated in some ethno-racial neighborhood types than others.

Conclusion

This dissertation drew on data from the NNCS2-P to explore the extent to which intra-neighborhood income inequality exerts uneven effects on crime across different communities, and especially neighborhoods of different colors, to achieve a better understanding of how relative inequality upholds the U.S. racial structure and ethno-racial criminal inequality. Although relative inequality does not exhibit the same dramatic variation across neighborhood areas as disadvantage and has racially invariant consequences for crime at a single point in time, I found that its influence on trajectories in crime over time does vary by neighborhood ethno-racial composition. Furthermore, relative inequality elevates crime more modestly in neighborhoods that are more disadvantaged, segregated, and embedded in cities with more community organizations and minority political empowerment, all characteristics that are more prevalent in cities that are more structurally disadvantaged and home to more Black, Latino, and other residents of color. Academics, policymakers, and community organizers who seek to lessen the burden of disproportionate exposure to crime for residents from the poorest and most racially segregated urban neighborhoods should remember that if the quality of life in these communities improves, relative inequality will represent one final obstacle to clear. The findings discussed here and elsewhere suggest that the impact of relative inequality on crime waxes even as the ubiquity of structural disadvantage wanes (Burraston et al., 2018). With this point in mind, I welcome future research to continue exploring the interactive dynamics of inequality and disadvantage on neighborhood crime across communities of varying racial and ethnic compositions.

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