The Pennsylvania State University

The Graduate School

College of Liberal Arts

BRINGING BACK THE CITY:
A MULTILEVEL ANALYSIS OF CRIME
AND ECOLOGICAL CONTEXT

A Dissertation in

Sociology

by

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Submitted in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

August 2016

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ABSTRACT

This dissertation focuses on the importance of unit of aggregation for the study of communities and crime. It begins with a conceptual chapter that makes the case for including constructs at multiple levels of aggregation to separate their effects at each level. Studies in this line of research typically include characteristics at only one level of analysis, without regard for the implications of doing so. I refer to this limitation as omitted level bias. Further, city characteristics have largely been omitted in recent research and I encourage their inclusion as a level.

The conceptual chapter is followed by two empirical chapters. Each of these concentrates on one community characteristic to reveal distinct effects of that construct at each level and to consider the implications of this separation for understanding underlying processes. The first empirical chapter, Chapter 2, focuses on a composite measure of disadvantage, separating its effects at the block-group, tract, and city levels using multilevel modeling. The second empirical chapter, Chapter 3, follows a similar procedure for income inequality. The data for both chapters are block-group level crime counts from the NIJ Foreclosure and Crime Data Archive and demographic information from the American Community Survey for 11,485 block-groups nested in 3,797 tracts nested in 35 cities.

Chapter 2 reveals that the association between disadvantage and crime depends on the level of aggregation. Disadvantage appeared associated with crime at all three levels when each was considered in isolation, but joint analyses to separate effects by level showed that only tract and city disadvantage increase crime. Further, I find cross-level interactions between the measures of disadvantage that suggest that the influence of disadvantage on crime is stronger when disadvantage at other levels of analysis is low. By contrast, in Chapter 3, tract inequality is the only measure of inequality that increases crime once the effect of inequality is separated across the levels of aggregation. As with disadvantage, I find cross-level interactions between inequality measures. Taken together, results support the continued pursuit of distinct effects for different levels of analysis and the incorporation of explicit reference to level of analysis in theory.

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ACKNOWLEDGEMENTS

I am extremely grateful for the many people who have helped me along the way and assisted with making this dissertation a finished product. First and foremost, I thank my advisor, Wayne Osgood for his incredible feedback and advice regarding research, writing, and academia in general. Thank you for your guidance throughout my graduate career and for devoting so much time and energy to me and my scholarship, especially in the last few months, weeks, days, and hours.

I am also thankful for Derek Kreager, with whom I worked on my master's thesis, and who had an impact on my development as a scholar long before my dissertation topic was finalized. The years I spent as his research assistant, and my continued collaboration with him in the years following have made me a better researcher and a better member of the academic community. Thank you, Derek, for all you have done for me.

I am also deeply indebted to remainder of my dissertation committee, Barry Lee, Eric Baumer, and Shannon Monnat, for their thoughtful feedback and suggestions for improving this project. I thank Barry Lee, for fostering my interest in communities research. The thought-work which ultimately led to this dissertation began in his classroom, and his feedback during that process was crucial to its development. I thank Eric for encouraging my pursuit of this research agenda, for joining my committee so late in the process, and especially for sharing his data with me. And I thank Shannon for providing a much needed outside perspective and for reminding me to think about the bigger picture.

I will also forever be grateful for the amazing support that I have received from my family and friends throughout my graduate career, but especially as I worked through my dissertation. To my mother, Ruth Wenger, thank you for your constant words of encouragement and for always taking the time to talk me through the harder days. To my father, David Wenger, thank you for pushing me to strive for more. To my sister and brother-in-law, Kirsten and Marvin Cooper, who are my biggest cheerleaders, thank you for the care packages, for your never-ending faith in me, for listening to me vent my frustrations, and for providing me with the much-appreciated distraction of a nephew just as my dissertation got rolling. To Lauren Hannscott, who began this journey with me six years ago, thank you for being a constant source of relief, laughter, and unconditional friendship. And to all my other Penn State friends and colleagues, thank you for being such an amazing community and for making my time at Penn State unforgettable.

Finally, to my best friend and amazing partner, Brendan Lantz, thank you for your relentless support, for your patience through my anxiety and frustration with the writing process, for continually reminding me that I was capable of finishing, and for providing me with delicious beer when I needed a break.

CHAPTER 1:

CRIME, ECOLOGICAL CONTEXT, AND OMITTED LEVEL BIAS

Scholars have long been interested in how community characteristics influence crime rates, and there is a large body of research revealing important relationships. However, there is ambiguity about the scale at which these relationships occur. In other words, it is unclear whether the influence of community characteristics is generated from qualities of the immediate neighborhood, the larger urban area, or from distinct influences at multiple scales. I argue that this is a major shortcoming of research to date, and that separating the effects of community characteristics by various levels of analysis is crucial for the advancement of this line of criminological research. Further, the potential influence of city characteristics has largely been omitted from recent research, and I argue that it is time to bring the city back into focus as a primary level of analysis to be studied simultaneously with neighborhoods and smaller units. In this dissertation, I lay out the theoretical groundwork for the importance of separating the effects of community characteristics at different levels and for including cities as an influential level of analysis. I then go on to present two empirical studies that demonstrate distinct effects of a community characteristic at different levels when separated in analyses.

In general, the study of communities and crime focuses on the association between crime rates and the characteristics of some type of geographic unit. However, within this field of research, little attention has been paid to identifying the contribution of one type of unit versus another, such as neighborhoods versus cities. Theories about communities and crime agree that certain characteristics matter for crime at a higher level of analysis than the individual, but there is no consensus regarding the most relevant level of analysis for each variable. The level of aggregation at which these characteristics are measured varies widely across studies, including census blocks, block groups, tracts, cities, nations, and more. Furthermore, almost all of these studies are unable to distinguish relationships at any particular level because each considers only one level of aggregation (Pratt and Cullen 2005), either out of convenience or preference (Boessen and Hipp 2015).

Prior work has generally produced consistent findings about the direction and significance of the relationships of these community characteristics to crime, but little attention has been paid to determining 1) whether the associations between these variables and crime *differ* depending on the level of aggregation used, and 2) at what level(s) of aggregation each concept matters (but see Boessen and Hipp 2015 for an exception). For example, greater levels of income inequality, racial diversity, family disruption, and disadvantage are generally associated with higher crime rates, while residential stability is associated with lower crime rates (Blau and Blau 1982; Kovandzic, Vieraitis, and Yeisley 1998; Krivo and Peterson 1996; Morenoff, Sampson, and Raudenbush 2001; Sampson and Groves 1989; Sun, Triplett, and Gainey 2004; Xie and McDowall 2008). However, this body of research includes each community characteristic at only one level of analysis per study. The relationship between a community characteristic and crime at one level of aggregation is distinct from the relationship between that characteristic and crime at a different level of aggregation, and they cannot be discerned from one another by analyzing either relationship alone. Therefore, separating out the effects of each construct at different levels of aggregation is important for better understanding the processes underlying the associations between community characteristics and crime.

THEORETICAL BACKDROP

To understand the importance of separating levels of analysis, it is important to consider the history of communities and crime research. While the majority of criminological theories attempt to explain individual offending, asking why certain people are more likely to commit crime than others, macro-level theories of communities and crime attempt to explain aggregate crime rates, asking why certain *places* have higher rates of crime than others. As Kubrin (2009) noted, “one of the most recognized facts about crime is that it is not randomly distributed across neighborhoods within a city” (p. 225). In other words, crime tends to cluster in certain areas and remain absent in others. In addition to identifying the characteristics of places which increase or decrease crime rates overall, the theories discussed here have varying implications about the levels at which processes operate. We will see that some theories are relatively clear about the most relevant levels of aggregation, which yields more definite empirical hypotheses and practical implications, while other theories leave this as an area of ambiguity.

EARLY WORK ON THE SPATIAL DISTRIBUTION OF CRIME

Although not often cited in literature reviews of communities and crime research, the idea that crime is not randomly distributed across space can be traced as far back as Guerry’s (1833) work in France, in which he demonstrated the spatial distribution of crime across the country using judicial statistics from public prosecutors. Prior to Guerry’s work, as Sampson (2012) explains, the common assumption was that crime was caused by individual free-will and was randomly distributed across space. Quetelet (1842) extended Guerry’s findings to compare the distribution of crime by crime type among France, Belgium, and the Netherlands, and argued that his research supported the idea of “social physics.” Rawson (1839) linked the distribution of crime with the primary occupation in an area, showing that areas with more metropolitan workers had the highest levels of crime in England and Wales, in comparison to areas with more agricultural, manufacturing, or mining workers.

Mayhew (1861) and Booth (1889) further extended research on the spatial distribution of crime by documenting the way that non-criminal characteristics of neighborhoods tended to co-occur with crime. For example, Mayhew argued that crime was linked to areas with high poverty, drunkenness, poor housing, and economic insecurity, and that opportunity for crime varied with the economic environment. Booth took the step of mapping poverty and wealth in London.

Although this early work addressed the spatial clustering of crime, it was mainly descriptive and the explanations for clustering were mainly compositional. That is, they attributed the spatial grouping of crime to the spatial grouping of individuals with particular characteristics. As a result, they did not specify any contextual processes whereby aggregate characteristics produce distinct social processes that affect everyone in the geographic area. Instead, a compositional effect would explain associations at all levels of aggregation rather than there being any contextual effects of a higher level.

DEVELOPMENT OF SOCIAL DISORGANIZATION THEORY

Despite this early attention to the importance of spatial distribution in the 19th century, most histories of communities and crime research begin with the research of Park and Burgess in Chicago in the 1920s. As part of their work at the University of Chicago, Park and Burgess (1925) noted important changes in urbanization, industrialization, and immigration in Chicago neighborhoods. They compared the city to an ecological environment, one in which humans are in competition for resources and space; this is why communities and crime research is often referred to as ecological research. Park and Burgess developed the Concentric Zone model, which suggested that the city was divided up into 5 successive zones, with the central business district at the core, followed by the transitional zone, the working class zone, the residential zone, and finally the commuter zone at the periphery. They argued that population density decreased and socioeconomic status increased from the central business district to the commuter zone. Additionally, they noted patterns of invasion, dominance, and succession as groups moved from the inner circle to the outer.

Shaw and McKay (1942) used the Park and Burgess model to show that crime tended to cluster in the transitional zone and then decrease from there to the outer zone. They argued that the social, economic, and cultural characteristics of neighborhoods were directly linked with crime rates. Specifically, they showed that neighborhood socioeconomic status, racial/ethnic heterogeneity, and residential instability were consistent predictors of crime rates, and that these crime rates continued over long periods of time despite population turnover. These findings were used to develop social disorganization theory, which argues that crime occurs in communities which are unable to realize the common values of their residents and maintain effective social controls (Bursik 1988; Kornhauser 1978; Sampson 2012).

Sampson and Groves (1989) later extended Shaw and McKay's theory to include urbanization and family disruption as two additional neighborhood characteristics indicative of social disorganization. Additionally, they explicated the intervening mechanisms between these community characteristics and crime to be friendship networks, supervision of youth, and organizational participation. Finally, Sampson, Raudenbush, and Earls (1997) coined the phrase 'collective efficacy' to mean "the linkage of mutual trust and the willingness to intervene for the common good” (p. 919). Collective efficacy is an additional mechanism which has the capacity to mediate the influence of community characteristics on crime.

Perhaps most important to social disorganization theory is its assertion that neighborhood characteristics have the potential to influence crime rates over and above the influence of the particular composition of individuals within the neighborhood. Given this assertion, and the explicit focus on explaining aggregate crime rates, social disorganization theory is the predominant theory used to explain variations in community crime rates. And indeed, the fact that social disorganization is, by definition, a theory about communities makes it particularly important for my work on separating effects by level of analysis. Social disorganization theory is widely accepted to be a neighborhood-level theory, with most social disorganization theorists suggesting that the constructs which characterize disorganization need to be measured at the neighborhood level. Most studies that test the theory use census tracts or similarly sized approximations of neighborhoods as their primary unit of analysis.

However, while its nature as a neighborhood theory may mean that social disorganization’s main prediction would be that associations between community characteristics and crime exist at the neighborhood level, the theory can be used to predict associations with crime at both smaller and larger units of analysis. I discuss this idea in more depth in the following two chapters for disadvantage and inequality in particular, but here I use the example of collective efficacy. As just mentioned, collective efficacy is one of the primary forces behind crime, according to social disorganization. And while it’s possible that collective efficacy is solidified at the neighborhood level and influences crime at the neighborhood level, it is also possible that collective efficacy between one’s most immediate neighbors is just as important, if not more so. Further, different community characteristics may matter in different ways at different levels, and therefore there may not be just one “appropriate” level at which to measure community characteristics.

STRAIN THEORY

While social disorganization is the predominant macro-level criminological theory, other less explicitly-macro criminological and sociological theories have been used to explain variations in crime rates as well, and these merit some discussion. Strain theory, for example, has been argued to be both a micro- and a macro-level theory. The father of strain theory, Robert Merton (1938, 1949, 1957, 1964, 1968), suggested that crime is a response to the strain resulting from blockage of the means necessary to achieve certain goals. In his original writing, Merton argued that criminal behavior will abound when a society’s cultural system places monetary success above all other forms of success for everyone, but at the same time access to culturally legitimate means of achieving monetary success are limited or nonexistent for a considerable part of the population. He called this mismatch between goals and means a “lack of cultural coordination” (Merton 1938:681).

Because of his emphasis on society and culture, Merton’s theory is often interpreted as a macro one. Further, Agnew (1999) has argued that differences in crime rates across communities result from variation in the amount of strain and in characteristics which influence the association between strain and crime. And Messner and Rosenfeld (1994), in their institutional anomie theory, suggested that within the United States, the economy is the most important social institution, overshadowing political, educational, and familial institutions. As a result, they argued that American society does not have the infrastructure to be able to combat the criminogenic pressures created by the imbalance in power between social classes.

Despite these macro-level arguments, strain theory is often interpreted to be a micro-level theory. Baumer (2007) suggested that rather than being either micro or macro, strain theory is best understood as a multilevel theory that combines both a micro and macro component. He argued that the cultural and structural characteristics associated with strain influence individuals' attitudes and values regarding both monetary success and the use of legitimate means of achievement. In turn, crime rates fluctuate in accordance with the amount of people in a given area who value both monetary success and legitimate means.

Taken together, expectations from strain theory are inherently related to the separation of effects by level. Merton may be right that a lack of cultural coordination is what leads to higher rates of crime, but at what level of aggregation does this matter? He (and Messner and Rosenfeld) wrote about societies, but this could refer to micro-communities, neighborhoods, cities, states, or countries. Additionally, Agnew (1999) defined community quite broadly as "settlement from the block level to standard metropolitan statistical areas" (p. 124) and he pointed out that while most studies suggest that strain theory is best tested using smaller units, "there are gross differences in the independent and intervening variables *between* larger aggregates. As such, the theory can also partly explain differences in crime rates across units like cities, SMSAs, and beyond" (p. 124). While variance at higher levels does not necessarily mean that there are causal processes operating at these levels, Agnew's point calls attention to the need for research to examine whether the higher-level variation is the result of compositional or context effects. Finally, Baumer's suggestion of a multilevel theory supports my call for separating effects by levels, as it explicitly addresses the possibility that there may be a context effect of some community characteristics on individual offending.

My examination of the effects of disadvantage and inequality over the next two chapters reveals that strain theory is underdeveloped in terms of its explication of the social process by which community characteristics translate into strain to increase crime. This lack of conceptual elaboration creates ambiguity about the empirical implications of the theory and its implications for program and policy. I address this limitation in my concluding chapter.

ROUTINE ACTIVITIES THEORY

In comparison to both social disorganization theory and strain theory, routine activities theory is a situational theory of crime. Rather than arguing that certain types of people are more likely than others to commit crime, or that certain types of places are more likely to have higher rates of crime by nature of the places themselves, routine activities theory suggests that crime occurs when certain elements converge in time and space. According to Cohen and Felson (1979) crime occurs when there is a combination of motivated offenders, suitable targets, and a lack of capable guardians. Therefore, certain places may have higher rates of crime because, for whatever reason, these three elements converge in them more often.

At its face, routine activities theory seems most applicable to pretty small units of aggregation. And indeed, this is where the motivation for hot spots policing and situational crime prevention originated. However, the exact size of the small unit is not clear. Additionally, victims and offenders are not stationary. So when examined more abstractly, routine activities theory can potentially be used to explain crime rates in any size unit of aggregation that has the potential to contain suitable targets, a lack of capable guardians, and motivated offenders willing to travel to find targets (Hipp 2007b). Hipp (2007b) has suggested that tracts are the best level of analysis for testing this theory because there is some evidence that offenders will travel an average of 1 to 2.5 miles, and tracts are an average of 1.4 miles across (Pyle 1974). However, given that this reasoning is based on the willingness of offenders to travel, it implies that the unit of aggregation encompasses both the offender's residence and the location of suitable targets where the crime actually occurs. Additionally, research about offender travel patterns shows that offenders select crime locations based on their awareness spaces and that these awareness spaces include more than just their residential areas (Bernasco 2010; Brantingham and Brantingham 1984, 2008; Lammers et al. 2015; Menting et al. 2016). Taken together, these complications make this theory more difficult to test than Hipp suggests. Further development of the theory is needed to tie it to particular levels of aggregation.

SUBCULTURAL THEORY

Another criminological theory which may be relevant to my work on separating levels of analysis is subcultural theory. While not a singular cohesive theory, subcultural theories generally argue that crime results through the process of exposure and socialization to pro-criminogenic ideas. For example, Anderson's (1990, 1999) ethnographic work in Philadelphia revealed a subculture within disadvantaged communities in which a code of the street had developed. The street code encouraged violence and toughness as essential to respect, and Anderson argued that crime abounds as a result of socialization into the street mentality. Subcultural theory, then, can be used to explain the association between community characteristics and crime, if these community characteristics can be argued to create or sustain the subculture.

Because subcultural theories focus on cultural values which are in opposition to, or at least are an alternative to, mainstream culture, they can be used to explain associations between community characteristics and crime only at smaller units of analysis. But the particular size of the unit is still up for debate. For example, subcultures may operate at very small units of aggregation, like city blocks or block groups, or they may characterize entire neighborhoods. It is unlikely however, that subcultural theory could explain a city-level association.

In summary, there are several criminological theories which can be used to explain the association between community characteristics and crime. Additionally, these theories help shed light on how the effects of community characteristics may differ depending on the level of analysis at which they are measured. Some theories have clear implications about which level(s) of analysis are consequential for crime, and research is needed to test that aspect of the theories. Other theories are ambiguous about the level of analysis at which processes operate. For these theories, research that separates effects by level is necessary to aid in developing clarity about the processes involved. Further, it is important to keep in mind that these theories suggest that the effect of a community characteristic might be different when measured at different levels, and that some community characteristics may matter at some levels but not others. As a result, community characteristics must be measured at multiple levels simultaneously to determine how associations differ by level of analysis.

OMITTED LEVEL BIAS AND THE IMPORTANCE OF SEPARATING LEVELS OF ANALYSIS

Although focus on macro-level patterns of offending fell out of favor for a brief period during the 1970s and early 1980s (Bursik 1988), hundreds of studies have been published on the topic since the 1980s (Pratt and Cullen 2005). Research has been conducted using several census-based units of aggregation, including blocks, block groups, tracts, cities, metropolitan statistical areas, states, and nations (Blau and Blau 1982; Kovandzic et al. 1998; Krivo and Peterson 1996; Land, McCall, and Cohen 1990; Sun et al. 2004; Xie and McDowall 2008). Other work has used non-census-based units like police jurisdictions, neighborhood clusters, people's own perceptions of their neighborhood, school districts, and so on (Hipp 2007a; Morenoff et al. 2001; Sampson and Groves 1989; Sampson et al. 1997). And some research has used macro-level theory to explain individual offending (Vogel and South 2016).

Based on theory and decades of research, we have a general idea of how each community characteristic associates with crime. For the most part, as already mentioned, research finds that greater amounts of racial diversity, income inequality, disadvantage, residential instability, family disruption, and urbanization all increase crime. However, there are some notable exceptions which find the expected associations to be null, or to operate in the opposite direction than expected. Additionally, although we have a basic understanding of how community characteristics influence crime, we do not know the scale at which each characteristic has its influence because research suffers from what I refer to as *omitted level bias*. Omitted level bias is a special form of omitted variable bias, in which the researcher fails to measure and include a given characteristic at all levels of analysis at which it has an association with crime. In this way, omitted level bias ties the issue of omitted variable bias directly to level of aggregation. It has broad implications for the study of community influences and has received little attention in the past.

Most studies include community characteristics at only one level of aggregation, but as previously mentioned, relationships at different levels are distinct phenomena, and their empirical contributions can't be distinguished unless they are measured simultaneously.

Therefore, including a community characteristic measured at only one level may result in omitting the level at which the influence is actually occurring or only including part of the overall association. The omitted level bias created by not separating the effects of a characteristic at multiple levels can lead to the overall relationship appearing quite similar at all levels, as typically seen in the literature, even if the processes are different at each level.

For example, the influence of neighborhood disadvantage on neighborhood crime is distinct from the influence of city disadvantage on city crime, and both of these are distinct from the influence of city disadvantage on neighborhood crime. Even if these associations are in the same direction, they would result from different processes. Neighborhood disadvantage might increase neighborhood crime by limiting social cohesion between residents and reducing their ability to access resources outside of the neighborhood. A totally different possibility would be that city disadvantage might increase neighborhood crime by limiting the availability of resources outside of the neighborhood, regardless of whether or not residents are willing to work together to access them. Because each of these associations results from distinct social forces, there is no a priori reason that all would be present or that they would be of similar magnitude. Studies that include a characteristic at only one level will estimate an undifferentiated mix of effects of processes at multiple levels. The key to avoiding omitted level bias is to include constructs at multiple levels simultaneously, which parses out the contributions of a given characteristic at each level. The empirical chapters that follow this conceptual chapter are examples of this method.

Land et al.'s (1990) research on the structural covariates of homicide is a primary example of the importance of separating out levels so as to not make unwarranted conclusions. They pointed out that at the time of their writing, "instead of the accumulated literature depicting an invariant set of findings across different time periods and different levels of analysis, it indicates a general pattern of inconsistent results" (p. 923). They believed that "a general theory of structural covariates of homicide should be capable of accommodating *all* these levels of analysis" (p. 933). What their research successfully showed was that inconsistencies across findings from prior research were partially due to collinearity between structural covariates which are better measured as components of index variables representing resource deprivation and population structure. And indeed, when they used these composite variables, they found consistent effects on homicide for analyses at the city level, the SMSA level, and the state level.

While this contribution was certainly useful, their consistency of findings across levels masked the issue of omitted level bias, as I discuss here. Including a construct like resource deprivation at only one level can obscure differing processes operating at multiple levels simultaneously. Rather than examining the association between crime and resource deprivation in a way that would differentiate their strength at each of the three levels they tested (city, SMSA, and state), Land et al. (1990), only looked at one level at a time. Their finding that resource deprivation is positively associated with crime at each level does not reveal whether there is an underlying mechanism actually operating at all three levels because they did not simultaneously control for resource deprivation at the other levels. The state-level association could simply be a composition effect of processes happening at the city or SMSA level. A contrasting possibility would be that there is little variation across cities and SMSAs within each state and the significant association is actually due to state-level differences in resource deprivation.

Further, the meaning of associations between community characteristics and crime differs depending on the level at which each structural covariate is measured because the level of aggregation determines the implied scope of the processes involved. By default, constructs measured at more micro levels of aggregation will have a smaller scope than constructs measured at more macro levels. This may seem straightforward or tautological, but it is important to note because when researchers choose a level of aggregation, they implicitly assume that a variable matters at *that* level, and not others. Without separating effects by level of analysis, however, it is impossible to know whether a significant relationship at that level results from a process actually occurring at that level or at a different level.

For example, one explanation for the link between income inequality and crime is that individuals compare themselves to others, and when they feel frustrated about their comparative position, they may commit crime either to raise their position or relieve their strain (Blau and Blau 1982; Hipp 2007b). When a researcher measures inequality at only one level of aggregation, they at least implicitly assume that this level represents the size and makeup of the actual reference group that produces the feeling of comparative deprivation. But without also controlling for inequality at other levels of analysis, it is impossible to know whether a significant association results from inequality at that level. It might instead result from inequality in a larger or smaller reference group which is not measured, but whose association is misleadingly captured at the level actually measured.

Substantively distinct processes with varying implications due to the difference in scope of the comparative measure may exist at each level of analysis. For example, the influence of income inequality on crime may differ at the census block level versus the entire city because the comparison group for inequality at the census block level is much smaller and more immediate than the comparison group at the city level. The larger comparison group for the city-level measure may or may not match the size of the comparison group that people use in real life.

Measuring inequality at only one of these levels makes it hard to determine which is the most relevant.

METHODOLOGICAL IMPLICATIONS OF SEPARATING LEVELS OF ANALYSIS

Methodologically, separating levels of analysis is important because a construct measured at any given level of aggregation can only affect crime rates to the extent that it varies at that level, so it is important to examine how much each construct varies at each level. Further, constructs measured at lower levels of aggregation can explain upper-level variance, but only to the extent that the constructs themselves vary across the upper level. For example, neighborhood-level residential stability can explain city-level variation in crime rates *if and only if* cities differ in the average amount of residential stability of their neighborhoods. If, however, cities all have similar means for neighborhood-level residential stability, then the difference in city-level crime rates must be explained by something other than neighborhood-level stability.

Differentiating the contribution of processes at different levels of analysis requires simultaneously analyzing relationships at multiple levels. Doing so allows for distinguishing among within-unit effects, context effects, and between-unit relationships (Alwin 1976; Firebaugh 1979), as has been well established for differentiating individual-level and aggregate relationships. Consider the case of a two-level model, with cities as the upper level, neighborhoods as the lower, and poverty as the variable of interest. In this scenario, the within-city effect refers to the effect of neighborhood-level poverty on neighborhood-level crime, separate from any differences across the cities on either measure. In contrast, the context effect would be the effect of city-level poverty on neighborhood crime, controlling for neighborhood-level poverty. A significant context effect, therefore, would imply that city-level poverty matters for neighborhood-level crime regardless of the amount of poverty in any given neighborhood. Thus, it captures the influence of a causal process operating at the level of entire cities, where the within-city neighborhood effect is distinct to processes at that level and not attributable to features of cities. Finally, the between-city relationship refers to the overall relationship of city-level poverty with city-level crime, jointly produced by the within-city effect applied to mean differences in neighborhood-level poverty between cities and by the context effect of city-level poverty itself.

The framework for distinguishing within-unit, between-unit, and context effects is possible because of the statistical principles behind the distinction of context effects and composition effects. Calculation of the overall between-unit effect requires group-mean centering the lower-level measure of the construct in question (e.g., neighborhood poverty, using the example above). When the lower-level variable is group-mean centered, the lower-level relationship excludes all of the between-unit variance, leaving the entirety of the between-unit variance to be explained by the higher-level association (i.e., the between-unit effect). But when the lower-level variable is grand-mean centered or uncentered, the higher-level association only reflects the effect of the higher-level variable on the lower-level outcome, independent of the value of the lower-level variable. As a result, the between-unit effect is equivalent to the sum of the within-unit effect and the context effect, and the context effect is the remaining difference between higher-level units after taking into account the lower-level relationship (Alwin 1976; Firebaugh 1979). In other words, using the example of neighborhood and city poverty predicting crime, the between-city effect of poverty is the sum of the within-city effect and the context effect of city poverty on neighborhood crime, and the context effect is the difference between cities after taking neighborhood poverty into account. If there is a significant city-level effect of poverty when neighborhood-level poverty is group-mean centered, but not when neighborhood-level poverty is grand-mean centered, then there is no context effect.

The distinction between context and between-unit effects has the critically important implication that the standard research design, which considers only a single level of aggregation, is limited to between-unit effects. Between effects found at the city level reflect an undifferentiated mixture of the neighborhood-level association, driven by the particular combination of neighborhoods within each city, and distinct effects from the cities themselves, beyond the influence of any given neighborhood. The former is a composition effect, in which differences in crime between cities are due to mean differences between cities in the predictor variable combined with the neighborhood-level effect (e.g. homicide rates could vary across cities because the average amount of disadvantage in each city varies). The latter is a context effect, in which the city-level predictor is associated with neighborhood-level crime regardless of the neighborhood-level value of the predictor (e.g. city-level disadvantage affects neighborhood-level homicide, regardless of whether the neighborhood is disadvantaged).

Additionally, without separating the levels, the three types of effects cannot be distinguished from one another. In fact, the between-unit effect is the only one that can be calculated. Leaving out the within-unit and context effects could lead to incorrect or muddled conclusions. And almost all prior aggregate research has been limited in this way. For example, returning to the study by Land, McCall, and Cohen (1990), the effects of resource deprivation may look similar at all levels because they are all composition effects from a true association at a lower level of aggregation.

Hipp (2007a) acknowledged a lack of attention to level-of-aggregation choice in macro-level studies of crime. He posed the issue of level of analysis differently than I do here, putting it in terms of choosing the “right” level for analysis rather than focusing on the more fundamental need for separating effects at different levels. As such, he states that “theorists positing such structural effects must ascertain the proper geographical aggregation for both the outcome measure employed and the structural predictors” (p. 660). In his study, Hipp created both block-level and tract-level measures of various community characteristics. However, his sample was a subsample of participants from the American Housing Survey (AHS). The AHS randomly selected housing units from the full AHS sample and interviewed the focal head of household and his/her ten closest neighbors. Therefore, Hipp’s (2007a) “block”-level measures were calculated by summing the responses of each group of eleven adjacent neighbors rather than on actual block-level data from the Census. Additionally, his outcome measure for crime was based on participant reports of the amount of crime they perceived in their neighborhood. Finally, and most importantly for my purposes, the data that he used were not nested (very few tracts contained more than one “block”), and he was therefore unable to incorporate the block and the tract as separate levels of aggregation. His study was able to show that the direction and magnitude of associations between certain community characteristics and crime vary depending on the level at which they’re measured, but because his models are not nested, his study does not actually differentiate effects at different level of analysis.

Later, Boessen and Hipp (2015) used nested data from seven cities to test how effects of various community characteristics varied across levels of aggregation. Their two primary levels were the block level and the block-group level. They also included tract-level measures, but as substitutes for block-group level measures, not using the tract as an additional level. They had too few cities to include city-level predictors. They found quite a bit of variation in effects across level of analysis, but they did not interpret their results in terms of within, between, or context effects. Additionally, because they looked at nine structural characteristics, each at multiple levels, they were unable to include a thorough conceptual framework for understanding the implications of their findings. Although this research is similar to my empirical research in the following chapters, I take a more informative approach by focusing on one community characteristic at a time to gain a more definitive sense of the substantive implications for that topic, by including cities as a primary level of analysis, and by developing implications for relationships between each community characteristic and crime at different levels in terms of the three types of effects.

IMPORTANCE OF THE CITY AS A LEVEL OF ANALYSIS

Recent research on communities and crime has given little attention to differences among cities. Social disorganization theory and other theories of communities and crime have focused on neighborhoods; Kubrin and Weitzer (2003) noted that "social disorganization theory focuses on the effects of 'kinds of place' – specifically, different types of neighborhoods" (p. 374). As a result, recent research has tended to concentrate on neighborhoods and smaller levels of aggregation while largely ignoring city-level processes (Boessen and Hipp 2015). The definition of neighborhood varies quite a bit from study to study (Hipp 2007a, Sampson 2012), but most studies omit city-level indicators or remove city-level differences, implicitly treating them as a nuisance factor. However, this omission is a lost opportunity because crime rates vary a lot across cities, and these differences result from real differences in the composition, culture, and history of each city. Assuming that these differences are due *only* to processes happening at the neighborhood level is not only an oversight, but also a missed opportunity to examine what it is about each city that leads to these vast differences in crime rates.

For example, consider two American cities: Cleveland, Ohio and Alexandria, Virginia. According to Peterson and Krivo's (2010) National Neighborhood Crime Study (NNCS)[1], the three-year average neighborhood burglary rate in Cleveland for 1999-2001 was 17.4 per 1,000 residents, while the comparable rate in Alexandria was only 4.7 per 1,000 residents. Additionally, within Cleveland, the neighborhood rate of burglary ranged from 3.8 per 1,000 residents to 70.6, while the range in Alexandria was only from 1.1 to 17.7 per 1,000 residents. This difference between Cleveland and Alexandria could simply be due to processes occurring at the neighborhood level in each city which add up to city-level differences. However, they could also be due to substantive differences between the cities themselves beyond the neighborhoods they are composed of. Cleveland is a northern city with a large percent of workers employed in the manufacturing industry (18% in 2000), while Alexandria is a southern city with a much smaller portion of workers in the manufacturing industry (3% in 2000). The racial composition of Cleveland in 2000 was 39% white, 50% black, 7% Hispanic, 1% Asian, and 2% other. In comparison, Alexandria was 54% white, 22% black, 15% Hispanic, 5% Asian, and 4% other. The two cities have similar levels of household income inequality (gini coefficient in Cleveland = .48, gini coefficient in Alexandria = .45), but the overall amount of disadvantage in Cleveland is much higher than in Alexandria[2]. In fact, 26% of Cleveland's population was in poverty in 2000, contrasted with only 9% of Alexandria's population. Again, the difference in crime rates between Cleveland and Alexandria could be due to processes occurring at the neighborhood level, but they could also be due to city-level processes, and this is a matter for empirical testing. In other words, the question remains whether there is something about living in a city with high disadvantage (or high residential instability or high inequality, and so on) that affects people in *all* neighborhoods within the city, both advantaged and disadvantaged, and my dissertation provides the answer.

Before including cities as a level of analysis, however, it is necessary to first determine whether there are differences among cities on the community characteristics associated with crime. The potential importance of cities as a level largely depends on the extent of variation across cities in both crime rates and in the community characteristics expected to influence crime. Therefore, using the NNCS, I calculated the amount of variance that exists at the city level for several index crimes as well as various measures associated with communities and crime research[3]. If there were no variance at the city level, then inclusion of the city as a level of analysis would be less important. However, there is quite a bit of variance at this upper level, both for crime and for its predictors, as shown in Table 1.1. Approximately 53% of the variance of the size of the foreign-born population is between cities rather than between neighborhoods, while 23% of the variance of racial diversity is between cities. And approximately 24% of the variance of burglary is at the city level, with 15% of the variance of robbery between cities. Therefore, both community characteristics and crime have variance at the city level, and this variance is an important phenomenon that has received little attention in modern research on communities and crime.

Further, even some of the earliest scholars in the social disorganization tradition acknowledged the importance of taking into account the larger context surrounding neighborhoods, including characteristics of the cities within which neighborhoods exist. For example, Bursik (1988) argued that:

> [I]n an important sense, the social disorganization model that has traditionally appeared in the literature is conceptually incomplete. A full specification will require a broadening of the perspective to include the broader economic,

> historical, and political dynamics in which the development of local communities is imbedded (P. 538).

At the time, Bursik was advocating for the use of longitudinal modeling in order to be able to capture historical processes, but I am extending Bursik's insight to argue for simultaneously looking at neighborhood effects and broader contextual effects of the cities that neighborhoods are imbedded within. Additionally, according to Sampson and Wilson (1995), "the goal of macrolevel research is not to explain individual involvement in criminal behavior but to isolate characteristics of communities, *cities*, or even societies that lead to high rates of criminality" (p. 38-39, emphasis added). As both Bursik (1988) and Sampson and Wilson (1995) acknowledge, cities themselves have the potential to substantively influence crime rates. Therefore, characteristics of cities should be a focus of analysis, rather than ignored or averaged out. In this dissertation, I make cities a primary focus to see how city-level characteristics affect crime.

Additionally, although out of favor now, a lot of the work on community characteristics from the 1980s used cities and similar levels of aggregation as the level of analysis. For example, Blau and Blau's (1982) seminal work on income inequality and crime used standard metropolitan statistical areas (SMSAs). And Bailey's (1984) research on poverty, inequality, and homicide, Messner (1983)'s work on poverty, inequality, and region, and Sampson's (1985) research on racial composition and crime all used cities as the level of analysis. Therefore, although neighborhoods have replaced cities as the preferred level of analysis for research on communities and crime, cities have played an important role in the history of communities and crime research.

In addition to cities having a direct effect on crime rates, I argue that cities may affect processes at lower levels of aggregation by shaping the larger political, economic, and racial context within which neighborhoods function. As Lyons, Velez and Santoro (2013) have pointed out, “neighborhoods are not islands unto themselves. Rather, they are nested within cities and city environments shape neighborhood outcomes” (p. 605). Therefore, in addition to having a direct effect on crime rates, cities have the potential to interact with neighborhoods to influence crime rates. For example, Lyons et al. (2013) have shown that the negative association between neighborhood immigrant concentration and neighborhood crime rates is weaker in cities with less favorable immigrant political opportunities. Additionally, using the NNCS I recently found that the amount of racial diversity existing at the city level influences the way that neighborhood racial diversity associates with neighborhood crime rates (Wenger, unpublished). I argue that this is because cities with greater racial diversity are more likely to be racially tolerant than cities with lower diversity, and therefore to provide a more welcome environment for diverse neighborhoods. Research that ignores the city-level context misses these important processes that influence crime rates.

POLICY IMPLICATIONS

Beyond the methodological and substantive implications for research and theory, separating the effects of community characteristics by level of aggregation has important implications for policy as well. Knowledge about the actual unit of aggregation at which criminogenic processes occur would help policymakers and programmers more effectively target the actual problematic community conditions leading to higher crime rates. Policymakers design programs that are intended to decrease crime by targeting certain criminogenic phenomena at particular levels of aggregation. But if they are unaware of, or have misguided expectations about, the level at which community characteristics like disadvantage, inequality, residential stability, and collective efficacy influence crime rates, then there is a mismatch between the policymakers' expectations and the reality of the process. In this case, programs are unlikely to be effective.

For example, if residential stability indeed reduces crime, and policymakers believe that it does so at a micro-scale, like the block or block-group level, then they will likely focus attention and resources on increasing stability at this small scale, in blocks or block-groups which have high amounts of instability. If the actual unit of analysis at which stability increases crime is the neighborhood or the city, then these resources diverted just to blocks or block-groups with high instability will likely be wasted without a concerted effort at increasing stability at the neighborhood or city level as well.

Further, although the focus of this dissertation is the influence of community characteristics on crime rates in particular, it has potential application to other criminological and non-criminological outcomes as well, like fear of crime and health. For example, separating the effects of community characteristics on health outcomes by level of aggregation may help policymakers decide the most effective strategy for reducing health risks as well.

MOVING FORWARD

In this chapter, I have argued that a more complete understanding of the association between community characteristics and crime requires separating the effects of community characteristics at multiple levels of aggregation. Additionally, I have suggested that cities should be considered a potentially important level of analysis to use when separating the effects. The following chapters provide empirical tests of the ideas put forth here, and they also present theoretical frameworks for understanding how theory can be used to make predictions about how associations may (or may not) differ by level of analysis. In Chapter 2, I examine the association between disadvantage and crime, measuring disadvantage at three different nested levels of aggregation. I look at not only the direct effects of disadvantage and crime at each level, but also whether or not the amount of disadvantage at one level of analysis influences the relationship between disadvantage and crime at the other levels of analysis. In Chapter 3, I follow a similar process for the association between inequality and crime. Finally, I provide a concluding chapter which ties my findings in Chapters 2 and 3 together with the ideas presented here and presents the next steps in my research agenda.

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ENDNOTES

[1]The NNCS is a dataset containing a sample of 9,593 census tracts nested within 91 cities, with tract-level and city-level sociodemographic information, as well as tract-level crime data.

[2]Disadvantage is measured using Peterson and Krivo's (2010) index which takes the average of the standardized scores of six variables: 1) percent of jobs in the secondary low-wage sector, 2) percent of the working age population that is unemployed or has dropped out of the labor market, 3) percent of households headed by females, 4) percent in poverty, 5) percent of employed persons working in managerial and professional occupations, and 6) percent of adults over the age of 24 who are high school graduates. Using this index, the level of disadvantage in Cleveland in 2000 was 1.57, while the level of disadvantage in Alexandria was –1.45.

[3]The amount of variance per level was calculated using one-way ANOVAs in SPSS.

Table 1.1. City-Level and Tract-Level Variance for 91 U.S. Cities

	Variance	
Variable	City-Level	Tract-Level
% Black	34%	66%
Disadvantage	19%	81%
Residential Stability	9%	91%
% Foreign Born	53%	47%
% Young Men	9%	91%
Diversity	23%	77%
Homicide	11%	89%
Robbery	15%	85%
Aggravated Assault	18%	82%
Rape	20%	80%
Burglary	24%	76%
Larceny	4%	96%
Motor Vehicle Theft	14%	86%

SOURCE: National Neighborhood Crime Study (Peterson and Krivo 2010)

CHAPTER 2:

DISADVANTAGE AND CRIME:

DISTINGUISHING BLOCK-GROUP, TRACT, AND CITY EFFECTS

Disadvantage is one of the strongest and most robust predictors of aggregate crime rates (Peterson and Krivo 2005; Pratt and Cullen 2005). In this chapter, I present a study addressing an important limitation of research on this topic, namely, a lack of attention to the level of aggregation of the causal processes that underlie this relationship. Studies of the association between community disadvantage and crime rates have been conducted using a variety of samples and a variety of units of analysis. However, despite the explicit focus on aggregate rather than individual characteristics, most studies do not devote much attention to the relevance of the particular level of aggregation used. As Hipp (2007) has argued, the oft-cited finding that aggregate effects are of smaller magnitude than individual effects (Liska 1990) may be due to misspecification of the level of aggregation used in communities and crime research. Further, I argue that research conducted using only one level of aggregation may suffer from omitted level bias. As explained in the previous chapter, omitted level bias occurs when a researcher does not measure the association between a given characteristic and the outcome at all levels of analysis at which an association exists. For example, one of the mechanisms through which disadvantage is expected to increase crime is through its impact on social control. If disadvantage interferes with social control at only small levels of aggregation like census block groups, then using only larger levels of aggregation, like neighborhoods, to measure disadvantage may obscure results. Researchers may conclude that disadvantage influences social control at that higher level, even though the causal process is actually at the lower level. In this case, the mechanism operates at the block-group level, but the research only detects its indirect consequences at the neighborhood level.

Decisions about which level to analyze are often the result of data availability rather than relevance. However, relationships between constructs at different levels are distinct phenomena, resulting from potentially distinct mechanisms. In other words, the influence of block-group disadvantage on crime is distinct from, and may have a different cause than, the influence of tract disadvantage on crime. Studying disadvantage at only one level of analysis is not sufficient to distinguish them empirically. As a result, research findings may represent exaggerated or understated associations.

The way to avoid omitted level bias and avoid misconstruing the level at which an influence occurs is by measuring the association at multiple levels simultaneously. Doing so provides the means to separate the effect of any given variable into different levels. For example, measuring the association between disadvantage and crime at both the block-group and neighborhood level would reveal whether the association between neighborhood disadvantage and crime is due to a neighborhood-level process or is simply a composition effect of the block groups within the neighborhood. In the current study, I measure disadvantage at three levels of aggregation (block groups, tracts as proxies for neighborhoods, and cities) and include them in models simultaneously in order to examine how the effect of disadvantage separates into associations at each level.

In the sections that follow, I begin by summarizing prior research on the association between disadvantage and crime and highlighting what we do and do not know about how the association varies across level of analysis based on this research. Afterward, I lay out my conceptual framework for understanding the meaning and importance of separating the effects of disadvantage at multiple levels. Additionally, I talk about the potential role of cities as a level of aggregation and about my choice for the levels of analysis used for the present study. I then discuss relevant criminological theories about the association between disadvantage and crime in light of the theoretical framework and I generate hypotheses for each theory's predictions about disadvantage and crime at different levels.

PRIOR RESEARCH ON DISADVANTAGE AND CRIME

Research to date on disadvantage and crime has been conducted at various levels of aggregation (e.g., blocks, block groups, tracts, cities, states, etc.), and most studies have found a strong positive association. Using census tracts in Columbus, Ohio, Krivo and Peterson (1996) found that extremely disadvantaged neighborhoods have higher levels of violent crime than neighborhoods with low or high disadvantage. Morenoff, Sampson, and Raudenbush (2001) used neighborhood clusters from the Project on Human Development in Chicago Neighborhoods (PHDCN) to find that concentrated disadvantage is a strong predictor of homicide rates. Results of Pratt and Cullen's (2005) meta-analysis are less straight forward for disadvantage than some other community characteristics because measures of disadvantage are often indexes formed from multiple variables, and Pratt and Cullen analyzed these variables separately. However, they found that some components of disadvantage – poverty, unemployment, and family disruption – were three of the strongest and most stable predictors of crime. They concluded that "when taken in its entirety, the present meta-analysis lends considerable support to the concentrated disadvantage thesis" (Pratt and Cullen 2005:425). Finally, in their review of recent research, Peterson and Krivo (2005) argued that disadvantage is a consistent predictor of crime across the many different ways it is measured, including “differing combinations of poverty, income, family disruption, and joblessness/unemployment” (p. 337).

Despite the consistency with which studies find a significant positive relationship between disadvantage and crime, almost all studies have analyzed only one level of aggregation at a time. Hipp (2007) called on scholars to attend to the proper level of aggregation for structural characteristics, and suggested that it may differ by specific characteristic. Indeed, he found that the effects of racial diversity were similar when measured at the block and tract level, but that economic resources was significantly associated with crime only at the block level when measured at both levels. His models were not multilevel, however, because he did not nest blocks within tracts, and his crime outcome was residents’ perceptions of the amount of crime in their neighborhood rather than the actual amount of crime. Boessen and Hipp (2015) improved upon this strategy by conducting multilevel models predicting crime in seven cities, with blocks nested within block groups and, separately, blocks nested within tracts in order to examine how structural characteristics relate to crime at different levels of analysis. They also included spatial lags of the structural characteristics to capture the influence of processes beyond the neighborhood. They included nine structural characteristics at each level simultaneously and found different effects for each variable across each level of aggregation.

While Boessen and Hipp (2015) demonstrated that there are differences in the effects of community variables across levels of analysis, they did not provide a conceptual framework for interpreting and understanding these differences. I will address this framework by using established distinctions between within-unit, between-unit, and context effects. Additionally, Boessen and Hipp (2015) included all nine structural characteristics at multiple levels simultaneously, which did not allow for sufficient attention to relevant theory and interpretation of each. Rather than examining nine structural characteristics at once, I focus on disadvantage in order to devote an adequate amount of attention to the meaning of its association with crime at different levels of aggregation.

THE IMPORTANCE OF CITIES

Although some of the earliest work on communities and crime used cities and metropolitan statistical areas as their units of analysis (Blau and Blau 1982), recent research has tended to focus on neighborhoods and smaller units of analysis. The reasons for this trend are two-fold: 1) social disorganization theory, as discussed shortly, is the predominant theory in the study of communities and crime, and the theory itself is widely considered a neighborhood theory, and 2) data for enough cities to conduct city-level analysis with lower-level outcomes are not commonly available. However, as shown in Chapter 1, and as I will show in my analyses here, there is quite a bit of city-level variation in community characteristics, and omitting city-level indicators is a lost opportunity to capture and model these differences. Additionally, some prior work has found that city-level processes have the potential to shape lower-level processes (Lyons, Velez, and Santoro 2013).

To highlight these points for disadvantage in particular, consider two cities: Seattle, Washington and Philadelphia, Pennsylvania. According to Peterson and Krivo's (2010) National Neighborhood Crime Study (NNCS), Seattle's robbery rate in 2000 was 293 per 100,000 residents while Philadelphia's was 687. Research focusing on neighborhood-level processes exclusively would implicitly assume that this city-level difference in robbery is due to differences between neighborhoods, which aggregate to create city-level differences (e.g., neighborhood-level disadvantage increases crime, and Philadelphia's neighborhoods are more disadvantaged). Indeed, a closer examination of the NNCS data reveals that the maximum amount of disadvantage in Philadelphia neighborhoods surpasses that of Seattle. Figure 2.1 displays a choropleth map of the distribution of disadvantage across tracts in Philadelphia and Seattle. Darker tracts have higher tract disadvantage and lighter tracts have lower tract disadvantage. The values of disadvantage used for the gradient are the quintiles of tract disadvantage in Philadelphia. As seen in the figure, there are no tracts in Seattle with disadvantage in the highest quintile. However, Philadelphia also has much more disadvantage overall (1.02 in comparison to -1.02, on an index based on standardized measures). Research that only looks at neighborhood-level processes would treat the circled tract in Philadelphia the same as the circled tract in Seattle because they have the same amount of tract disadvantage. Yet it seems unreasonable to ignore the possibility that outcomes for a disadvantaged neighborhood will differ, depending on whether it is nested within a disadvantaged city like Philadelphia or an affluent city like Seattle.

LEVELS USED IN CURRENT STUDY

To separate the effects of disadvantage at any level of analysis, disadvantage must be measured at multiple levels. In the current study, I use three levels of analysis based on census designation. The first level is block groups, which are designed to have populations between 600 and 3,000 people. At the time of the 2000 Census, there were 208,790 block groups in the United States with an average number of 39 blocks per block group. Block groups are the smallest level of aggregation at which the Census publishes sample data. Census block groups are nested within census tracts, which are the second level of aggregation used in this study. Census tracts are made up of anywhere from one to nine block groups with an average of three block groups per tract. Tracts have between 1,500 and 8,000 people and are designed to have an average population of 4,000 people. There were 65,443 tracts in the United States in the 2000 Census. Finally, census tracts are nested within cities, which are the third level of aggregation for this study. Cities themselves are not a census designation, but census places include census-designated places, consolidated cities, and incorporated places, and they are most commonly used in data analysis as proxies for cities. Approximately 73% of the population in the United States were living in places at the time of the 2000 census and there were 25,150 census places total. There were an average of 8,000 people per place, which may seem low for cities, but the places used in this study to represent cities have an average population of around 445,000 people.

THEORETICAL FRAMEWORK FOR UNDERSTANDING MULTILEVEL ASSOCIATIONS BETWEEN DISADVANTAGE AND CRIME

There are four broad macro theories used to explain the association between disadvantage and crime, and they provide some insight into how the association between disadvantage and crime may depend on the level of aggregation used: social disorganization theory, concentration effects, strain/anomie theory, and subcultural theory. While they all suggest that disadvantage should be associated with higher crime rates, they provide different underlying mechanisms. My discussion of the theories will focus on their implications for relationships at different levels of analysis.

SOCIAL DISORGANIZATION THEORY

As explained in the previous chapter, social disorganization theory is the predominant macro-level theory. Shaw and McKay (1942) studied juvenile court records in Chicago in the early 1900s. Their research revealed that certain areas of the city maintained high levels of crime, despite changes in the areas' residential populations. They argued that crime rates were better explained by certain characteristics of the areas themselves, rather than by characteristics of the individuals living therein. They found that high crime areas tended to be characterized by low socioeconomic status, high residential mobility, and high ethnic diversity. Sampson and Groves (1989) later updated Shaw and McKay's theory to include family disruption and urbanization as additional indicators of social disorganization. As Bursik (1988) explained, these community characteristics were assumed to combine to create 'socially disorganized' areas. Social disorganization itself can be defined as "the inability of a community to realize the common values of its residents and maintain effective social controls" (Sampson 2012:37).

Sampson, Raudenbush, and Earls (1997) extended the theory with their concept of 'collective efficacy,' arguing that social cohesion and trust between neighbors is an important intervening mechanism between the characteristics of socially disorganized communities and crime rates. Socioeconomic status and family disruption are two of the indicators used to measure disadvantage, and disadvantaged areas tend to have lower collective efficacy (Sampson et al. 1997) and, as a result, limited informal social controls and limited agency. Therefore, social disorganization theory would predict that disadvantage will be positively associated with crime because people are less willing and able a) to deter or regulate criminal behavior (Bellair 1997; Peterson, Krivo, and Harris 2000; Sampson and Groves 1989; Warner and Rountree 1997) and b) to intervene in order to help one another to access resources from outside of the community which may help reduce crime.

Social disorganization theory is widely considered a neighborhood-level theory, and as a result, many studies have used neighborhoods, often measured using census tracts, as their unit of analysis. Accordingly, social disorganization would predict that tract-level disadvantage has the strongest influence on crime. Block groups may be too small to capture the influence of limited social control. However, disadvantage at a higher level, like the city, might reduce the availability of resources for residents to access to reduce crime. In this way, city disadvantage may have a context effect on neighborhood crime, but it may also effect the association between neighborhood disadvantage and crime. Neighborhoods are the primary emphasis of social disorganization theory, so the city-level contribution is expected to be secondary to the tract-level process.

CONCENTRATION EFFECTS

Wilson's (1987) book, *The Truly Disadvantaged*, attempted to explain and call attention to the plight of the black underclass. His theory has been used to argue that communities with predominantly black populations have higher rates of crime than those that are predominantly white because of the overwhelming concentration of disadvantaged blacks within certain areas. As a result, his propositions about concentration effects are relevant to the topic of disadvantage and crime. According to Wilson, deindustrialization combined with the out-migration of middle- and upper-class blacks to transform the inner city. This transformation "resulted in a disproportionate concentration of the most disadvantaged segments of the urban black population, creating a social milieu significantly different from the environment that existed in these communities decades ago" (Wilson 1987:58). In other words, disadvantaged communities represent a distinct structural environment characterized by social isolation from mainstream society.

Linking Wilson's concept of concentration effects specifically to crime, Sampson and Wilson (1995) argued that the social isolation and ecological concentration of disadvantage create an environment with limited economic opportunities and few positive role models, which in turn undermines social organization and crime control. Therefore, the structural conditions of the most disadvantaged communities would increase crime in any community, regardless of race, but black communities are much more isolated and disadvantaged than white communities. As Sampson and Wilson (1995) state, "the sources of violent crime appear to be remarkably invariant across race and rooted instead in the structural differences among communities, cities, and states" (p. 4).

Wilson's (1987) arguments are not necessarily about neighborhoods, but he referred to different areas within the city as having differing amounts of disadvantage, which suggests that he was thinking about processes at a smaller level of aggregation than the city. However, Sampson and Wilson (1995) mention the importance of structure among cities and states as well. Additionally, although Wilson (1987) defines "concentrated" in terms of the disproportionate representation of underprivileged persons, the combined influence of multilevel disadvantage may be a unique form of concentrated disadvantage. Thus, the combined influence of being in a disadvantaged block group within a disadvantaged tract within a disadvantaged city may be particularly criminogenic. In other words, block-group disadvantage, tract disadvantage, and city disadvantage may all increase crime, but the combination of any two, or all three at once, may increase crime more than just adding their separate effects. For example, turning back to the distribution of disadvantage in Philadelphia and Seattle depicted in Figure 2.1, the high amount of disadvantage in the circled tracts may result in those tracts having higher rates of crime than other tracts in each respective city. Yet the tracts in Philadelphia may have higher rates of crime than comparable tracts in Seattle due to the higher amount of disadvantage in Philadelphia. The circled tract in Philadelphia may have an exceptionally high rate of crime, greater than would be expected by adding the influence of tract-level disadvantage and city-level disadvantage. This would result in a positive interaction between the different levels of disadvantage.

Interestingly, there is evidence that the concentration of disadvantage may instead have the opposite effect. Rather than exacerbating the effect of disadvantage at any one level, disadvantage at multiple levels may result in a threshold or ceiling effect. Krivo and Peterson (2000) and Hipp and Yates (2011) have found evidence of such a diminishing effect of disadvantage. In other words, rather than disadvantage always increasing crime, both teams of researchers found that crime increased with disadvantage to a certain point and then leveled off. The proposed explanation is what Hipp and Yates (2011) refer to as a “satiation effect” (p. 961) in which an area’s disadvantage reaches a point at which its consequences cannot get any worse. For example, disadvantage may decrease social control to the point where any additional increase in disadvantage results in no further increase in crime because social controls are already nonexistent. Extending this to multilevel disadvantage would suggest that the association between disadvantage and crime at any level is weaker when disadvantage at other levels is higher. For example, in a city like Seattle, which is relatively affluent, higher disadvantaged block groups or tracts may have lower social control than less disadvantaged block groups or tracts, and this difference in block-group and tract disadvantage would lead to differences in crime rates. But in a city like Philadelphia, which is so disadvantaged overall, the amount of disadvantage in any given block group or tract within the city may not have any additional impact on social control and therefore on crime, over and above the influence of city disadvantage. If a satiation effect occurs, it would result in an opposite interaction to the one expected from Wilson's concentration hypothesis.

STRAIN AND ANOMIE THEORIES

In his original formulation of Strain Theory, Merton (1938) argued that people commit crime as one possible response to a perceived blockage of the means necessary to achieve certain goals. While there is some disagreement about whether Merton intended his theory and later revisions (Merton 1949, 1957, 1964, 1968) to be as an individual or macro-level theory, his propositions are at least implicitly macro in their connotation. Merton asserted that criminal behavior on a substantial scale results from strain only when the cultural system values monetary success above all else for the entire population, while also limiting or eliminating access to culturally approved means of acquiring that success for a substantial part of the population. He called this phenomenon a "lack of cultural coordination" (Merton 1938:681). Agnew (1992) extended Merton's theory into a General Strain Theory, arguing that strain can result from additional sources other than economic goal blockage. He further revised the theory to explain community differences in crime rates, arguing that differences in community crime rates result from differences in the amount of strain present in communities and in the community characteristics that shape the influence of strain on crime (Agnew 1999).

Finally, Messner and Rosenfeld (1994) put forth their institutional anomie theory in an attempt to explain the exceptionally high rate of violent crime in the United States in comparison to other industrialized countries. Their theory is explicitly a macro-level theory, in which they argue that the institutional structure and balance of power in America creates a society that is incapable of restraining criminogenic cultural pressures due to the overwhelming dominance of the economy over political, educational, and familial institutions.

Although strain and anomie theories are often thought to best explain the effects of relative deprivation (e.g., income inequality), they have also been used to explain the relationship between disadvantage and crime. Agnew (1999) denoted economic deprivation as one of the primary community characteristics that increases strain, ultimately leading to crime. In general, areas with greater disadvantage have fewer economic opportunities, and therefore fewer non-criminal means to achieve economic goals. Additionally, some research suggests that monetary goals, or at least displays of monetary success, are more highly valued over other goals in disadvantaged areas (Anderson 1990).

Strain and anomie theories have been used to explain both individual and aggregate offending at various levels of aggregation. Strain may operate on a relatively small scale because it results from individual social psychological processes, and any macro-level association results from aggregating an individual-level effect. In this case, I would expect the primary influence of disadvantage to operate at the block-group level because this is the closest level to the individual. On the other hand, as suggested by Messner and Rosenfeld (1994), strain may operate at the macro level by creating structural imbalances that lead to aggregate differences in crime rates. Structural imbalances are more likely to exist at the city level than the block-group level because of economic structure. Therefore, in this case, I would expect disadvantage to have its strongest influence on crime at the city level.

Baumer (2007) has suggested that, rather than being either macro or micro, Merton's theory is best understood as a multilevel theory in which macro-level characteristics influence individual offending. He argues that cultural and structural characteristics influence individuals' commitment to monetary success and commitment to using legitimate means to achieve it through socialization, and that crime rates vary based on the prevalence of individuals who share these commitments. Therefore, disadvantaged areas should have higher crime rates, but this should be a composition effect that reflects influences mainly occurring at the lowest level of aggregation, the block group.

SUBCULTURAL THEORIES

A third explanation for the association between disadvantage and crime is that crime may result from subcultural approval or socialization. For example, Anderson (1990) found evidence of a 'code of the street' subculture within some disadvantaged communities in which crime is actually encouraged and applauded, rather than discouraged, as a mechanism of survival. He argued that residents of disadvantaged communities are socially isolated and distrust formal authorities like police. The code of the street, then, developed in response to this isolation and distrust. As Anderson put it, the informal rules of the code "regulate the use of violence and so supply a rationale allowing those who are inclined to aggression to precipitate violent encounters in an approved way" (Anderson 1999:33). Indeed, Kubrin and Weitzer (2003) found that "cultural retaliatory homicides" were more common in neighborhoods with higher levels of disadvantage and Sampson and Bartusch (1998) found that there was more tolerance for crime and deviance in neighborhoods with more disadvantage.

Finally, as an alternative to the mainstream culture, subcultural theories are generally considered to be relevant at the neighborhood level or below. Since subcultural attitudes are expected to be transmitted through socialization, they are most likely to develop through everyday interactions between people that come in direct contact. Therefore, subcultural theories would generally expect that disadvantage has its influence on crime at smaller levels of aggregation like the block-group level. If city disadvantage has a significant and distinct influence, it is likely not the result of subcultural values. Further, any influence that disadvantage has on crime through subculture should not apply to non-disadvantaged parts of tracts or cities, so I would not expect a context effect based on this theory.

THE CURRENT STUDY

In addition to establishing the theoretical framework just outlined, the current study goes beyond prior studies in three ways. First, most prior research has only examined relationships at one level of analysis at a time. I analyze the relationship between disadvantage and crime at multiple levels of analysis simultaneously in order to separate the effects of disadvantage at different levels. Second, most research, especially recently, has focused on neighborhoods and smaller levels of analysis. I include cities as a primary level of analysis. Finally, we do not know whether the amount of disadvantage at one level of analysis affects the association between disadvantage and crime at other levels. I test for cross-level interactions between the three measures of disadvantage to see whether the relationship between disadvantage and crime at one level is dependent on the amount of disadvantage at other levels.

HYPOTHESES

A close reading of the theories, as described above, provides some insight into whether and how the association between disadvantage and crime would differ by level of analysis. First, all theories linking disadvantage and crime predict that greater disadvantage leads to higher crime rates, and when disadvantage is included at only one level of analysis its effect is a composite of the relationship between disadvantage and crime at all levels. Therefore, I hypothesize that when measures of disadvantage are considered individually, they will all be associated with higher rates of crime:

Hypothesis 1: Prior to controlling for disadvantage at other levels of analysis, disadvantage will have a positive relationship with crime at the block-group, tract, and city levels.

The theories differ in their predictions about how disadvantage should associate with crime when they are distinguished by considering all three levels of aggregation at once. At the block-group level, both strain and subcultural theory provide reasons to expect a positive association between disadvantage and crime, even after controlling for tract and city disadvantage. Strain theorists who argue that strain leads to crime through its effect on individual behavior would predict a positive association between disadvantage and crime at the block-group level because it is the smaller level of analysis and the closest to the individual. In this case, a positive block-group level effect would be the result of the specific composition of individuals within the block group. Additionally, subcultural theory predicts a positive block-group effect of disadvantage on crime. Therefore:

Hypothesis 2: After controlling for tract and city disadvantage, block-group disadvantage will have a positive association with crime.

Turning to tract disadvantage, social disorganization theory would predict that the association should be positive and have the strongest effect at the tract level, which is the closest approximation to a neighborhood effect. Subcultural theory could also predict a positive association between tract disadvantage and crime, if subcultures can occupy units as large as neighborhoods. Based on social disorganization and subcultural theory:

Hypothesis 3: After controlling for block-group and city disadvantage, tract disadvantage will have a positive association with crime.

Finally, both social disorganization and strain theories suggest that city disadvantage may have a positive association with crime after adjusting for block-group and tract disadvantage. Social disorganization predicts that the association should be positive, albeit weaker, at the city level because the city is often the level at which resources for deterring crime are available. Alternatively, strain theorists who argue that strain leads to higher rates of crime because of structural imbalances would predict a positive association between city disadvantage and crime. Based on these theories:

Hypothesis 4: After controlling for block-group and tract disadvantage, city disadvantage will have a positive association with crime.

In addition to the additive main effects of the three measures of disadvantage, I will investigate whether the association between disadvantage and crime at one level of analysis is dependent on the amount of disadvantage at the other levels of analysis. As discussed, the combined effect of disadvantage at multiple levels could influence crime in two different directions. On the one hand, extending Wilson's (1987) propositions about concentrated disadvantage, multilevel disadvantage may create a unique form of concentration which produces an exacerbating effect, such that greater disadvantage at a higher level of analysis actually intensifies the association between disadvantage and crime at a lower level of analysis. In other words, while disadvantage may have a positive association with crime at all three levels, disadvantaged block groups nested within disadvantaged tracts or disadvantaged cities may have particularly high rates of crime, beyond what would be expected simply by adding the effect of disadvantage at two levels together. This would produce a positive interaction in which the association between block-group disadvantage and crime is stronger in high disadvantage tracts than low disadvantage tracts. Additionally, the association between block-group disadvantage and crime and between tract disadvantage and crime would be stronger in high disadvantage cities like Philadelphia than in low disadvantage cities like Seattle.

Hypothesis 5: The association between disadvantage and crime at one level of analysis is dependent on the amount of disadvantage at other levels, such that greater disadvantage at one level of analysis exacerbates the magnitude of the association between disadvantage and crime at other levels (positive interaction).

Alternatively, however, there may be a threshold effect of disadvantage (Hipp and Yates 2011; Krivo and Peterson 2000) in which disadvantage at one level of analysis has no further influence once the amount of disadvantage at another level hits a certain point. In this case, disadvantage would have a weaker association with crime at a lower level of analysis when the amount of disadvantage is greater at higher levels of analysis (and vice versa). For example, disadvantage may increase crime at all three levels, but the association between block-group (or tract) disadvantage is weaker in disadvantaged cities like Philadelphia than in less disadvantaged cities like Seattle.

Hypothesis 6: The association between disadvantage and crime at one level of analysis is dependent on the amount of disadvantage at other levels, such that greater disadvantage at one level of analysis diminishes the magnitude of the association between disadvantage and crime at other levels (negative interaction).

DATA AND METHOD

DATA

The data for this project come from the NIJ Foreclosure and Crime Data Archive and from the American Community Survey (ACS) 2005 – 2009 five-year estimates. The NIJ Foreclosure and Crime Data Archive was collected by Eric Baumer and colleagues at Florida State University (see Baumer et al. 2014). The investigators reached out to police departments in 109 cities across the United States and requested crime-incident data in whatever format was most convenient for the police departments. They received data in some format from police in 79 cities, and they received address-based crime-incident data for 35 of these cities (see Appendix A for list of cities). The data include index crimes reported to these police departments between 2005 and 2009. Minneapolis provided data for burglary, but not for robbery. Therefore, results for robbery are based on 34, rather than 35 cities.

The ACS is a national annual survey collected by the U.S. Census Bureau as a supplement to the decennial census. The survey gathers demographic, social, economic, and housing information. I use the 2005 – 2009 five-year estimates because the five-year estimates are available at the block-group level and because the time range matches the years of the crime data being analyzed.

Because the data from the NIJ Foreclosure and Crime Data Archive are address-based, I was able to geocode the location of each crime incident as point data. I joined these point data with block-group, tract, and city shapefiles from the 2000 U.S. Census and aggregated the point data by crime type into block-group counts. I then linked the crime-incident data with the ACS data in order to create measures of block-group, tract, and city demographic characteristics. The final robbery sample includes 11,086 block groups nested within 3,676 tracts nested within 34 cities. The final burglary sample is 11,485 block groups nested in 3,797 tracts in 35 cities.

Measures

Because one fewer city contributes to models predicting robbery than those predicting burglary, the sample descriptive statistics are slightly different. Table 2.1 displays descriptive statistics of each of the independent and dependent variables for both samples. The descriptive statistics described in this section are based on the full sample of 35 cities (i.e., the burglary sample).

Robbery and Burglary. The dependent variables used for this study are block-group level counts of robbery and of burglary for the years 2005 – 2009. I use these two outcomes because one is a violent crime and the other is a property crime, and they occur frequently enough to have substantial counts even at the block-group level. As mentioned previously, burglary counts were available for all 35 of the cities providing address-based data, but robbery was included for only 34 of them. The average count of robbery across block groups is 24.59 with an average rate of 3.0 per 100 residents over five years (i.e., .6 per 100 annually). The average count of burglary across block groups is 75.67 with an average rate of 7.9 per 100 residents over this time period.

Disadvantage. The primary independent variables of interest are three measures of disadvantage, each at a different level of aggregation: block group, tract, and city. The block-group-level measure uses the average of the standardized scores of six block-group variables associated with disadvantage: 1) percent of jobs in the secondary low-wage sector, 2) percent of the working age population (16 and older) that is unemployed or has dropped out of the labor market, 3) percent of households headed by females, 4) percent in poverty, 5) percent of employed persons working in managerial and professional occupations (reverse-coded), and 6) percent of adults over the age of 24 who are not high school graduates (α = .76). The tract- and city-level measures of disadvantage were created using the same six variables at the corresponding level of analysis. However, these variables were standardized based on the mean and standard deviation of the block-group measure so that scores have a consistent metric, which enhances the comparability of coefficients (α_{tract} = .82; α_{city} = .79). The average value of disadvantage is .05 at the block-group level, .07 at the tract level, and –.22 at the city level. As the index of disadvantage is based on standardized scores, the mean is expected to be close to zero. The mean for city disadvantage is further from zero because it is not weighted by the number of tracts or block groups in each city. This simply means that cities with fewer tracts have lower disadvantage.

Control Variables. I control for an assortment of other characteristics at various levels of aggregation known to be associated with community crime and disadvantage. At the lowest level, the block-group level, I control for income inequality, the size of the young male population, racial diversity, proportion Black, and proportion Hispanic. *Inequality* is calculated using a robust Pareto midpoint estimator (*rpme* command in Stata) and binned household income intervals (von Hippel, Scarpino, and Holas 2015), using the formula:

$$G = \sum_{i=1}^{n}(X_i \times Y_{i+1}) - \sum_{i=1}^{n}(X_{i+1} \times Y_i)$$

where n is the number of income categories, X_i is the cumulative proportion of households in income category i, and Y_i is the cumulative proportion of household income in income category i. The measure ranges from zero to one with zero representing complete equality and one representing complete inequality. The average value of block-group inequality is .39 with a standard deviation of .09. The size of the *young male population* is measured as the proportion of the population in the unit that is male and between the ages of 15 and 34. The average size of the young male population per block group is 7%. *Racial diversity* is measured as the entropy score, which is calculated based on the population share of five groups in each unit: non-Hispanic Whites, non-Hispanic Blacks, Asians, Hispanics, and people of another race. Therefore, the entropy score for each unit represents the degree of equal representation of these five groups. The formula used for calculation of the entropy score is:

$$E = \frac{\sum_{k=1}^{K} \pi_k \ln\left(\frac{1}{\pi_k}\right)}{\ln(K)}$$

where π_k is the proportion of people in race *k* (e.g. proportion white) and *K* is the total number of racial groups, which is five for this project. Dividing the total entropy score by the natural log of the total number of groups constrains the measure to have values between zero and one, with higher values representing greater diversity, and lower values representing less diversity. A diversity value of 0 indicates that only one group is represented in the area. The average amount of block-group diversity is .42. Additionally, I control for the size of the non-Hispanic Black population (*Proportion Black*; mean = .29) and the size of the Hispanic population (*Proportion Hispanic*; mean = .19).

At the tract level, I control for residential instability and immigrant concentration. *Residential instability* is an index calculated by taking the average of the standardized scores of two variables: 1) percent of renters, and 2) percent of residents that lived in a different census tract five years previously, with higher values representing greater instability. The average value of tract instability is .11. *Immigrant concentration* is measured as the proportion of the population in the unit that is foreign born, with a mean of 13%.

At the city level, I include a control for Black-White segregation between tracts using the index of dissimilarity, following this formula:

$$D_{bw} = \frac{\sum_{j=1}^{n} \left| \left(\frac{b_j}{B}\right) - \left(\frac{w_j}{W}\right) \right|}{2}$$

where n is the number of tracts in the city, b_j is the number of Blacks in tract j, w_j is the number of Whites in tract j, B is the number of Blacks in the city, and W is the number of Whites in the city. The index is on a scale from zero to one and average Black-White segregation at the city level is .52.

Spatial Lag of Crime. Prior research on communities and crime finds that crime tends to be clustered across space, such that places with high crime rates tend to be surrounded by other places with high crime rates. I conducted preliminary exploratory spatial data analysis in order to test for this type of spatial autocorrelation for robbery and burglary. My analyses revealed significant autocorrelation for both robbery (Moran's I = .068, $p < .01$) and burglary (Moran's I = .040, $p < .01$), so I created spatially lagged measures of each. In addition to adjusting for the spatial autocorrelation, the spatial lag itself captures the relationship between crime in an individual neighborhood and crime in surrounding neighborhoods.

Since robbery and burglary are measured at the block-group level, so too are my spatially lagged measures of robbery and burglary. To create these measures, I created variables representing the robbery rate and the burglary rate per 100 residents in each block group. The spatial lag variables were then calculated from these rates using a first-order queen's criterion contiguity matrix in GeoDa 1.4.6, which identifies neighbors as all geographic areas with a common border or corner with the focal area. The value of the spatial lag variable is a simple average of the values of the rates in the neighboring block groups.

ANALYTIC STRATEGY

In order to clarify the potential importance of including cities as a level of analysis in communities research, I begin by conducting an analysis of variance of my dependent and independent variables. By partitioning the variance between my three levels of analysis, I determine the amount of non-chance variation that exists in the dependent variable at the tract and city level which needs to be explained, and how much non-chance variation exists in the independent variables that may help explain the tract- and city-level variation in the dependent variable. To conduct the three-level analysis of variance, I use null models with the variable of interest as the dependent variable in HLM7.0. In continuous models, the residual variance estimates from null HLM models indicate the amount of variance that exists at each level, so I use continuous models with disadvantage as the outcome for the analysis of variance of disadvantage. I use overdispersed Poisson regression in my multivariate analyses because my outcome measures are counts. In overdispersed Poisson regression, however, only the level-two and level-three variance terms provide meaningful information about the amount of variance per level. Therefore, in order to conduct the analyses of variance for robbery and burglary, I first turn the counts into block-group rates based on block-group population, and then log the rates. I then use continuous models with the logged robbery and burglary rates as the dependent variable.

After conducting the analysis of variance, I use three-level hierarchical linear regression models to estimate the association of disadvantage and crime at three levels of aggregation. The nested nature of census designations allows me to use block groups as the level-one unit of analysis, tracts as the level-two unit, and cities as the level-three unit. Osgood (2000) has demonstrated that aggregate crime rates are appropriately analyzed using Poisson-based regression models that use crime counts as the dependent variable. Therefore, my analyses use

Poisson-based regression with block-group population size (in hundreds) as the variable of exposure in order to treat the analysis as one of rates. The basic Poisson model assumes that the fitted mean of the dependent variable is equivalent to its conditional variance, an assumption violated in these data. However, allowing for overdispersion in the analyses avoids the assumption and allows me to proceed with Poisson models. Poisson models with overdispersion are comparable to negative binomial regression models (Gardner, Mulvey, and Shaw 1995).

For each dependent variable (robbery and burglary), I estimate a series of eight regression models. All models include the aforementioned control variables and the spatial lag measure of the dependent variable. To demonstrate the influence of separating the effect of disadvantage by level of aggregation, my first three models introduce each measure of disadvantage, one level at a time, and the fourth model includes all three together. Finally, to test whether the associations found at each level are dependent on the value of disadvantage at the other levels, I estimate four additional models, individually introducing cross-level interactions between block-group disadvantage and tract disadvantage, between block-group disadvantage and city disadvantage, between tract disadvantage and city disadvantage, and then including all three cross-level interactions at once.

RESULTS

ANALYSIS OF VARIANCE

The analysis of variance results appear in Table 2.2. As shown in the table, there is significant variation in disadvantage at all three levels of analysis. Approximately 31% of the variance in disadvantage exists the block-group level, 41% at the tract level, and 28% at the city level. The variation in robbery and burglary also is spread across the three levels of analysis.

While 40% of the variance in robbery exists at the block-group level, 36% exists at the tract level, and 24% at the city level. Similarly, 36% of the variance in burglary rates exists at the block-group level, 49% at the tract level, and less than 15% at the city level.

This analysis of variance demonstrates that there is substantial variation in disadvantage, robbery, and burglary at all three levels of analysis. Therefore, there is plenty of tract and city variation in robbery and burglary to be explained, and plenty of tract and city variation in disadvantage to do the explaining.

MULTIVARIATE ANALYSES

Results of multilevel models for robbery are presented in tables 2.3 and 2.4, while results for burglary are presented in tables 2.5 and 2.6. I present unstandardized Poisson regression coefficients, which represent the difference in the log of the expected robbery/burglary count per unit increase in the independent variable. Standard errors are in parentheses. I also show the exponentiated coefficients in the columns labeled e^b, which represent the proportional change in robbery/burglary rate per unit increase in the independent variable. Finally, to make the results more interpretable, I calculate the percent change in the robbery/burglary rate per standard deviation increase in the independent variable, using the following formula:

$$\%\ Change = ((e^b)^{SD} - 1) * 100$$

where *b* is the unstandardized coefficient, and *SD* is the standard deviation of the independent variable in question. These values are included in the column labeled "%Δ" in each model.

All variables in the analyses are grand-mean centered. In addition to easing the interpretation of individual coefficients, grand-mean centering (rather than group-mean centering) the disadvantage measures allows me to interpret the tract-level and city-level results as context effects on block-group robbery/burglary when all three measures of disadvantage are included. When only one disadvantage measure is included, its coefficient represents the between-unit effect of disadvantage on robbery/burglary (e.g., the average effect of tract disadvantage on tract robbery/burglary). But when all three measures of disadvantage are included and grand-mean centered, the coefficient for tract disadvantage represents the tract-level context effect. This is the average effect of tract disadvantage on block-group robbery/burglary, regardless of the amount of block-group disadvantage in any given block group and the amount of city disadvantage in the city within which the tract is nested. And the coefficient for city disadvantage, when all three measures are included, represents the average effect of city disadvantage on block-group robbery/burglary, regardless of the amount of block-group disadvantage in any given block group and the amount of tract disadvantage in any given tract within the city.

Robbery

Main Effects of Disadvantage

Models 1 through 3 in Table 2.3 provide support for Hypothesis 1, that the association between disadvantage and robbery is positive when each measure of disadvantage is included separately. As seen in Model 1, with all control variables included but without controlling for tract or city disadvantage, block-group disadvantage is positively and significantly associated with the robbery rate (b = .28, $p < .001$). A single standard deviation (.66) increase in block-group disadvantage is associated with a 20.5% increase in the rate of block-group robbery. Model 2 reveals that without controlling for block-group or city disadvantage, tract disadvantage is also positively and significantly associated with the robbery rate (b = .33, $p < .001$), with a standard deviation (.96) increase in tract disadvantage corresponding to a 37.3% increase in the tract robbery rate. Finally, according to Model 3, without controlling for block-group or tract disadvantage, city disadvantage is associated with a positive and significant increase in the robbery rate (b = .69, $p < .01$), such that a standard deviation (.35) increase in city disadvantage is associated with a 27.5% increase in the robbery rate. Interestingly, then, with only one measure of disadvantage included at a time, disadvantage appears to be a significant and positive predictor of robbery at all three levels, and the magnitude of the association increases with the size of the unit of aggregation.

Model 4 of Table 2.3, with all control variables and all three measures of disadvantage included, tells a different story, providing support for hypotheses 3 and 4, but not Hypothesis 2. While the tract and city disadvantage associations remain positive and significant, the association between block-group disadvantage and robbery disappears, with a coefficient near zero (b = –.04) and a p-value of .299. Additionally, the coefficients for tract and city disadvantage decrease in size, especially for city, which is reduced by about 22% (b_{tract} = .35, b_{city} = .54). Controlling for disadvantage at the other two levels of disadvantage, a standard deviation (.96) increase in tract disadvantage is associated with a 39.3% increase in the block-group robbery rate, while a standard deviation (.35) increase in city disadvantage is associated with a 20.8% increase. In other words, increasing the amount of disadvantage in a tract increases robbery in all block groups within that tract, regardless of the amount of disadvantage in any of the block groups. And increasing the amount of disadvantage in a city increases robbery in all block groups within that city, regardless of the amount of disadvantage in any of the block groups. Returning to the earlier example, block groups in highly disadvantaged cities like Philadelphia have higher robbery rates than comparable block groups in less disadvantaged cities like Seattle, controlling for the other variables in the model.

Interaction Effects

Models 5 through 8 in Table 2.4 introduce cross-level interactions between the different measures of disadvantage. Importantly, all three levels of disadvantage are included in all models, such that city disadvantage is controlled for when estimating an interaction between block-group and tract disadvantage and tract disadvantage is controlled for when estimating an interaction between block-group and city disadvantage, and so on. As shown in Model 5, the coefficient for the interaction between block-group and tract disadvantage is negative and significant ($b = -.19$, $p < .001$), providing partial support for Hypothesis 6 but not Hypothesis 5. Therefore, the association between block-group disadvantage and robbery becomes weaker (i.e., less positive) as the amount of tract disadvantage increases. Additionally, the association between tract disadvantage and robbery becomes weaker (i.e., less positive) as the amount of block-group disadvantage increases. In other words, while block-group disadvantage is not associated with robbery rates on the average, the significant interaction suggests that it may be associated with robbery rates under certain conditions (e.g., certain amounts of tract-level disadvantage).

To more easily understand the interaction, I calculated predicted block-group robbery rates at varying values of block-group and tract disadvantage, holding all other variables constant at their means. Figure 2.2 displays the interaction, with the “low,” “medium,” and “high” categories corresponding to one standard deviation below the mean, the mean itself, and one standard deviation above the mean of tract disadvantage. Predicted rates are only plotted for the range of block-group disadvantage that was actually present in the data itself at each value of tract disadvantage. For example, block-group disadvantage within tracts with low tract disadvantage ranged from –1.5 to 1.1, rather than the full range of block-group disadvantage (–2 to 3.2), so the line for that group extends over only the limited range.

Additionally, in supplementary analyses, I re-centered tract disadvantage using the low, medium, and high values, and then re-estimated the interaction models using the re-centered variables instead of the original ones (see Table B2.2 in Appendix B for the full models). The conditional effects of block-group disadvantage produced from these analyses reveal whether the plotted trend lines at low, medium, and high tract disadvantage are significantly increasing or decreasing. For example, the coefficient for block-group disadvantage in the model with an interaction between block-group disadvantage (grand-mean centered) and tract disadvantage (centered on low disadvantage) represents the association between block-group disadvantage and robbery for tracts with low disadvantage (Model 1 in Table B2.1). Asterisks next to each trend line in the figure legend indicate whether the respective trend line is significantly increasing or decreasing based on these supplementary analyses.

As seen in Figure 2.2, the negative interaction between block-group and tract disadvantage corresponds to a positive association between block-group disadvantage and robbery in tracts with low disadvantage, and a negative association between block-group disadvantage and robbery in tracts with high disadvantage. The slope of the association between block-group disadvantage and robbery in tracts with medium disadvantage is positive, but the trend is not significant. Therefore, while the average effect of block-group disadvantage on robbery is null, this association is dependent on the amount of disadvantage in the tract within which it is nested, and it is significant in tracts with lower tract disadvantage.

Turning back to Table 2.4, the cross-level interaction between block-group and city disadvantage in Model 6 reveals a similar pattern to the previous interaction (*b* = –.53, p <.001), such that the association between block-group disadvantage and robbery is weaker (i.e., less positive) in cities with greater amounts of disadvantage and vice versa. This provides further support for Hypothesis 6 over Hypothesis 5. Therefore, block-group disadvantage leads to greater increases in robbery rates in cities with low disadvantage, like Seattle, than in cities with high disadvantage, like Philadelphia. Figure 2.3 depicts the interaction between block-group and city disadvantage with predicted block-group robbery rates calculated in a similar manner as in Figure 2.2. Here, low, medium, and high city disadvantage correspond to one standard deviation below the mean, the mean, and one standard deviation above the mean of city disadvantage. Predicted rates are only plotted for the range of block-group disadvantage that exists in cities with the corresponding value of city disadvantage. As with Figure 2.2, asterisks next to each trend line in the figure legend indicate whether that trend line is significant, based on supplemental analyses (see Table B2.2 in Appendix B).

The negative interaction between block-group and city disadvantage in Figure 2.3 shows a similar pattern to the previous figure, with the slopes of the association between block-group disadvantage and robbery increasing in cities with low and medium disadvantage and decreasing in cities with high disadvantage. However, only the association in low disadvantage cities is significant. Therefore, while block-group disadvantage does not increase robbery on average, it is does in cities like Seattle, which are otherwise quite affluent.

As with models 5 and 6, Model 7 in Table 2.4 reveals a negative and significant cross-level interaction between tract and city disadvantage (*b* = –.36, p < .001), with the association between tract disadvantage and robbery becoming weaker (i.e., less positive) as city disadvantage increases and vice versa. This means that tract disadvantage is more likely to lead to higher robbery rates in cities with low disadvantage overall than in cities with high disadvantage, as is shown in Figure 2.5 (which uses the same low, medium, and high values of city disadvantage as Figure 2.4). Additionally, results from the supplementary analyses used to determine whether each trend line is significant can be found in Table B2.3 in Appendix B.

In contrast to the prior two figures, all three plotted trends in Figure 2.4 are positive and significant, which suggests that while the interaction between tract and city disadvantage is negative, tract disadvantage increases robbery rates, regardless of the amount of disadvantage at the city level. Therefore, tract disadvantage increases block-group robbery rates in all block groups within the tract *more* in a city like Philadelphia than in a city like Seattle, but the association between tract disadvantage and robbery is positive nonetheless in both types of cities. Taken together, the three cross-level interactions suggest that for robbery, there is indeed a threshold effect of disadvantage as expected by Hypothesis 6, rather than an exacerbating effect of concentrated disadvantage as expected by Hypothesis 5.

In order to make more sense of the two-way interactions, Model 8 of Table 2.4 includes all three cross-level interactions at once. Interestingly, it appears that when all three are included, only the interaction between block-group and tract disadvantage remains significant, though somewhat reduced in magnitude ($b = –.14$, $p < .05$). The interaction between tract and city disadvantage is only marginally significant and the coefficient for the interaction is cut in half ($b = –.15$, $p < .10$). This finding suggests that the interaction between block-group disadvantage may in fact be driving the other two interactions when they are included without it. For additional perspective, I also estimated a model including a three-way cross-level interaction between block-group, tract, and city disadvantage. The interaction is significant and positive (b =

.28, $p < .05$). Additionally, with the three-way interaction included, the two-way interaction between block-group and tract disadvantage remains negative and significant ($b = –.22$, $p < .001$). The full model with the three-way interaction is included in Appendix B, Table B2.4.

Control Variables

Though the control variables are only of secondary importance, it should be noted that the associations between the control variables and robbery are largely consistent throughout the model progression in tables 2.3 and 2.4. For example, while the magnitudes of the associations vary from model to model, proportion Black and proportion Hispanic at the block-group level, residential instability at the tract level, and Black-White segregation at the city level are all positively associated with robbery rates in all models. Also, the size of the young male population is negatively associated with robbery in all models.

Interestingly, block-group inequality is significant only in Model 3, when city-level disadvantage is the only measure of disadvantage included. Block-group racial diversity is positively associated with robbery in models 2 and 4 and marginally associated with robbery in models 6 and 7. The spatial lag of robbery is positive and significant in all models, with the exception of model 2 in which it is only marginally significant. And finally, immigrant concentration at the tract level is only significant when tract disadvantage is not included.

Burglary

Main Effects of Burglary

Results for burglary are presented in tables 2.5 and 2.6. As shown in Model 1 of Table 2.5, controlling for all control variables, but with only the block-group measure of disadvantage included, disadvantage is positively and significantly associated with burglary rates (*b* = .23, $p < .001$). A standard deviation (.67) increase in block-group disadvantage is associated with a 16.7% increase in the block-group burglary rate. Model 2 of Table 2.5 includes only the tract-level measure of disadvantage, which has a positive and significant association with burglary (*b* = .28, $p < .001$). A standard deviation (.96) increase in tract disadvantage is associated with a 30.9% increase in tract burglary rates. Finally, Model 3 includes only the city measure of disadvantage, which also has a positive association with burglary, but this association is only marginally significant (*b* = .26, $p < .10$). The city burglary rate increases by 9.5% with every standard deviation (.35) increase in city disadvantage. Therefore, as with robbery, disadvantage appears to increase burglary rates, whether measured at the block-group level, the tract level, or the city level, when only included at one level of analysis at a time, confirming Hypothesis 1.

Model 4 of Table 2.5 includes all three measures of disadvantage at once. As with robbery, these results show that the magnitude and significance of the disadvantage coefficients change once all three are included simultaneously. Similar to results for robbery, block-group disadvantage is no longer a significant predictor of burglary. However, in contrast to results for robbery, city disadvantage does not have an additive effect on burglary. Only tract-level disadvantage is significantly associated with burglary rates when all three levels are controlled (*b* = .30, $p < .001$). Even after controlling for block-group and city disadvantage, the block-group burglary rate increases 32.9% for every standard deviation (.96) increase in tract disadvantage. This means that an increase in tract disadvantage is associated with an increase in burglary in all block groups within the tract, regardless of their amount of block-group disadvantage. The coefficients for block-group and city disadvantage, however, are reduced to non-significance ($b_{\text{block group}} = -.04$, $p = .242$; $b_{\text{city}} = .14$, $p = .263$).

Interaction Effects

Table 2.6 presents the cross-level interactions between the three levels of disadvantage. As with robbery, all three of the cross-level interactions [i.e., between block-group and tract disadvantage (in Model 5), between block-group and city disadvantage (in Model 6), and between tract and city disadvantage (in Model 7)] are negative and significant, providing further support for Hypothesis 6 over Hypothesis 5. This suggests that the association between block-group disadvantage and burglary is weaker (i.e., less positive) in tracts with greater amounts of disadvantage and vice versa ($b = -.19$, $p < .001$). Similarly, the association between block-group disadvantage and burglary is weaker (i.e., less positive) in cities with greater amounts of disadvantage and vice versa ($b = -.35$, $p < .01$). As a reminder, the main association between block-group disadvantage and robbery was not significant when all three measures of disadvantage were controlled in Model 4 of Table 2.5. The significant interactions here between block-group and tract disadvantage and between block-group and city disadvantage suggest that while block-group disadvantage may not increase burglary on the average, it may increase burglary in certain conditions (e.g., specific amounts of tract and/or city disadvantage).

The interaction between tract and city disadvantage suggests that the association between tract disadvantage and block-group burglary is weaker (i.e., less positive) in cities with greater amounts of disadvantage and vice versa ($b = -.24$, $p < .001$). Therefore, while tract disadvantage increases block-group burglary rates, it increases them more in cities with low disadvantage (e.g., Seattle) than in cities with high disadvantage (e.g., Philadelphia).

To make the cross-level interactions more clear, I calculated predicted rates of burglary at varying amounts of disadvantage. As with the predicted rates of robbery, all control variables were controlled at their mean, and the “low,” “medium,” and “high” values of disadvantage at each level of aggregation correspond to one standard deviation below the mean, the mean itself, and one standard deviation above the mean of disadvantage for that level. Figure 2.5 displays the Model 5 interaction between block-group and tract disadvantage, Figure 2.6 displays the Model 6 interaction between block-group and city disadvantage, and Figure 2.7 displays the Model 7 interaction between tract and city disadvantage. Again, predicted rates are plotted only for the ranges of disadvantage in the data. Finally, asterisks next to trend lines in figure legends correspond to the statistical significance of that trend line based on supplementary analyses with re-centered measures of disadvantage (see tables B2.5 – B2.7 in Appendix B for full results).

The negative interactions between block-group and tract disadvantage and between block-group and city disadvantage displayed in figures 2.4 and 2.5, respectively, are quite similar to the corresponding figures for robbery. As with robbery, Figure 2.5 reveals a positive and significant association between block-group disadvantage and block-group burglary in tracts with low disadvantage, a negative and significant association between block-group disadvantage and block-group burglary in tracts with high disadvantage, and a non-significant association between block-group disadvantage and block-group burglary in tracts with medium disadvantage. The latter finding is not surprising, given the non-significant association between block-group disadvantage and burglary in Model 4 of Table 2.5. Figure 2.6 shows that while the slope for block-group disadvantage is positive in cities with low and medium disadvantage, only the negative slope for block-group disadvantage in cities with high disadvantage (like Philadelphia) is significant at the $p < .05$ level. The positive slope in cities with low disadvantage (like Seattle) is marginally significant with a p-value of .056.

The negative interaction shown between tract and city disadvantage shown in Figure 2.7 is also similar to the corresponding figure for robbery. While the significant interaction coefficient indicates that the slopes are different, tract disadvantage has a positive association with block-group burglary in cities with low, medium, and high disadvantage, it has the largest positive association with burglary in cities with low disadvantage.

Model 8 of Table 2.6 includes all three two-way cross-level interactions at once. As with robbery, once all three interactions are included simultaneously, only the interaction between block-group and tract disadvantage is significant ($b = –.17$, $p < .001$). The coefficients for the other two interactions are non-significant and close to zero, which suggests that the block-group by tract disadvantage interaction may be driving the other two when they are included without it. In supplementary analysis shown in Appendix B, Table B2.8, I estimated a three-way cross-level interaction between block-group, tract, and city disadvantage and found that the interaction was only marginally significant ($b = .13$, $p = .071$). Additionally, the two-way interaction between block-group and tract disadvantage remained negative and significant ($b = –.20$, $p < .001$).

Control Variables

As with results for robbery, there is quite a bit of consistency in the effects of the control variables across models. Proportion Black at the block-group level, the spatial lag of burglary, and residential stability at the tract level are positively and significantly related to burglary rates in all models. Additionally, the size of the young male population at the block-group level and immigrant concentration at the tract level are negatively and significantly related to burglary rates in all models.

Block-group inequality has a positive and significant association with burglary when block-group or city disadvantage are the only disadvantage measures included, but the association is only marginally significant whenever tract disadvantage is controlled. Similarly, proportion Hispanic at the block-group level is only significant when tract disadvantage is not included. A pattern for block-group racial diversity is hard to identify, as it has a positive association when tract disadvantage is the only disadvantage measure controlled for, when all three measures of disadvantage are included, and when city disadvantage is interacted with the other two levels of disadvantage, but no association otherwise. And finally, Black-White segregation is a positive and significant predictor of burglary until city disadvantage is controlled.

DISCUSSION

Prior research has generally found a positive association between disadvantage and crime, whether disadvantage is measured using just an indicator of poverty or as an index of different kinds of deprivation (Peterson and Krivo 2005). As a result, Pratt and Cullen (2005) have stated that indicators of disadvantage are "among the strongest macro-level predictors" (p. 379). Despite this consistency, this research has not been informative about the level of aggregation at which disadvantage is consequential because the majority of research has only measured disadvantage at one level of analysis. This approach risks masking important multilevel relationships between disadvantage and crime and creates the potential for misconstruing the meaning of results. Additionally, recent research has focused on neighborhoods and smaller units of analysis, thereby omitting the possibility of capturing a city-level effect.

The current study has extended prior research in four ways. First, I developed a conceptual framework for distinguishing how disadvantage may influence crime differently at different levels of analysis. Second, to determine how the association between disadvantage and crime actually differs by level of analysis, I measured the influence of disadvantage on crime at multiple levels of aggregation simultaneously to separate the effect of disadvantage at each level. Third, I included cities as a level of aggregation, measuring the influence of city disadvantage on crime. And fourth, I tested cross-level interactions between the three levels of disadvantage. Results from the current study reveal three important findings, which are discussed in light of their theoretical implications.

First, prior to distinguishing the effect of disadvantage at different levels, results including disadvantage at only one level of aggregation are consistent with prior research. Greater disadvantage is correlated with higher rates of both robbery and burglary when disadvantage is measured at only the block-group level, only the tract level, and only the city level. These findings are consistent with the expectations of social disorganization theory, strain theory, and subcultural theory, but they cannot tell us whether there are actually processes occurring at each level leading to the corresponding association. For example, the effect of block-group disadvantage could be due to a block-group-level process, but could also result from a tract-level process that produces differences in disadvantage across tracts, which are then captured by the block-group-level association because tract disadvantage is not controlled for. Alternatively, if there *is* a process operating at the block-group level, then the tract-level effect could be the result of that association combined with the particular combination of block groups in each tract, which aggregate up to a tract-level effect, rather than a tract-level process.

Therefore, examination of the models with disadvantage included at only one level of analysis allows for comparison with prior research, but does not provide evidence that specific processes are occurring at any given level. This leads to the second important finding of the study, which is that, as expected, the relationship between disadvantage and crime at each level of analysis is different when all three measures are included simultaneously in comparison to when each is included by itself. Consistent with the expectation of social disorganization theory, when all three levels of disadvantage are controlled for, block-group disadvantage has no influence on crime rates. Instead, tract disadvantage leads to higher rates of robbery and burglary and city disadvantage leads to higher rates of robbery. This suggests that neighborhoods are the primary unit of analysis at which disadvantage influences crime through its effect on collective efficacy and social control, but that city disadvantage also increases some crime types, perhaps through its influence on the resources available to lower units of aggregation.

The city-level relationship between disadvantage and robbery is also partially supportive of strain theory's macro-level expectation that city disadvantage increases crime, suggesting that the larger economic structure of a city influences crime rates. Additionally, the null effect of block-group disadvantage when adjusting for all three levels is inconsistent with the expectation from strain theory that disadvantage leads to crime because it increases individual offending which aggregates up to the block-group level. The null effect of block-group disadvantage also suggests that subcultural theory is not the best explanation for the association between disadvantage and crime, though it may partially explain the tract association if subcultural socialization of criminogenic attitudes occurs at the neighborhood level.

Finally, contrary to expectations based on Wilson's propositions about concentration effects, I found no evidence of an exacerbating effect of multilevel disadvantage. Instead, the negative interactions between each combination of disadvantage measures suggest that there is a threshold effect of disadvantage in which disadvantage increases crime to a point, but has no substantial (or at least a smaller) effect when disadvantage is already high at another level of disadvantage. In other words, the average effect of disadvantage is to increase crime, but once a tract or city has enough disadvantage, the disadvantage in any particular block group within the tract or city has little discernible effect. In this case, social control has been reduced so much in the tract or city that no further reduction can come from an increase in block-group disadvantage. The interaction between tract and city disadvantage is interesting because in contrast with the block-group interactions, tract disadvantage always increases crime, no matter the amount of city disadvantage; it just increases crime less in high disadvantage cities. However, this is still evidence of a threshold effect because tract disadvantage becomes less consequential as city disadvantage increases.

The results from this study have several ramifications for both theory and research on communities and crime. My findings suggest that there is not one "appropriate" level of analysis at which to measure community characteristics, but rather that community characteristics can influence crime at multiple levels and that the mechanism of influence can differ by level. In this chapter, I developed a theoretical framework to explain how each macro-level criminological theory might predict the association between disadvantage and crime at different levels of analysis. However, the framework I developed was based on my interpretation of the implications of each theory for level of analysis, rather than on explicit predictions from the theories themselves. More work can and should be done to tie each theory to specific levels of aggregation more closely and explicitly.

For example, most social disorganization theorists argue that the theory is most appropriately applied to neighborhoods. Although my findings regarding tract-level disadvantage are supportive of the importance of neighborhoods, my city-level findings suggest that social disorganization theory needs to be extended to include cities as influential as well. If city characteristics can influence crime rates beyond neighborhood characteristics and influence the association between neighborhood characteristics and crime, then it is irresponsible for social disorganization researchers to ignore them simply because they do not consider cities to be the "appropriate" level of analysis for social disorganization research.

As another example, strain theorists are in disagreement about whether strain theory should be used as a micro- or macro-level theory. If strain is the mechanism through which disadvantage increases crime, then my findings suggest that the theory is at least partially macro. Block-group disadvantage does not increase crime once tract and city disadvantage are controlled for, which suggests that strain has its influence through disadvantage on more than just individual offending.

In addition to revealing the need to address level of analysis more explicitly in theory, this study also reveals how complex the relationship with crime is for just one community characteristic. While my focus in this chapter is on disadvantage, attention should be paid to other community characteristics as well. In the next chapter, I focus on inequality with this in mind. However, there is a whole assortment of other community characteristics expected to influence crime, each with its own potentially varying effects at different levels of analysis. Researchers should consider each characteristic individually, using theory to anticipate how each associates with crime across levels.

Beyond advancing the multilevel aspects of theory, similar advancement is needed for data collection. One reason that prior research has not separated effects by level of analysis is that the available data has not allowed for it. Data collection of crime-incident data at a low level of aggregation (e.g., blocks and block groups) across multiple cities is difficult because there is no central database to which crime is reported in this form. The FBI collects crime counts from police agencies across the country and publically releases the Uniform Crime Reports (UCR), but counties are the smallest level of aggregation at which these crime counts are released. As a result, most datasets used in communities and crime research come in one of two forms: 1) county- or city-level crime counts across multiple cities, like those from the UCR, or 2) crime-incident data from only one or a few cities. This means that most studies have been unable to include city-level effects while predicting crime at lower levels.

The data used in the analyses here are exceptional because they include crime-incident data aggregated to the block-group level for 35 cities. This allowed me to include cities as a level of analysis, and my analyses revealed that city characteristics influence crime, and should not be excluded from analysis. Therefore, there is a need for more data collection of crime at a small scale, but also across many cities, like the data used in this project and the National Neighborhood Crime Study (Peterson and Krivo 2010), so that cities can be used as a level in more studies.

Although prior studies including characteristics at only one level of analysis do not necessarily produce incorrect findings, they are missing part of the picture. Future work separating levels of analysis may help elucidate prior inconsistent findings.

LIMITATIONS

This study is not without limitations. First, I do not measure the mechanisms through which each theory is expected to produce to the relationship between disadvantage and crime. I assume support for specific theories based on the hypothesized relationship at each level of analysis. Therefore, these analyses should not be interpreted as specific tests of each theory but rather a test of one aspect of the broad implications of the theory.

Additionally, control variables are included only at the lowest level of analysis at which they are available. I decided to do this, rather than include them at all levels of analysis at which they are available because I wanted to concentrate the multilevel discussion on disadvantage. Including multiple variables at multiple levels of analysis, as Boessen and Hipp (2015) did, complicates the interpretation of each, and I wanted to concentrate on the separate associations between disadvantage and crime by level of analysis. For this reason, I do not devote much attention to discussing the results of the control variables. Research addressing relationships at multiple levels for multiple variables will be more feasible as the body of knowledge for separate variables accumulates. Relatedly, I tried to control for all community characteristics that might influence the association between disadvantage and crime, but my study may still suffer from omitted variable bias if there is an additional characteristic that I have missed.

Finally, this study is cross-sectional rather than longitudinal. Therefore, I cannot discuss causal influences of disadvantage on crime, but instead must concentrate on associations. Additionally, rather than high disadvantage mattering for crime, it may be that a large increase in disadvantage is what matters, and I cannot measure this. Future research should combine the data used here in the NIJ Foreclosure and Crime Data Archive with the National Neighborhood Crime Study to conduct a longitudinal analysis.

CONCLUSION

Taken together, results of this study highlight the importance of separating the effects of community characteristics by level of analysis. Distinguishing the effect of disadvantage at the block-group, tract, and city level revealed importance nuances in the way it relates to robbery and burglary that could not have been found by including disadvantage at only one level of analysis. Additionally, city disadvantage had an effect on robbery over and above the effect of block-group and tract disadvantage, and had an effect on the lower-level associations between disadvantage and crime. Therefore, city-level effects should not be omitted from communities and crime research.

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Table 2.1. Descriptive Statistics

	Robbery Sample[a]		Burglary Sample[b]	
	Mean/%	SD	Mean/%	SD
Block Group Level				
Burglary Count	75.94	71.47	75.67	70.66
Burglary Rate (per 100)	7.89	24.99	7.88	24.57
Robbery Count	24.59	32.38	24.59	32.38
Robbery Rate (per 100)	3.04	9.27	3.04	9.27
Spatial Lag of Burglary Rate	8.30	13.54	8.29	13.32
Spatial Lag of Robbery Rate	3.31	5.69	3.31	5.69
Disadvantage	.06	.66	.05	.67
% in Low Wage Sector Jobs	25.37%		25.25%	
% Unemployed	42.39%		42.08%	
% Female-Headed Household	17.95%		17.79%	
% in Poverty	17.48%		17.41%	
% Not in Professional or Managerial Occupation	68.98%		68.61%	
% with Less than HS Degree	18.32%		18.11%	
Inequality (Gini)	.39	.09	.39	.09
Racial Diversity	.42	.24	.43	.24
% White	45.03%		45.71%	
% Black	29.86%		29.41%	
% Hispanic	18.90%		18.55%	
% Asian	3.90%		3.95%	
% Other Race	2.30%		2.38%	
% Young Male	7.36%		7.37%	
Population	1420.85	1428.83	1404.54	1408.82
Tract Level				
Disadvantage	.08	.96	.07	.96
% in Low Wage Sector Jobs	24.70%		24.66%	
% Unemployed	41.73%		41.52%	
% Female-Headed Household	17.18%		17.08%	
% in Poverty	17.08%		17.11%	
% Not in Professional or Managerial Occupation	68.16%		67.89%	
% with Less than HS Degree	19.77%		19.61%	

Residential Instability	.10	.95	.11	.96
Immigrant Concentration	13.07%		13.14%	
Population	4522.22	3176.67	4478.02	3144.53
City Level				
Disadvantage	-.21	.35	-.22	.35
% in Low Wage Sector Jobs	21.86%		21.86%	
% Unemployed	38.77%		38.62%	
% Female-Headed Household	14.73%		14.63%	
% in Poverty	12.95%		13.01%	
% Not in Professional or Managerial Occupation	64.93%		64.69%	
% with Less than HS Degree	15.65%		15.56%	
Black-White Segregation	.52	.15	.52	.15
Population	444534.60	411042.40	442676.50	405101.80

ABBREVIATION: SD = standard deviation; HS = high school

[a]$N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34

[b]$N_{BLOCK\ GROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35

Table 2.2. Analysis of Variance

	Variance per Level		
Variable	Block Group	Tract	City
Disadvantage	31%	41%	28%
Robbery[a]	40%	36%	24%
Burglary[b]	36%	49%	15%

[a] $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34
[b] $N_{BLOCK\ GROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35

Table 2.3. Multilevel Poisson Models (with Variable Exposure and Overdispersion) Predicting Block Group Robbery with Disadvantage Measured at Three Levels

	Model 1				Model 2				Model 3				Model 4			
	b	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ
Block Group Level																
Disadvantage	.28 ***	(.04)	1.32	20.5									-.04	(.04)	.96	-2.5
Inequality	.40	(.26)	1.49	3.6	.35	(.26)	1.41	3.1	.58 *	(.25)	1.78	5.2	.36	(.24)	1.43	3.2
Proportion Black	.91 ***	(.12)	2.48	37.1	.69 ***	(.12)	1.99	27.0	1.27 ***	(.14)	3.54	55.2	.71 ***	(.12)	2.04	28.0
Proportion Hispanic	.81 ***	(.09)	2.25	21.9	.36 **	(.11)	1.44	9.2	1.20 ***	(.09)	3.31	33.8	.37 ***	(.11)	1.45	9.4
Racial Diversity	.07	(.08)	1.07	1.6	.17 *	(.08)	1.18	4.1	.04	(.07)	1.04	.9	.17 *	(.08)	1.18	4.1
Young Male Population	-.66 **	(.22)	.52	-4.2	-.64 **	(.22)	.53	-4.1	-.47 *	(.20)	.62	-3.1	-.63 **	(.22)	.54	-4.0
Spatial Lag of Outcome	.02 *	(.01)	1.02	11.3	.02 †	(.01)	1.02	10.2	.02 *	(.01)	1.02	11.7	.02 *	(.01)	1.02	10.2
Tract Level																
Disadvantage					.33 ***	(.04)	1.39	37.3					.35 ***	(.04)	1.41	39.3
Residential Instability	.26 ***	(.02)	1.29	27.7	.25 ***	(.02)	1.28	26.8	.28 ***	(.02)	1.32	29.9	.25 ***	(.02)	1.29	27.1
Immigrant Concentration	.51 *	(.22)	1.67	6.3	.17	(.16)	1.18	2.0	.44 †	(.23)	1.55	5.3	.15	(.17)	1.16	1.8
City Level																
Disadvantage									.69 **	(.22)	2.00	27.5	.54 *	(.22)	1.72	20.8
Black-White Segregation	2.34 ***	(.52)	10.37	42.9	2.30 ***	(.49)	9.95	42.0	1.79 ***	(.49)	5.97	31.4	1.78 ***	(.45)	5.93	31.2
Intercept	.19 **	(.06)	1.21		.16 *	(.06)	1.18		.16 *	(.06)	1.17		.15 *	(.06)	1.16	
Residual Variance	*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)		
City Level	.14 ***	(.37)			.13 ***	(.36)			.12 ***	(.34)			.11 ***	(.33)		
Tract Level	.04 *	(.20)			.04 **	(.21)			.05 *	(.22)			.04 **	(.20)		
Block Group Level	38.30	(6.19)			36.79	(6.07)			38.51	(6.21)			37.23	(6.10)		

NOTES: $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Table 2.4. Multilevel Poisson Models (with Variable Exposure and Overdispersion) Predicting Block Group Robbery with Cross-Level Disadvantage Interactions

	Model 5				Model 6				Model 7				Model 8			
	b	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ
Block Group Level																
Disadvantage	.11	(.07)	1.11	7.3	.13	(.08)	1.14	8.8	-.03	(.04)	.97	-2.1	.12	(.09)	1.13	8.4
Inequality	.38	(.25)	1.46	3.4	.32	(.24)	1.38	2.9	.36	(.25)	1.43	3.2	.35	(.25)	1.42	3.2
Proportion Black	.50 ***	(.09)	1.65	18.9	.67 ***	(.12)	1.96	26.2	.66 ***	(.11)	1.94	25.8	.52 ***	(.10)	1.69	20.0
Proportion Hispanic	.25 *	(.12)	1.28	6.1	.37 ***	(.11)	1.45	9.5	.39 ***	(.12)	1.47	9.9	.29 *	(.13)	1.34	7.3
Racial Diversity	.04	(.08)	1.04	.9	.15 †	(.08)	1.16	3.6	.15 †	(.09)	1.16	3.7	.06	(.09)	1.06	1.4
Young Male Population	-.82 **	(.25)	.44	-5.3	-.66 **	(.21)	.52	-4.3	-.64 **	(.21)	.52	-4.2	-.78 **	(.25)	.46	-5.0
Spatial Lag of Outcome	.02 *	(.01)	1.02	10.4	.02 *	(.01)	1.02	10.1	.02 *	(.01)	1.02	10.2	.02 *	(.01)	1.02	10.4
Tract Level																
Disadvantage	.38 ***	(.04)	1.46	43.2	.33 ***	(.04)	1.40	37.7	.44 ***	(.05)	1.55	52.0	.40 ***	(.03)	1.49	46.7
Residential Instability	.28 ***	(.02)	1.32	29.9	.25 ***	(.02)	1.29	27.1	.25 ***	(.02)	1.28	26.6	.27 ***	(.02)	1.31	29.1
Immigrant Concentration	-.09	(.23)	.91	-1.1	.06	(.20)	1.07	.8	.05	(.22)	1.05	.5	-.11	(.24)	.90	-1.3
City Level																
Disadvantage	.41 †	(.24)	1.51	15.4	.41 †	(.22)	1.51	15.6	.51 *	(.21)	1.67	19.7	.40	(.24)	1.49	15.0
Black-White Segregation	1.82 ***	(.45)	6.18	32.0	1.73 ***	(.43)	5.64	30.2	1.75 ***	(.44)	5.74	30.6	1.78 ***	(.44)	5.96	31.3
Disadvantage Interactions																
Block Group x Tract	-.19 ***	(.05)	.83										-.14 *	(.06)	.87	
Block Group x City					-.53 ***	(.15)	.59						-.16	(.16)	.85	
Tract x City									-.36 ***	(.08)	.70		-.15 †	(.08)	.86	
Intercept	.25 **	(.07)	1.28		.22 **	(.06)	1.25		.18 **	(.06)	1.19		.25 **	(.08)	1.29	
Residual Variance	*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)		
City Level	.11 ***	(.33)			.10 ***	(.32)			.10 ***	(.32)			.11 ***	(.33)		
Tract Level	.02 **	(.15)			.06 ***	(.25)			.04 **	(.20)			.04 ***	(.20)		
Block Group Level	38.61	(6.21)			33.78	(5.81)			36.77	(6.06)			35.87	(5.99)		

NOTES: $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Table 2.5. Multilevel Poisson Models (with Variable Exposure and Overdispersion) Predicting Block Group Burglary with Disadvantage Measured at Three Levels

	Model 1				Model 2				Model 3				Model 4			
	b	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ
Block Group Level																
Disadvantage	.23 ***	(.04)	1.26	16.7									-.04	(.03)	.96	-2.5
Inequality	.35 *	(.17)	1.42	3.2	.27 †	(.15)	1.30	2.4	.50 **	(.16)	1.64	4.5	.28 †	(.15)	1.32	2.5
Proportion Black	.75 ***	(.09)	2.11	29.3	.53 ***	(.08)	1.70	20.0	1.04 ***	(.09)	2.84	43.2	.55 ***	(.08)	1.73	20.9
Proportion Hispanic	.42 ***	(.08)	1.52	10.7	.05	(.10)	1.05	1.1	.71 ***	(.07)	2.04	18.8	.06	(.10)	1.06	1.4
Racial Diversity	.07	(.06)	1.08	1.8	.17 **	(.06)	1.19	4.2	.05	(.07)	1.05	1.2	.17 **	(.06)	1.19	4.2
Young Male Population	-.80 ***	(.19)	.45	-5.1	-.78 ***	(.19)	.46	-5.1	-.63 ***	(.19)	.53	-4.1	-.77 ***	(.19)	.47	-5.0
Spatial Lag of Outcome	.01 **	(.00)	1.01	8.7	.01 **	(.00)	1.01	8.3	.01 **	(.00)	1.01	9.6	.01 **	(.00)	1.01	8.3
Tract Level																
Disadvantage					.28 ***	(.03)	1.33	30.9					.30 ***	(.03)	1.35	32.9
Residential Instability	.12 ***	(.02)	1.13	12.4	.12 ***	(.02)	1.12	11.8	.13 ***	(.02)	1.14	13.8	.12 ***	(.02)	1.13	12.0
Immigrant Concentration	-.34 *	(.16)	.71	-3.9	-.72 ***	(.13)	.49	-8.2	-.35 *	(.17)	.71	-4.0	-.74 ***	(.13)	.48	-8.4
City Level																
Disadvantage									.26 †	(.14)	1.30	9.5	.14	(.12)	1.15	4.9
Black-White Segregation	.69 *	(.33)	1.99	10.9	.67 *	(.31)	1.96	10.6	.53	(.38)	1.70	8.3	.55	(.34)	1.74	8.7
Intercept	1.69 ***	(.05)	5.40		1.67 ***	(.04)	5.31		1.67 ***	(.05)	5.30		1.67 ***	(.04)	5.29	
Residual Variance	*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)		
City Level	.08 ***	(.27)			.07 ***	(.26)			.08 ***	(.28)			.07 ***	(.26)		
Tract Level	.02	(.14)			.04 ***	(.20)			.03	(.17)			.04 ***	(.20)		
Block Group Level	62.59	(7.91)			51.90	(7.20)			62.43	(7.90)			51.36	(7.17)		

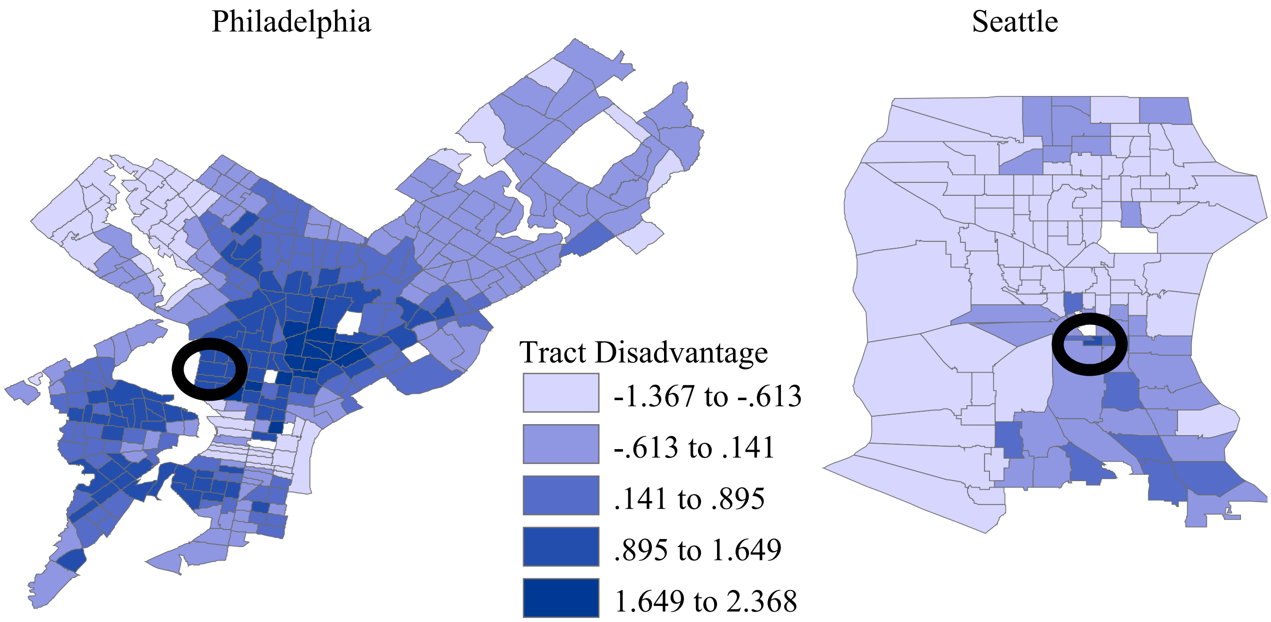
NOTES: $N_{\text{BLOCK GROUPS}}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Table 2.6. Multilevel Poisson Models (with Variable Exposure and Overdispersion) Predicting Block Group Burglary with Cross-Level Disadvantage Interactions

	Model 5				Model 6				Model 7				Model 8			
	b	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ
Block Group Level																
Disadvantage	.08	(.05)	1.08	5.1	.04	(.05)	1.04	2.6	-.04	(.03)	.96	-2.4	.08	(.05)	1.08	5.3
Inequality	.27 †	(.15)	1.32	2.5	.28 †	(.15)	1.32	2.5	.29 †	(.15)	1.34	2.6	.28 †	(.15)	1.32	2.5
Proportion Black	.38 ***	(.07)	1.46	14.0	.53 ***	(.08)	1.70	20.0	.52 ***	(.08)	1.68	19.6	.39 ***	(.08)	1.47	14.3
Proportion Hispanic	-.07	(.09)	.93	-1.7	.05	(.10)	1.05	1.2	.07	(.10)	1.07	1.7	-.06	(.10)	.94	-1.4
Racial Diversity	.03	(.06)	1.03	.6	.15 *	(.06)	1.16	3.5	.15 *	(.06)	1.16	3.5	.03	(.06)	1.03	.7
Young Male Population	-.96 ***	(.19)	.38	-6.2	-.80 ***	(.19)	.45	-5.2	-.78 ***	(.19)	.46	-5.0	-.95 ***	(.18)	.39	-6.1
Spatial Lag of Outcome	.01 **	(.00)	1.01	8.2	.01 **	(.00)	1.01	8.2	.01 **	(.00)	1.01	8.2	.01 **	(.00)	1.01	8.1
Tract Level																
Disadvantage	.32 ***	(.03)	1.37	35.4	.29 ***	(.03)	1.34	32.4	.35 ***	(.02)	1.41	39.1	.32 ***	(.02)	1.38	36.1
Residential Instability	.14 ***	(.02)	1.14	13.8	.12 ***	(.02)	1.12	11.8	.11 ***	(.02)	1.12	11.6	.13 ***	(.02)	1.14	13.6
Immigrant Concentration	-.93 ***	(.15)	.39	-10.5	-.79 ***	(.14)	.46	-8.9	-.83 ***	(.14)	.44	-9.4	-.94 ***	(.15)	.39	-10.5
City Level																
Disadvantage	.03	(.12)	1.03	1.1	.07	(.13)	1.07	2.4	.11	(.12)	1.11	3.8	.02	(.12)	1.02	.9
Black-White Segregation	.57 †	(.33)	1.77	8.9	.47	(.35)	1.60	7.3	.49	(.34)	1.64	7.7	.54	(.34)	1.72	8.5
Disadvantage Interactions																
Block Group x Tract	-.19 ***	(.03)	.83										-.17 ***	(.04)	.84	
Block Group x City					-.35 **	(.11)	.71						-.06	(.11)	.94	
Tract x City									-.24 ***	(.06)	.79		-.04	(.06)	.96	
Intercept	1.77 ***	(.05)	5.88		1.72 ***	(.04)	5.56		1.70 ***	(.04)	5.45		1.77 ***	(.05)	5.90	
Residual Variance	*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)		
City Level	.06 ***	(.25)			.06 ***	(.25)			.06 ***	(.25)			.06 ***	(.25)		
Tract Level	.04 ***	(.21)			.04 ***	(.20)			.04 ***	(.20)			.04 ***	(.21)		
Block Group Level	46.48	(6.82)			50.49	(7.11)			50.34	(7.09)			46.57	(6.82)		

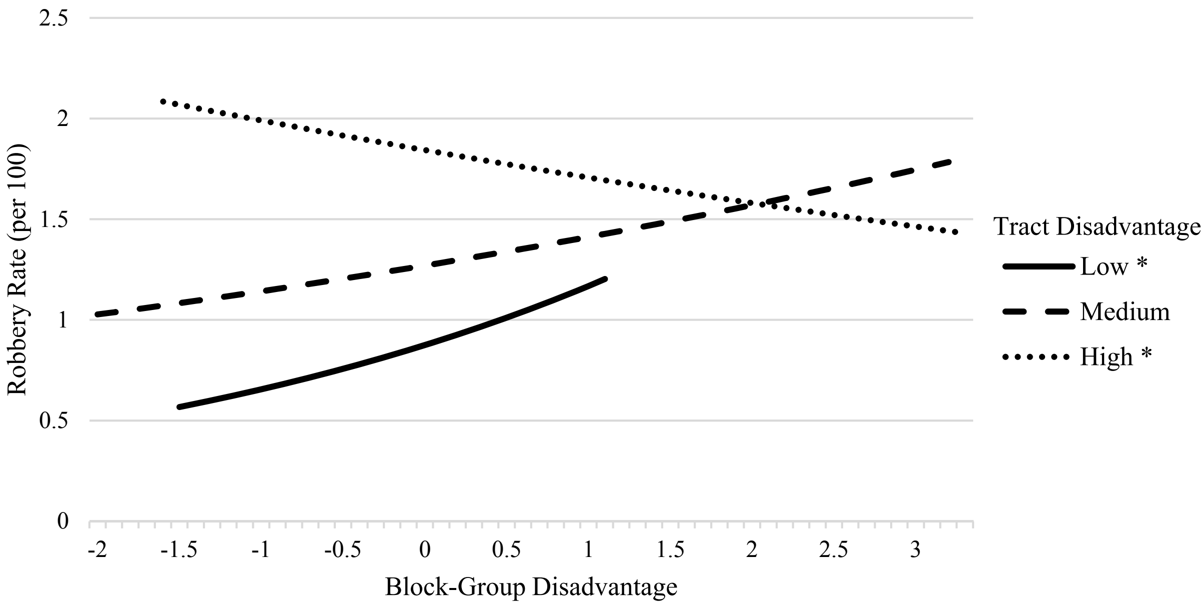
NOTES: $N_{\text{BLOCK GROUPS}}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Figure 2.1. Spatial Distribution of Disadvantage Across Tracts in Philadelphia and Seattle



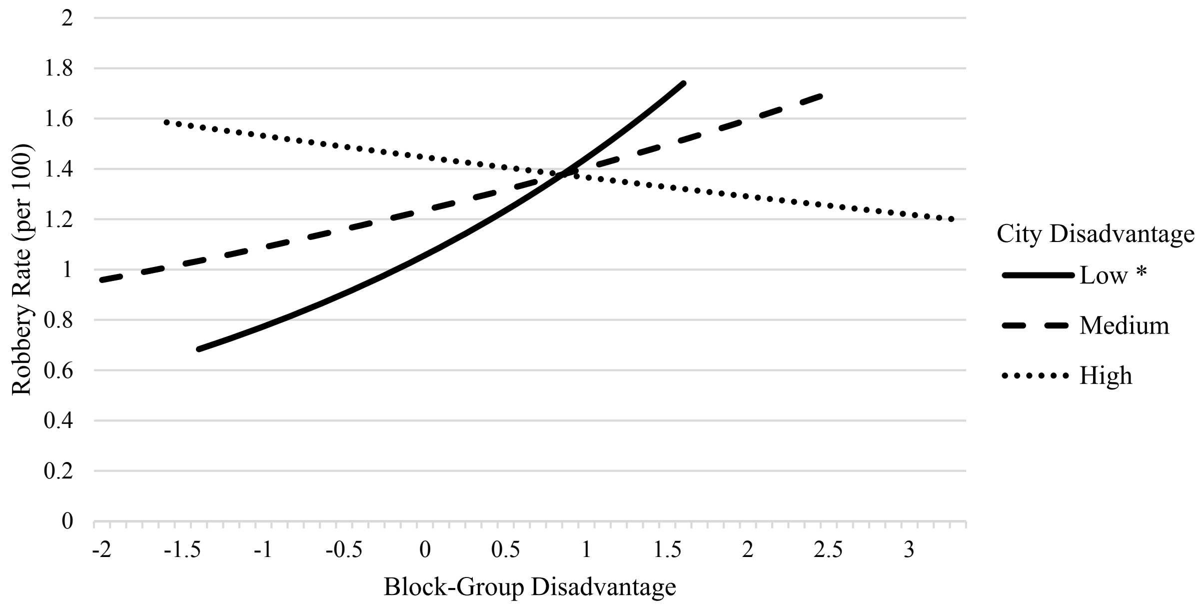
NOTE: The black circles highlight tracts in each city with nearly identical amounts of disadvantage

Figure 2.2. Predicted Robbery Rates at Varying Amounts of Block-Group and Tract Disadvantage



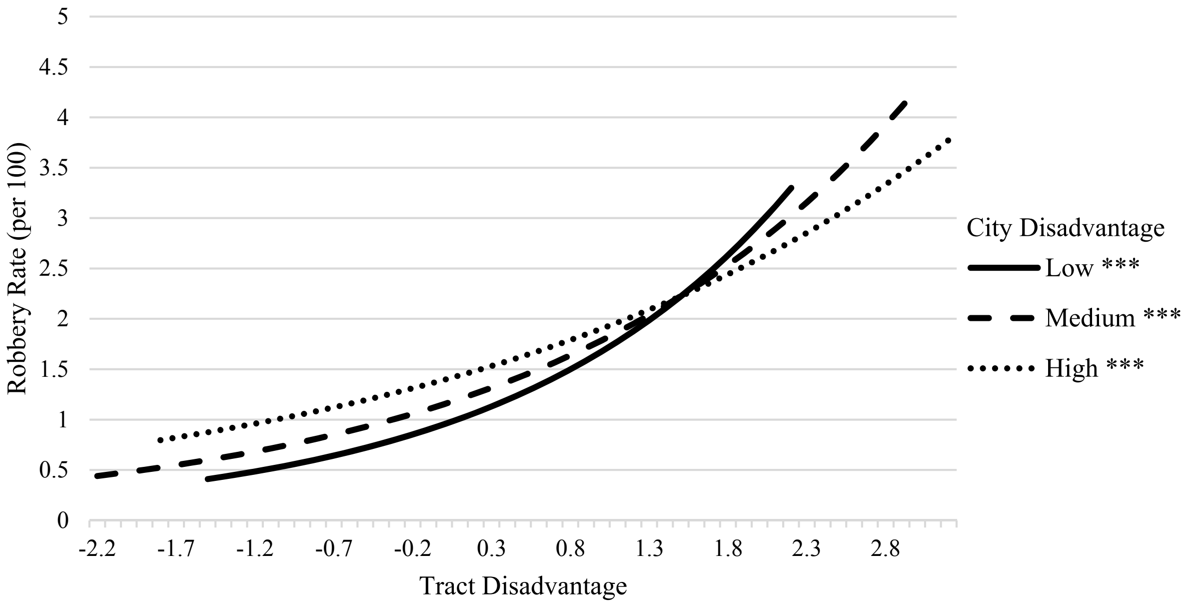
* p < .05 for separate trend lines

Figure 2.3. Predicted Robbery Rates at Varying Amounts of Block-Group and City Disadvantage



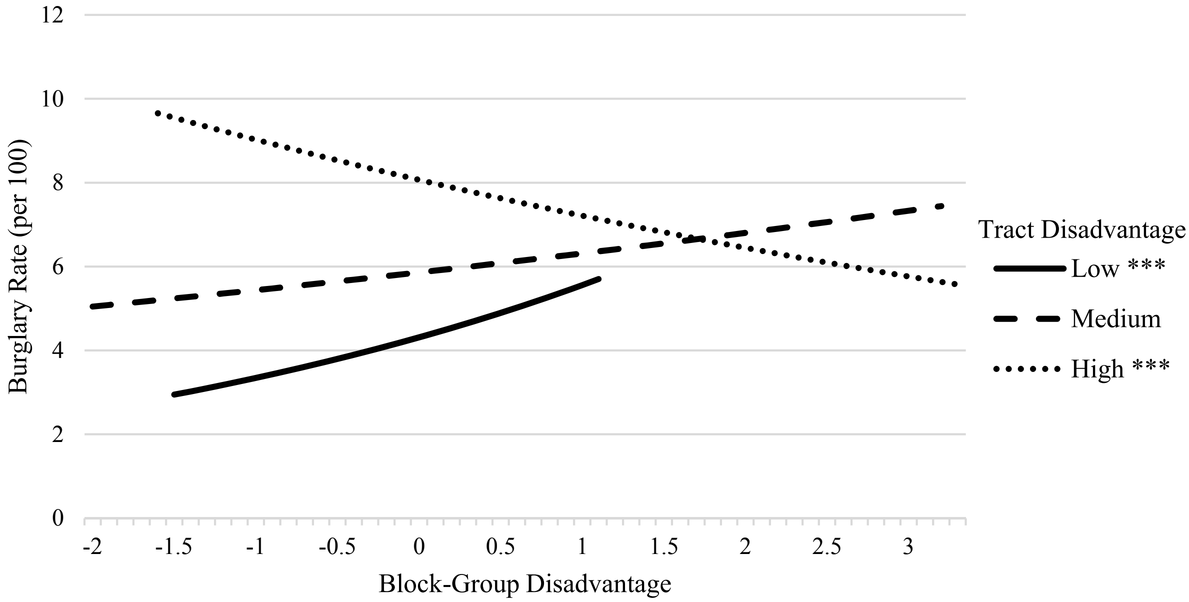
* p < .05 for separate trend lines

Figure 2.4. Predicted Robbery Rates at Varying Amounts of Tract and City Disadvantage



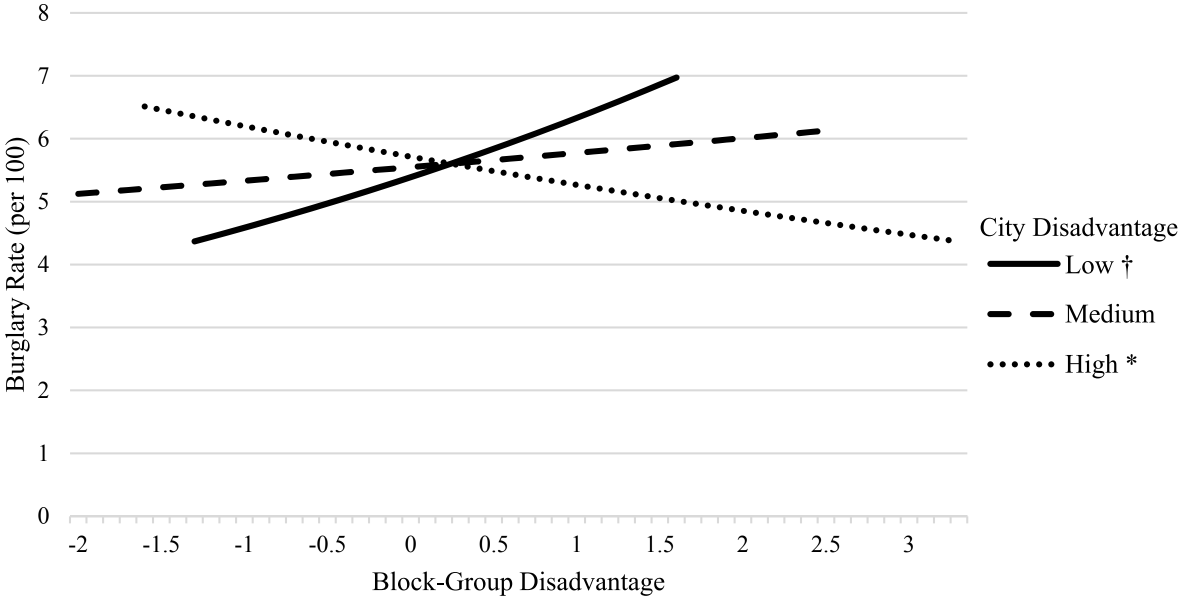
*** p < .001 for separate trend lines

Figure 2.5. Predicted Burglary Rates at Varying Amounts of Block-Group and Tract Disadvantage



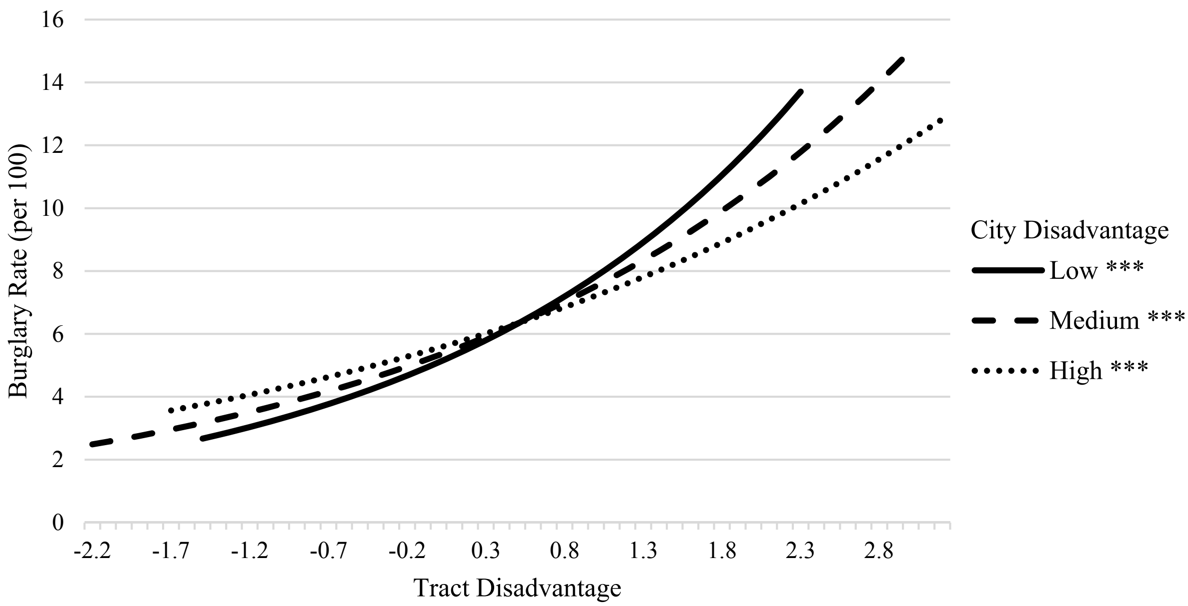
*** p < .001 for separate trend lines

Figure 2.6. Predicted Burglary Rates at Varying Amounts of Block-Group and City Disadvantage



† p < .10; * p < .05 for separate trend lines

Figure 2.7. Predicted Burglary Rates at Varying Amounts of Tract and City Disadvantage



*** p < .001 for separate trend lines

APPENDIX A. LIST OF CITIES

City	Block Groups	Tracts
Akron, Ohio	247	71
Arlington, Texas	199	65
Atlanta, Georgia	274	111
Austin, Texas	447	165
Carrollton, Texas	63	24
Chandler, Arizona	109	42
Charlotte, North Carolina	321	127
Chula Vista, California	107	39
Cincinnati, Ohio	313	125
Cleveland, Ohio	525	213
Evansville, Indiana	126	41
Fort Collins, Colorado	103	38
Fort Wayne, Indiana	164	67
Fort Worth, Texas	476	148
Glendale, Arizona	183	52
Greensboro, North Carolina	155	66
Houston, Texas	1,238	439
Las Vegas, Nevada	350	107
Lexington, Kentucky	143	60
Lincoln, Nebraska	169	53
Memphis, Tennessee	592	179
Milwaukee, Wisconsin	592	223
Minneapolis, Minnesota[a]	399	121
Newport News, Virginia	111	34
Oklahoma City, Oklahoma	428	172
Orlando, Florida	144	76
Philadelphia, Pennsylvania	1,762	362
Plano, Texas	158	48
Raleigh, North Carolina	134	69
Sacramento, California	326	111
St. Petersburg, Florida	196	65
Tampa, Florida	309	91
Tempe, Arizona	103	34
Tucson, Arizona	417	120
Waco, Texas	102	36

[a]Excluded from robbery analyses.

APPENDIX B. SUPPLEMENTARY TABLES

Table B2.1. Multilevel Poisson Models of Cross-Level Interaction between Block Group and Tract Disadvantage Predicting Block Group Robbery with Tract Disadvantage Re-Centered at Low, Medium, and High Values

	Model 1			Model 2			Model 3		
	Low			Medium			High		
	b	(SE)	e^b	*b*	(SE)	e^b	*b*	(SE)	e^b
Block Group Level									
Disadvantage	.29 *	(.12)	1.3	.11	(.07)	1.1	-.08 *	(.03)	.9
Inequality	.38	(.25)	1.5	.38	(.25)	1.5	.38	(.25)	1.5
Proportion Black	.50 ***	(.09)	1.6	.50 ***	(.09)	1.6	.50 ***	(.09)	1.6
Proportion Hispanic	.25 *	(.12)	1.3	.25 *	(.12)	1.3	.25 *	(.12)	1.3
Racial Diversity	.04	(.08)	1.0	.04	(.08)	1.0	.04	(.08)	1.0
Young Male Population	-.82 **	(.25)	.4	-.82 **	(.25)	.4	-.82 **	(.25)	.4
Spatial Lag of Outcome	.02 *	(.01)	1.0	.02 *	(.01)	1.0	.02 *	(.01)	1.0
Tract Level									
Disadvantage (re-centered)	.38 ***	(.04)	1.5	.38 ***	(.04)	1.5	.38 ***	(.04)	1.5
Residential Instability	.28 ***	(.02)	1.3	.28 ***	(.02)	1.3	.28 ***	(.02)	1.3
Immigrant Concentration	-.09	(.23)	.9	-.09	(.23)	.9	-.09	(.23)	.9
City Level									
Disadvantage	.41 †	(.24)	1.5	.41 †	(.24)	1.5	.41 †	(.24)	1.5
Black-White Segregation	1.82 ***	(.45)	6.2	1.82 ***	(.45)	6.2	1.82 ***	(.45)	6.2
Disadvantage Interaction									
Block Group x Tract	-.19 ***	(.05)	.8	-.19 ***	(.05)	.8	-.19 ***	(.05)	.8
Intercept	-.11	(.08)	.9	.25 **	(.07)	1.3	.61 ***	(.09)	1.8

NOTES: $N_{\text{BLOCK GROUPS}}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table B2.2. Multilevel Poisson Models of Cross-Level Interaction between Block Group and City Disadvantage Predicting Block Group Robbery with City Disadvantage Re-Centered at Low, Medium, and High Values

	Model 1				Model 2				Model 3			
	Low				Medium				High			
	b		(SE)	e^b	*b*		(SE)	e^b	*b*		(SE)	e^b
Block Group Level												
Disadvantage	.31	*	(.13)	1.4	.13		(.08)	1.1	-.06		(.04)	.9
Inequality	.32		(.24)	1.4	.32		(.24)	1.4	.32		(.24)	1.4
Proportion Black	.67	***	(.12)	2.0	.67	***	(.12)	2.0	.67	***	(.12)	2.0
Proportion Hispanic	.37	***	(.11)	1.5	.37	***	(.11)	1.5	.37	***	(.11)	1.5
Racial Diversity	.15	†	(.08)	1.2	.15	†	(.08)	1.2	.15	†	(.08)	1.2
Young Male Population	-.66	**	(.21)	.5	-.66	**	(.21)	.5	-.66	**	(.21)	.5
Spatial Lag of Outcome	.02	*	(.01)	1.0	.02	*	(.01)	1.0	.02	*	(.01)	1.0
Tract Level												
Disadvantage	.33	***	(.04)	1.4	.33	***	(.04)	1.4	.33	***	(.04)	1.4
Residential Instability	.25	***	(.02)	1.3	.25	***	(.02)	1.3	.25	***	(.02)	1.3
Immigrant Concentration	.06		(.20)	1.1	.06		(.20)	1.1	.06		(.20)	1.1
City Level												
Disadvantage (re-centered)	.41	†	(.22)	1.5	.41	†	(.22)	1.5	.41	†	(.22)	1.5
Black-White Segregation	1.73	***	(.43)	5.6	1.73	***	(.43)	5.6	1.73	***	(.43)	5.6
Disadvantage Interaction												
Block Group x City	-.53	***	(.15)	.6	-.53	***	(.15)	.6	-.53	***	(.15)	.6
Intercept	.08		(.12)	1.1	.22	***	(.06)	1.2	.37	***	(.08)	1.4

NOTES: $N_{\text{BLOCK GROUPS}}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table B2.3. Multilevel Poisson Models of Cross-Level Interaction between Tract and City Disadvantage Predicting Block Group Robbery with City Disadvantage Re-Centered at Low, Medium, and High Values

	Model 1			Model 2			Model 3		
	Low			Medium			High		
	b	(SE)	e^b	*b*	(SE)	e^b	*b*	(SE)	e^b
Block Group Level									
Disadvantage	-.03	(.04)	1.0	-.03	(.04)	1.0	-.03	(.04)	1.0
Inequality	.36	(.25)	1.4	.36	(.25)	1.4	.36	(.25)	1.4
Proportion Black	.66 ***	(.11)	1.9	.66 ***	(.11)	1.9	.66 ***	(.11)	1.9
Proportion Hispanic	.39 ***	(.12)	1.5	.39 ***	(.12)	1.5	.39 ***	(.12)	1.5
Racial Diversity	.15 †	(.09)	1.2	.15 †	(.09)	1.2	.15 †	(.09)	1.2
Young Male Population	-.64 **	(.21)	.5	-.64 **	(.21)	.5	-.64 **	(.21)	.5
Spatial Lag of Outcome	.02 *	(.01)	1.0	.02 *	(.01)	1.0	.02 *	(.01)	1.0
Tract Level									
Disadvantage	.56 ***	(.07)	1.8	.44 ***	(.05)	1.5	.31 ***	(.04)	1.4
Residential Instability	.25 ***	(.02)	1.3	.25 ***	(.02)	1.3	.25 ***	(.02)	1.3
Immigrant Concentration	.05	(.22)	1.0	.05	(.22)	1.0	.05	(.22)	1.0
City Level									
Disadvantage (re-centered)	.51 *	(.21)	1.7	.51 *	(.21)	1.7	.51 *	(.21)	1.7
Black-White Segregation	1.75 ***	(.44)	5.7	1.75 ***	(.44)	5.7	1.75 ***	(.44)	5.7
Disadvantage Interaction									
Tract x City	-.36 ***	(.08)	.7	-.36 ***	(.08)	.7	-.36 ***	(.08)	.7
Intercept	.00	(.11)	1.0	.18 **	(.06)	1.2	.36 ***	(.08)	1.4

NOTES: $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table B2.4. Multilevel Poisson Models (with Variable Exposure and Overdispersion) predicting Block Group Robbery with Three-Way Cross-Level Interaction

	Outcome: Robbery Rate				
	b		(SE)	e^b	%Δ
Block Group Level					
Disadvantage	.16	†	(.10)	1.17	11.2
Inequality	.38		(.25)	1.46	3.4
Proportion Black	.52	***	(.10)	1.68	19.7
Proportion Hispanic	.27	*	(.12)	1.31	6.8
Racial Diversity	.04		(.09)	1.04	.9
Young Male Population	-.82	**	(.27)	.44	-5.3
Spatial Lag of Outcome	.02	*	(.01)	1.02	10.4
Tract Level					
Disadvantage	.38	***	(.04)	1.46	43.7
Residential Instability	.26	***	(.02)	1.30	28.2
Immigrant Concentration	-.07		(.24)	.93	-.8
City Level					
Disadvantage	.23		(.27)	1.26	8.5
Black-White Segregation	1.77	***	(.44)	5.87	31.0
Disadvantage Interactions					
Block Group x Tract	-.22	***	(.06)	.80	
Block Group x City	-.34	†	(.20)	.71	
Tract x City	-.12		(.07)	.89	
Block Group x Tract x City	.28	*	(.11)	1.32	
Intercept	.31	***	(.08)	1.36	
Residual Variance	*Var.*		(SD)		
City Level	.10	***	(.32)		
Tract Level	.03	***	(.18)		
Block Group Level	36.32		(6.03)		

NOTES: $N_{\text{BLOCK GROUPS}}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Table B2.5. Multilevel Poisson Models of Cross-Level Interaction between Block Group and Tract Disadvantage Predicting Block Group Burglary with Tract Disadvantage Re-Centered at Low, Medium, and High Values

	Model 1				Model 2				Model 3			
	Low				Medium				High			
	b		(SE)	e^b	*b*		(SE)	e^b	*b*		(SE)	e^b
Block Group Level												
Disadvantage	.26	***	(.07)	1.3	.07		(.05)	1.1	-.11	***	(.03)	.9
Inequality	.27	†	(.15)	1.3	.27	†	(.15)	1.3	.27	†	(.15)	1.3
Proportion Black	.38	***	(.07)	1.5	.38	***	(.07)	1.5	.38	***	(.07)	1.5
Proportion Hispanic	-.07		(.09)	.9	-.07		(.09)	.9	-.07		(.09)	.9
Racial Diversity	.03		(.06)	1.0	.03		(.06)	1.0	.03		(.06)	1.0
Young Male Population	-.96	***	(.19)	.4	-.96	***	(.19)	.4	-.96	***	(.19)	.4
Spatial Lag of Outcome	.01	**	(.00)	1.0	.01	**	(.00)	1.0	.01	**	(.00)	1.0
Tract Level												
Disadvantage (re-centered)	.32	***	(.03)	1.4	.32	***	(.03)	1.4	.32	***	(.03)	1.4
Residential Instability	.14	***	(.02)	1.1	.14	***	(.02)	1.1	.14	***	(.02)	1.1
Immigrant Concentration	-.93	***	(.15)	.4	-.93	***	(.15)	.4	-.93	***	(.15)	.4
City Level												
Disadvantage	.03		(.12)	1.0	.03		(.12)	1.0	.03		(.12)	1.0
Black-White Segregation	.57	†	(.33)	1.8	.57	†	(.33)	1.8	.57	†	(.33)	1.8
Disadvantage Interaction												
Block Group x Tract	-.19	***	(.03)	.8	-.19	***	(.03)	.8	-.19	***	(.03)	.8
Intercept	1.47	***	(.05)	4.4	1.78	***	(.05)	5.9	2.08	***	(.06)	8.0

NOTES: $N_{BLOCKGROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.

ABBREVIATION: SE = standard error

† p < .10; * p < .05; ** p < .01; *** p < .001

Table B2.6. Multilevel Poisson Models of Cross-Level Interaction between Block Group and City Disadvantage Predicting Block Group Burglary with City Disadvantage Re-Centered at Low, Medium, and High Values

	Model 1				Model 2				Model 3			
	Low				Medium				High			
	b		(SE)	e^b	*b*		(SE)	e^b	*b*		(SE)	e^b
Block Group Level												
Disadvantage	.16	†	(.08)	1.2	.04		(.05)	1.0	-.08	*	(.04)	.9
Inequality	.28	†	(.15)	1.3	.28	†	(.15)	1.3	.28	†	(.15)	1.3
Proportion Black	.53	***	(.08)	1.7	.53	***	(.08)	1.7	.53	***	(.08)	1.7
Proportion Hispanic	.05		(.10)	1.0	.05		(.10)	1.0	.05		(.10)	1.0
Racial Diversity	.15	*	(.06)	1.2	.15	*	(.06)	1.2	.15	*	(.06)	1.2
Young Male Population	-.80	***	(.19)	.4	-.80	***	(.19)	.4	-.80	***	(.19)	.4
Spatial Lag of Outcome	.01	**	(.00)	1.0	.01	**	(.00)	1.0	.01	**	(.00)	1.0
Tract Level												
Disadvantage	.29	***	(.03)	1.3	.29	***	(.03)	1.3	.29	***	(.03)	1.3
Residential Instability	.12	***	(.02)	1.1	.12	***	(.02)	1.1	.12	***	(.02)	1.1
Immigrant Concentration	-.79	***	(.14)	.5	-.79	***	(.14)	.5	-.79	***	(.14)	.5
City Level												
Disadvantage (re-centered)	.07		(.13)	1.1	.07		(.13)	1.1	.07		(.13)	1.1
Black-White Segregation	.47		(.35)	1.6	.47		(.35)	1.6	.47		(.35)	1.6
Disadvantage Interaction												
Block Group x City	-.35	**	(.11)	.7	-.35	**	(.11)	.7	-.35	**	(.11)	.7
Intercept	1.69	***	(.07)	5.4	1.72	***	(.04)	5.6	1.74	***	(.05)	5.7

NOTES: $N_{BLOCKGROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table B2.7. Multilevel Poisson Models of Cross-Level Interaction between Tract and City Disadvantage Predicting Block Group Burglary with City Disadvantage Re-Centered at Low, Medium, and High Values

	Model 1				Model 2				Model 3			
	Low				Medium				High			
	b		(SE)	e^b	*b*		(SE)	e^b	*b*		(SE)	e^b
Block Group Level												
Disadvantage	-.04		(.03)	1.0	-.04		(.03)	1.0	-.04		(.03)	1.0
Inequality	.29	†	(.15)	1.3	.29	†	(.15)	1.3	.29	†	(.15)	1.3
Proportion Black	.52	***	(.08)	1.7	.52	***	(.08)	1.7	.52	***	(.08)	1.7
Proportion Hispanic	.07		(.10)	1.1	.07		(.10)	1.1	.07		(.10)	1.1
Racial Diversity	.15	*	(.06)	1.2	.15	*	(.06)	1.2	.15	*	(.06)	1.2
Young Male Population	-.78	***	(.19)	.5	-.78	***	(.19)	.5	-.78	***	(.19)	.5
Spatial Lag of Outcome	.01	**	(.00)	1.0	.01	**	(.00)	1.0	.01	**	(.00)	1.0
Tract Level												
Disadvantage	.43	***	(.04)	1.5	.35	***	(.03)	1.4	.26	***	(.03)	1.3
Residential Instability	.11	***	(.02)	1.1	.11	***	(.02)	1.1	.11	***	(.02)	1.1
Immigrant Concentration	-.83	***	(.14)	.4	-.83	***	(.14)	.4	-.83	***	(.14)	.4
City Level												
Disadvantage (re-centered)	.11		(.12)	1.1	.11		(.12)	1.1	.11		(.12)	1.1
Black-White Segregation	.49		(.34)	1.6	.49		(.34)	1.6	.49		(.34)	1.6
Disadvantage Interaction												
Tract x City	-.24	***	(.06)	.8	-.24	***	(.06)	.8	-.24	***	(.06)	.8
Intercept	1.66	***	(.06)	5.2	1.70	***	(.04)	5.4	1.73	***	(.05)	5.7

NOTES: $N_{BLOCKGROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.

ABBREVIATION: SE = standard error

† p < .10; * p < .05; ** p < .01; *** p < .001

Table B2.8. Multilevel Poisson Models (with Variable Exposure and Overdispersion) predicting Block Group Burglary with Three-Way Cross-Level Interaction

	Outcome: Burglary Rate				
	b		(SE)	e^b	%Δ
Block Group Level					
Disadvantage	.08		(.05)	1.08	5.5
Inequality	.28	†	(.15)	1.32	2.5
Proportion Black	.39	***	(.08)	1.48	14.4
Proportion Hispanic	-.06		(.10)	.94	-1.5
Racial Diversity	.02		(.06)	1.02	.5
Young Male Population	-.97	***	(.19)	.38	-6.2
Spatial Lag of Outcome	.01	**	(.00)	1.01	8.1
Tract Level					
Disadvantage	.31	***	(.03)	1.36	34.6
Residential Instability	.13	***	(.02)	1.14	13.3
Immigrant Concentration	-.92	***	(.15)	.40	-10.3
City Level					
Disadvantage	-.05		(.15)	.95	-1.8
Black-White Segregation	.53		(.34)	1.69	8.3
Disadvantage Interactions					
Block Group x Tract	-.20	***	(.03)	.82	
Block Group x City	-.12		(.13)	.88	
Tract x City	-.02		(.06)	.98	
Block Group x Tract x City	.13	†	(.07)	1.14	
Intercept	1.79	***	(.05)	6.02	
Residual Variance	*Var.*		(SD)		
City Level	.06	***	(.25)		
Tract Level	.04	***	(.21)		
Block Group Level	46.07		(6.79)		

NOTES: $N_{BLOCKGROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors.
ABBREVIATION: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

CHAPTER 3:

INCOME INEQUALITY AND CRIME:

A MULTILEVEL APPROACH

Several theories suggest that high economic inequality has deleterious consequences for communities. One such consequence is the amount of crime in a community. In their meta-analysis of macro-level predictors of crime, Pratt and Cullen (2005) concluded that economic deprivation theories have received strong empirical support and that the effect of inequality on crime is relatively robust. However, findings from this research have not been entirely consistent, with some studies finding a positive effect of inequality on crime (Blau and Blau 1982; Hipp 2007b; Hipp and Yates 2011; Kovandzic, Vieraitis, and Yeisley 1998; Peterson and Bailey 1988), and others finding no association once other factors are controlled for (Bailey 1984; Messner 1983; Pridemore 2008, 2011; Sampson 1985). One possible explanation for this inconsistency is omitted variable bias, whereby researchers fail to control for some important variables that might explain the primary association. As a result, inequality may be found to be a significant predictor even though its relationship with crime is spurious. For example, Pridemore (2008, 2011) has argued that poverty explains the effect of inequality. However, Pridemore's research was cross-national, and other studies have found that inequality still has an effect on crime even after controlling for poverty (Blau and Blau 1982; Kovandzic et al. 1998).

An alternative explanation for the inconsistency in findings across studies is what I have previously referred to as omitted level bias. Level of analysis choice is often based on data availability or convenience rather than theoretical consideration of the implications of the level of analysis for interpretation. As I have argued in previous chapters, relationships at different levels of analysis are distinct phenomena that cannot be distinguished without jointly analyzing more than one level at a time. An influence of neighborhood-level inequality on crime could result from a different process than an influence of city-level inequality on crime, and either could create associations at both levels.

However, it is impossible to determine at which level an aggregate construct influences an outcome without including the construct at multiple levels simultaneously. Therefore, research including inequality at only the census-tract level does not allow for distinguishing the influence of block-group inequality on crime from the influence of tract inequality on crime or the influence of city inequality on crime. Most studies only include each construct at one level of analysis, making it impossible to separate the distinct relationships by level. As a result, findings from this research may be misleading or erroneous. For example, Land, McCall, and Cohen (1990) found that their measure of resource deprivation had a positive association with crime when it was measured at the city level, the standard metropolitan statistical area (SMSA) level, and the state level. However, because they did not test the associations simultaneously, it is unclear whether there are separate processes operating at each level which cause resource deprivation at all three levels to influence crime, or whether the state-level effect is a composition effect of processes happening at the city level. In the latter case, the actual mechanism connecting inequality and crime would be occurring at the city level, but it would be picked up in the state-level measure because city-level differences aggregated up to the state level.

To avoid omitted level bias, and to distinguish the influence of inequality on crime at different levels of analysis, I measure income inequality at three levels of aggregation (block groups, tracts, and cities). I then include these measures in one hierarchical model to see whether and how the influence of inequality on crime separates into effects at each level.

Although including a characteristic at multiple levels is necessary for distinguishing multilevel effects, the connection between the different levels is more complex for inequality than for many other constructs within the realm of communities and crime research. Normally, a higher-level aggregate construct in a multilevel model is an average of values of that construct from a lower level of analysis. For example, with census tracts nested within cities, the proportion of the population that is Black at the city level is equal to an average of the proportion of the population that is Black at the tract level, weighted by the size of each tract. This direct correspondence between the measures at the two levels yields a well-defined relationship between alternative forms of the association at each level. If the tract-level measure is group-mean centered, then the city-level coefficient of proportion Black is a between-city effect. If the tract-level measure is either uncentered or grand-mean centered, then the coefficient of proportion Black at the city level is a context effect. And if there is a significant between-city effect, but no context effect, then the between-city effect is a simple composition effect in which the true association occurs at the tract level, but the particular combination of tracts present within each city produces mean differences at the city level.

With inequality, measures at each level are constructed independently from one another rather than as means of the lower level. This is because of the relative nature of the variable, in which its value is based on the range and variation of income at each level. Averaging the value of inequality across tracts to create a city-level measure would distort the actual amount of inequality in the city because doing so would ignore the full range and variation of incomes across tracts. Two tracts can have equal amounts of inequality, but very different income ranges and means. For example, a tract in which everyone has incomes over 200,000 and a tract in which everyone is living in poverty will have similarly low values on tract inequality. In this case, averaging the tract inequality values to create a city-level measure of inequality would result in a low value of city inequality that is quite inconsistent with the sizable inequalities of the combined population of the two tracts. Therefore, a meaningful measure of inequality at any level of aggregation must be calculated independently using income information for the full population at that level.

Because higher-level inequality measures are not means of a lower-level measure, some features of multilevel models of higher-level means do not apply. In particular, a composition effect is not applicable. If the city-level measure is not an average of the tract-level measure across tracts, then whatever city-level relationship is generated by a tract-level effect will not necessarily equal the tract-level coefficient multiplied by the city-level inequality measure. Thus, the city-level effect does not produce a simple correspondence between results for models with and without group-mean centering. Even so, there is likely to be considerable association between measures of inequality at the different levels that could create the spurious relationships I have referred to as omitted level bias. Thus, the basic principle still applies that obtaining a meaningful estimate of the impact of inequality at one level of aggregation requires controlling for measures of inequality at other levels.

This chapter follows a similar progression as Chapter 2. I first summarize the current state of research on the topic of inequality and crime. I then develop my conceptual framework for explaining the significance of separating the effects of inequality by level of analysis. Additionally, I introduce the potential importance of cities as a unit of aggregation and I explain my choice of levels of aggregation in this study. Finally, I tie my conceptual framework with criminological theories about inequality, and I generate hypotheses about how each theory predicts the effects of inequality to matter at different levels.

PRIOR RESEARCH ON INEQUALITY AND CRIME

Prior work on the association between economic inequality and crime has yielded somewhat mixed results. As mentioned previously, research has been conducted at various levels of analysis, including census block groups, tracts, cities, states, and nations (Bailey 1984; Blau and Blau 1982; Boessen and Hipp 2015; Hipp 2007b; Kovandzic et al. 1998; Land et al. 1990; Messner 1983; Pridemore 2008, 2011). Using metropolitan statistical areas (MSAs), Blau and Blau (1982) found that income inequality was positively associated with violent crime. Land et al. (1990) found that their measure of relative deprivation was positively associated with crime at the city level, at the state level, and at the MSA level. But in a cross-national study of homicide, Pridemore (2008) argued that poverty explains the effect of inequality. In their meta-analysis of macro-level predictors, Pratt and Cullen (2005) found that economic inequality is "in the top tier of predictive strength," (p. 412) and they argue that "the empirical status of resource/economic deprivation theory is favorable" (p. 412). However, their analysis does not reveal at which level economic inequality has the strongest effect size, and none of the included studies measure inequality at multiple levels simultaneously.

Reacting to this issue, Hipp (2007a) argued that researchers should pay more attention to why levels of aggregation are chosen, and that the "proper" level of aggregation may differ by characteristic. Indeed, he found that racial heterogeneity was a significant predictor of crime at both the block and tract level, but that economic resources was only a significant predictor at the block level. However, his data were not nested and he could therefore not estimate multilevel models to separate effects at different levels. Additionally, his outcome measure was based on perceptions of the amount of crime in participants' neighborhoods rather than crime itself. Extending this research to multilevel models, Boessen and Hipp (2015) analyzed models using blocks nested within block groups, and using blocks nested within tracts. Their analysis was quite complex, with nine structural characteristics measured at each level. They also included spatial lags of each characteristic. As expected, they found varying effects for each characteristic depending on the level of aggregation at which it was measured. Regarding inequality in particular, they found a positive relationship with robbery and burglary at both the block-group level and the tract level.

Although Boessen and Hipp's (2015) research was an important contribution, there are remaining questions regarding the relationship between inequality and crime. They included all of their structural characteristics at every level simultaneously. As discussed previously, while seemingly comprehensive, this strategy made it difficult for them to present a framework for understanding and interpreting their results in terms of theory and it complicated the interpretation of any one coefficient. In the current study, I concentrate on inequality in particular in order to provide a conceptual framework for understanding how inequality may operate at different levels of analysis. Additionally, Boessen and Hipp (2015) analyzed characteristics measured at the block, block-group, and tract level, but they treated block-group- and tract-level measures as interchangeable, so they were never included together. Further, they did not have information about the income distribution at the block level, so inequality was only included at one level of analysis at a time. In this study, I nest block groups within tracts within cities to include inequality at multiple levels, which allows me to separate its effects by level.

THE IMPORTANCE OF CITIES

Much of the early work on communities and crime used cities and SMSAs as their unit of analysis (Bailey 1984; Blau and Blau 1982; Sampson 1985). However, most of the more recent research has used neighborhoods and smaller units of analysis both because of the influence of social disorganization as a neighborhood-level theory and because the data necessary to include city-level variables in analyses with a smaller-level outcome are hard to come by. However, leaving out the potential impact of city characteristics on crime is a problematic omission. As the preliminary analyses in this study reveal, there is substantial city-level variation in inequality, and ignoring this variation in statistical models may leave out an important part of the picture. Additionally, city characteristics have been found to shape some lower-level associations (Lyons, Velez, and Santoro 2013).

To gain a sense of the importance of including city-level characteristics, consider two cities: Virginia Beach, Virginia and Miami, Florida. Data from the National Neighborhood Crime Study (NNCS; Peterson and Krivo 2010) reveal that the robbery rate in Virginia Beach in 2000 was 106 per 100,000 residents while the robbery rate in Miami in 2000 was 848 per 100,000. Neighborhood-level research would attribute this city-level difference in robbery to variation across neighborhoods which translates into city-level differences when aggregated to the city level. In other words, they would argue that neighborhood-level inequality increases neighborhood crime, and Miami has more neighborhood inequality than Virginia Beach. A look at the NNCS data reveals that neighborhoods in Miami indeed have higher inequality than neighborhoods in Virginia Beach. The choropleth map in Figure 3.1 displays the distribution of inequality across tracts in Virginia Beach and Miami. Lighter tracts have lower inequality and darker tracts have higher. The values of inequality used to create the gradient are based on the full range of tract inequality in both cities, split into .08 unit intervals. As depicted in the figure, Virginia Beach has no tracts in the highest inequality interval, while Miami has no tracts in the lowest *two* inequality intervals. However, city inequality in Virginia Beach is also much lower than city inequality in Miami (.40 in comparison to .58, on a scale from 0 to 1). Research examining only neighborhood-level effects would treat the circled tract in Virginia Beach the same as the circled tract in Miami because they have the same amount of tract inequality. I argue that there may be a context effect of city inequality on crime, such that the high inequality tract in Miami should have higher crime rates than the high inequality tract in Virginia Beach because the first is nested in a low inequality city, whereas the second is nested within a high inequality city, despite the fact that the tracts themselves have the same amount of tract inequality.

LEVELS USED IN CURRENT STUDY

As already mentioned, I use the same levels of aggregation to separate the effects of inequality as were used in the previous chapter for disadvantage. For a full description of the levels, please refer to Chapter 2. As a brief summary, block groups are clusters of blocks designed to have populations ranging from 600 to 3,000 people. Block groups are nested within tracts, which are designed to have populations between 1,500 and 8,000 people with an average of 4,000. Finally, tracts are nested within places, which I use as proxies for cities. Taken together, places have an average of 8,000 people per place, but the places used as proxies for cities in this study are much large, with an average population of 445,000 people per place.

THEORETICAL FRAMEWORK FOR UNDERSTANDING MULTILEVEL ASSOCIATIONS BETWEEN INEQUALITY AND CRIME

Economic inequality is a relative, rather than absolute, measure of deprivation, and thus it is a comparative construct. The magnitude of economic inequality in any given place is dependent on the range and distribution of income in that place. Two of the primary theories that have been used to explain the association between inequality and crime are strain theory and social disorganization theory. Each provides some insight into how the association may differ by level of analysis. Both of these theories, are also discussed in chapters 1 and 2 but I address them here as well to establish their explanations for the link between inequality and crime in particular.

STRAIN THEORY

Strain theory originated with Merton's (1938) argument that crime results from a mismatch between people's means and goals. According to Merton, people experience strain when they desire to achieve particular goals but perceive a blockage of the means that would be necessary to achieve these goals. Researchers have debated about whether Merton's theory and later revisions (Merton 1949, 1957, 1964, 1968) represent an individual- or macro-level theory. For example, some have argued that the theory is intended to explain how strain causes individual criminal behavior through social psychological processes (Agnew 1987), while others argue that the theory is about how societal imbalances in culture and structure lead to differences in aggregate crime rates (Bernard 1987; Messner and Rosenfeld 1994). Despite this disagreement, the connotations of Merton's arguments seem at least implicitly macro, and I will focus on the latter of these two arguments in my application of strain theory to the association between income inequality and crime.

In his original formation, Merton suggested that strain brings about crime only when the entire population values monetary success more highly in the cultural system than anything else, but access to the culturally approved means of achieving that success are limited or nonexistent for many. He referred to this mismatch as a “lack of cultural coordination” (Merton 1938:681). In the United States then, inequality brings about crime because our society values monetary success highly. Inequality is an indication that the means of achieving that success are much more limited for some people than others. However, people must perceive inequality in order to react to it. Therefore, the influence of inequality through strain is dependent on the composition of people in the reference group that people use to assess their comparative position. Larger units of aggregation necessarily combine larger groups of people, implying a larger assumed reference group.

For his part, Agnew (1999) made the connection between strain theory and macro-level research explicit by arguing that variation in the amount of strain existing in different communities and variation in the community characteristics that impact the way that strain influences crime result in variation in aggregate crime rates across communities. Additionally, his definition of community included a wide range of geographic units, ranging from blocks to SMSAs, and he suggested that the theory could be used to explain variation in crime rates across cities, SMSAs, and larger units.

Finally, in their institutional anomie theory, Messner and Rosenfeld (1994) argued that American society values the economy over political, educational, and familial institutions, and that this imbalance of structural power creates a societal environment in which criminogenic cultural pressures cannot be sufficiently restrained. Therefore, inequality might be associated with higher crime rates to the extent that it signifies a structural imbalance, but this should be at a larger level of aggregation.

In contrast to those arguing that strain theory is either a micro or macro theory, Baumer (2007) has suggested that it is actually a multilevel theory, whereby macro-level characteristics associated with strain bring about individual offending. He took the position that structural and cultural characteristics are associated with differences in individuals' socialization experiences, and these create variation in commitment to monetary success and to using legitimate means to achieving success. Variation in the prevalence of individuals who have both of these commitments lead to variation in crime rates. Therefore, Baumer's argument suggests that the appropriate level of analysis for the outcome would be the individual level, but that predictors like inequality should be measured at some level higher than the individual. This position implies that inequality will have a context effect on individual behavior.

While Baumer's (2007) multilevel strain theory suggests that inequality should be measured at an aggregate level, the specific unit of aggregation is not indicated. As already mentioned, the size of the unit of aggregation determines the assumed reference group that individuals are using to assess their relative position. As the level of analysis gets larger, so does the size of the included social comparison group. The amount of inequality in a given unit should matter, but only to the extent that it matches people's typical reference group for judging their own economic success, relative to their expectations.

Some scholars have suggested that people's reference groups include only those individuals with whom they come into direct contact (Alwin 1987; Crutchfield 1989; Homans 1974), which means that inequality should influence crime at the neighborhood level or below, depending on how locally concentrated contacts typically are (Hipp 2007b). From this point of view, higher levels of aggregation may combine higher income individuals who are physically and socially more separated from lower income individuals, which means that the two groups do not compare themselves to one another. In this case inequality should have its strongest effect at the block-group level, followed by the tract level, but have a small or non-existent effect at the city level.

Alternatively, other scholars have suggested that cities are a better unit of analysis to measure inequality's association with crime because people may compare themselves to a wider population than just their most frequent contacts (Kovandzic et al. 1998; Merton 1968). This perspective takes the position that people are aware of and affected by the economic position of people in other parts of the city, even if they do not come into direct contact with them. In this case, inequality could have an effect on crime at all three levels.

SOCIAL DISORGANIZATION THEORY

Although strain/anomie theory is the predominant theory used to explain the association between inequality and crime, social disorganization theory has been used as well. As discussed in the previous chapters, Shaw and McKay (1942) argued that low socioeconomic status, high residential instability, and high racial/ethnic diversity combine to create "socially disorganized" communities with the "inability…to realize the common values of its residents and maintain effective social controls" (Sampson 2012:37; see also Bursik 1988 and Kornhauser 1978). In addition, Sampson and Groves (1989) suggested family disruption and urbanization as additional measures of disorganization. Further, Sampson, Raudenbush, and Earls (1997) asserted that collective efficacy, which they defined as social cohesion and trust between neighbors that produces the willingness to intervene on each other's behalf, is the intervening mechanism between the community characteristics which represent disorganization and the resulting crime rate. More broadly, social disorganization theory argues that crime results when there is low social cohesion and collective efficacy between residents of a given community, due to deleterious community characteristics.

Although most social disorganization research tends to focus on absolute deprivation (e.g., poverty), the logic has been used to explain the association between relative deprivation (i.e., inequality) and crime as well (Hipp 2007b; Hipp 2011). Inequality may lead to higher rates of crime because it creates social distance between residents of different economic status and reduces cohesion, which in turn reduce social control.

Social disorganization is generally considered to be a neighborhood-level theory, so most researchers in the tradition would argue that inequality should have an association with crime at the tract level (Hipp 2007a). Additionally, since the theory postulates that inequality increases crime through its creation of social distance and subsequent reduction in social control, it is unlikely that block-group or city inequality influence crime through social disorganization. Block groups may be too small, and cities too large, to create the sort of social distance among people who are in direct contact which would result in lowered social control. Therefore, based on social disorganization theory, I expect a context effect of tract-level inequality on block-group crime, but no effect of block-group or city inequality.

THE CURRENT STUDY

Beyond the conceptual framework already outlined, this study extends prior research in three ways. Prior work generally has only analyzed relationships between inequality and crime at one level of analysis at a time. I measure inequality at three different nested levels of analysis and analyze their relationship with crime simultaneously to distinguish the effect of inequality and crime at each level. Additionally, cities and their potential influence on crime have largely been omitted from communities and crime research in favor of neighborhoods and lower levels of analysis. In this study, however, I include cities as their own level of analysis in order to measure their influence on crime over and above the influence of neighborhoods and lower levels. Finally, because research generally has examined the relationship between inequality and crime at only one level of analysis at a time, little is known about whether the association between inequality and crime at one level of analysis depends on the amount of inequality at other levels. The current study tests for cross-level interactions between inequality at three different levels.

HYPOTHESES

As with disadvantage in the prior chapter, hypothesizing about how the association between inequality and crime differs (or not) by level of analysis requires a close reading of the theories already discussed. While they differ in their explanation for it, however, both theories anticipate higher rates of crime in places with higher inequality. Additionally, because analyses including inequality at only one level are unable to separate effects by level, I hypothesize that each measure of inequality will be associated with higher crime rates when they are included without the other two. In other words:

Hypothesis 1: Prior to controlling for inequality at other levels of analysis, inequality will have a positive association with crime at the block-group, tract, and city levels.

When all three measures of inequality are included, predictions about the association at each level differ by theory. While strain theory can be used to predict a block-group, a tract, and a city-level effect on block-group crime, social disorganization theory predicts only a tract-level effect. Both strain's and social disorganization's expectations about the association between inequality and crime are based on a social comparison of some sort. For social disorganization, the social comparison is with the group of people relevant to create feelings of social cohesion versus distance. This comparison is expected to operate at the neighborhood level. Therefore, based on social disorganization theory:

Hypothesis 2: After controlling for block-group and city inequality, tract inequality will have a positive association with crime.

For strain, the social comparison is to the reference group that individuals compare themselves with in order to assess their relative financial position. As already mentioned, the size of the aggregation level determines the assumed size of the reference group. Tracts represent a larger reference group than block groups, but a smaller one than cities. Cities are a larger reference group than both block groups and tracts. If people compare themselves only to individuals with whom they come into direct contact, then the influence of inequality on crime would be expected to operate at either the block-group or tract level, depending on the degree of local concentration of contacts, because these more closely match the typical reference groups used. Therefore, strain theory would make the same prediction about tract inequality as social disorganization (see Hypothesis 2), but also:

Hypothesis 3: After controlling for tract and city inequality, block-group inequality will have a positive association with crime.

However, if people compare themselves to more than just their direct contacts when assessing their comparative position, and the larger assumed comparison group of the inequality measure for entire cities matches the social comparisons that people make in the real world, then city inequality should have a context effect on crime at the block-group level.

Hypothesis 4: After controlling for block-group and tract inequality, city inequality will have a positive association with crime.

It is important to note that if Baumer (2007) is correct, and inequality should increase individual offending, then a more appropriate outcome measure would be individual offending. I do not have a measure of individual offending, but block-group offending rates can be interpreted as a composite of individual offending.

Aside from the main effect(s) of inequality on crime, there may be cross-level interactions between the economic inequality measures. These interactions are exploratory, rather than grounded in theory, but I test for them for two reasons. First, I hypothesized about, and found evidence for, cross-level interactions between the disadvantage measures in Chapter 2. Therefore, it seems useful to determine whether there are similar cross-level influences occurring for inequality. Second, a primary purpose of this dissertation has been to reveal the nature of the relationship between a community characteristic and crime once level of aggregation is considered. To gain a reasonably complete picture of that relationship, it is necessary to discover whether there are cross-level processes that reveal further nuances as well. As these interactions are exploratory, I make no predictions about the direction of the cross-level interaction, but I expect tract (and city) inequality to influence the association between block-group inequality and crime. Therefore:

Hypothesis 5: The association between inequality and crime at one level of analysis is dependent on the amount of inequality at other levels, such that greater inequality at one level changes the magnitude of the association between inequality and crime at other levels.

DATA AND METHOD

DATA

Data for this project come from two sources: the NIJ Foreclosure and Crime Data Archive and the American Community Survey (ACS). Eric Baumer and colleagues collected the NIJ Foreclosure and Crime Data Archive in an effort to obtain neighborhood-level crime data for a large number of cities (see Baumer et al. 2014). The investigators contacted police departments in 109 cities across the United States to request crime-incident data in whatever format the departments deemed most convenient. Police in 79 cities sent data, and 35 of these sent address-based crime-incident data (see Appendix C for list of cities). The crime-incident data include index crimes reported to the police in those cities between 2005 and 2009. Although most cities sent incident data for both crime outcomes analyzed here, Minneapolis provided data for burglary, but not robbery. Therefore, models predicting robbery only include 34 cities.

The U.S. Census Bureau collects the ACS annually as a supplement to the decennial census. The survey collects data on demographic, social, economic, and housing characteristics from participants. The ACS releases data in one-year, three-year, and five-year groupings. The one-year and three-year estimates are generally more current than the five-year estimates, but they don’t include information at small levels of aggregation. I use the 2005 – 2009 five-year estimates because they cover a larger sample size and are released at the block-group level.

Additionally, the five years of ACS data correspond perfectly with the five years of crime data from the NIJ Foreclosure and Crime Data Archive.

I was able to geocode the location that each crime incident in the NIJ Foreclosure and Crime Data Archive occurred into point data. These point data were joined with block-group, tract, and city shapefiles from the 2000 U.S. Census and then aggregated by crime type into block-group counts. I then joined the ACS data with the crime-incident data to create demographic variables at the block-group, tract, and city level. The final sample for robbery models includes 11,086 block groups nested within 3,676 tracts nested within 34 cities. The final sample for burglary is 11,485 block groups nested within 3,797 tracts in 35 cities.

Measures

As mentioned previously, one city provided counts for burglary but not robbery, and as a result, the samples slightly differ between models for robbery and for burglary. Descriptive statistics of each of the independent and dependent variables used in analyses for each sample are presented in Table 3.1. The descriptive statistics described in this section are for the full sample of 35 cities (i.e., the burglary sample).

Robbery and Burglary. Block-group counts of robbery and burglary for the years 2005 – 2009 are the two dependent variables used in this study. I focus on robbery and burglary because one is a violent crime while the other is a property crime, and because they occur often enough to have substantial counts and meaningful variation even at the block-group level. The average five-year count of robbery across block groups is 24.59 with an average rate of 3.0 per 100 residents (i.e., .6 per 100 annually). The average count of burglary across block groups is 75.67 with an average rate of 7.9 per 100 residents for the same period.

Inequality. The primary independent variables of interest are three measures of income inequality, each measured at a different level of aggregation: block group, tract, and city. Income inequality at all three levels is measured using the Gini coefficient. The Gini measures how much a given distribution differs from the distribution of a completely proportionate one, on a scale from zero to one, with zero representing perfect equality and one representing perfect inequality. Normally, it is calculated by measuring the difference between a diagonal line and the distribution of actual values, using a Lorenz curve. The tract- and city-level measures of the Gini were provided with the ACS five-year estimates. Unfortunately, the ACS does not release the Gini coefficient based on the full range of household incomes at the block-group level, even in the five-year estimates. It does, however, provide the distribution of household incomes across twelve income intervals. To calculate the block-group measure of inequality, I used the *rpme* (robust Pareto midpoint estimator) command in Stata to conduct a robust estimation of inequality from binned incomes, following von Hippel, Scarpino, and Holas (2016). The command essentially assigns each case to the midpoint of its income interval and calculates the Gini using these values, according to this formula:

$$G = \sum_{i=1}^{n}(X_i \times Y_{i+1}) - \sum_{i=1}^{n}(X_{i+1} \times Y_i)$$

where *n* is the number of income categories, X_i is the cumulative proportion of households in income category *i*, and Y_i is the cumulative proportion of household income in income category *i*. The scale of the block-group Gini measure mimics that of the tract and city measures. The average value of block-group inequality is .39, the average value of tract inequality is .42, and the average value of city inequality is .46.

Control Variables. I control for several other community characteristics at various levels of aggregation that may associate with crime rates and inequality. At the block-group level, I control for disadvantage, the size of the young male population, racial diversity, proportion Black, and proportion Hispanic. *Disadvantage* is calculated as the average of the standardized scores of six variables: 1) percent of jobs in the secondary low-wage sector, 2) percent of the working age population (16 and older) that is unemployed or has dropped out of the labor market, 3) percent of households headed by females, 4) percent in poverty, 5) percent of employed persons working in managerial and professional occupations (reverse-coded), and 6) percent of adults over the age of 24 who are not high school graduates ($\alpha = .76$). The average value of block-group disadvantage is .05. The size of the *young male population* is measured as the proportion of the block-group population that is male and between the ages of 15 and 34. The average size is 7%. *Racial diversity* is measured using the entropy score, which is calculated based on the population share of five groups in each block group: non-Hispanic Whites, non-Hispanic Blacks, Asians, Hispanics, and people of another race. Therefore, the entropy score represents the degree of equal representation of these five groups. The formula used for calculation of the entropy score is:

$$E = \frac{\sum_{k=1}^{K} \pi_k \ln\left(\frac{1}{\pi_k}\right)}{\ln(K)}$$

where π_k is the proportion of people in race *k* (e.g. proportion white) and *K* is the total number of racial groups, which is five for this project. Dividing the total entropy score by the natural log of the total number of groups constrains the measure to have values between zero and one, with higher values representing greater diversity, and lower values representing less diversity. A diversity value of zero indicates that only one group is represented in the area. The average amount of block-group diversity is .43. Additionally, I control for the size of the non-Hispanic Black population (*proportion Black*; mean = .29) and the size of the Hispanic population (*proportion Hispanic*; mean = .19).

I also control for residential instability and immigrant concentration at the tract level. *Residential instability* is an index calculated by taking the average of the standardized scores of two variables: 1) percent of renters, and 2) percent of residents that lived in a different census tract five years previously, with higher values representing greater instability. The average value of tract instability is .11. *Immigrant concentration* is measured as the proportion of the population in the unit that is foreign born, with a mean of 13%.

At the city level, I control for the amount of Black-White segregation using the index of dissimilarity, according to the following formula:

$$D_{bw} = \frac{\sum_{j=1}^{n} \left| \left(\frac{b_j}{B}\right) - \left(\frac{w_j}{W}\right) \right|}{2}$$

where n is the number of tracts in the city, b_j is the number of Blacks in tract j, w_j is the number of Whites in tract j, B is the number of Blacks in the city, and W is the number of Whites in the city. The scale of the dissimilarity index ranges from zero to one. In this sample, the average Black-White segregation value at the city level is .52.

Spatial Lag of Crime. Communities and crime research generally finds that crime tends to cluster across space. In other words, places that have higher rates of crime tend to be near other places with high rates of crime, and places with lower rates of crime tend to be near other places with low rates of crime. To test for this sort of spatial autocorrelation of robbery and burglary, I conducted preliminary exploratory spatial data analysis. I found significant autocorrelation for both robbery (Moran's I = .068, $p < .01$) and burglary (Moran's I = .040, $p < .01$), so I created spatially lagged measures of each to account for the spatial patterning. Spatially lagged measures not only adjust for the spatial autocorrelation, but also capture the relationship between crime in an individual neighborhood and crime in surrounding neighborhoods.

The spatially lagged measures of robbery and burglary are measured at the block-group level to correspond with the outcomes. To generate these measures, I calculated the robbery rate and the burglary rate per 100 residents in each block group. I then used a first-order queen's criterion contiguity matrix in GeoDa 1.4.6 to calculate the spatial lag variables themselves. The queen's criterion identifies neighbors as all geographic areas that share a border or corner with the focal area. The value of the spatial lag variable is a simple average of the values of the rates in the neighboring block groups.

ANALYTIC STRATEGY

A primary motivation of this paper is to demonstrate the importance of including cities as a level of aggregation in communities and crime research. To demonstrate the possible contribution of cities as a level, I begin my analyses by conducting an analysis of variance of the dependent and primary independent variables. Doing so partitions the variance into the three levels of aggregation. The amount of non-chance variance in the dependent variables at the tract and city level reveals the amount of variation across tracts and cities that can potentially be explained by tract and city characteristics. The amount of non-chance variance in the independent variable at the tract and city levels reveals the amount of variation across tracts and cities that can explain the tract- and city-level variation in the dependent variables.

I use HLM7.0 to conduct the three-level analysis of variance, using the variable of interest as the dependent variable in null models. In null models for continuous outcome measures, the residual variance estimates indicate how much variance there is at each level, so I calculate an analysis of variance for inequality using continuous models. However, as inequality at the tract and city level are calculated independently from block-group inequality, residual variance estimates for inequality in a null HLM model are less straight forward than they would be if the measures were averages of block-group inequality. Therefore, I also compare the standard deviations of the independently calculated tract and city inequality measures to what their standard deviations would be if they were calculated as averages of the block-group measure.

As robbery and burglary are count measures, I use overdispersed Poisson models with variable exposure to model these outcomes in the multivariate analyses. In overdispersed Poisson null models, the level-one residual variance estimate is not meaningful, and therefore not useful for this purpose. To conduct the analysis of variance for robbery and burglary, I first turn the block-group counts into rates, then log the rates. Finally, I estimate continuous models with logged robbery and burglary rates as the outcomes.

After the analysis of variance, I conduct three-level hierarchical linear regression models to estimate the association between inequality and crime at three different levels of aggregation. Because the Census divides space using nested geographies, I use block groups as the level-one unit of analysis, tracts as the level-two unit, and cities as the level-three unit. As demonstrated by Osgood (2000), Poisson-based regression models with count outcomes are an appropriate strategy for modeling aggregate crime rates, so I use Poisson regression for all of my models, with the size of the block-group population (in hundreds) as the exposure variable in order to treat the analysis as one of rates.

An assumption of Poisson models is that the fitted mean of the dependent variable is equivalent to the conditional variance of the variable. These data violate that assumption, but I allow for overdispersion in the analyses, which avoids the assumption. Poisson models with overdispersion are comparable to negative binomial regression models (Gardner, Mulvey, and Shaw 1995).

I estimate a series of eight regression models each for robbery and burglary. All of the control variables previously mentioned and the spatial lag of the dependent variable are included in every model. The first three models each include inequality at only one level, first block-group inequality, then tract inequality, then city inequality. The fourth model includes all three measures of inequality simultaneously. The last four models include cross-level interaction terms between the measures of inequality, first between block-group and tract inequality, then between block-group and city inequality, then between tract and city inequality, and finally all three interactions at once.

RESULTS

ANALYSIS OF VARIANCE

Results from the analysis of variance are presented in Table 3.2. The results reveal some variation in inequality at all three levels of analysis. Around 84% of the variance in block-group inequality exists at the block-group level, 9% exists at the tract level, and 6% at the city level. However, as mentioned previously, the tract and city measures of inequality that are included in multivariate analyses were calculated independently, and therefore this partition of variance is only part of the story. To see how this analysis of variance compares to the variance in the actual tract and city inequality measures, I created two additional measures of tract and city inequality, with block-group inequality averaged to the tract and to the city level.

The standard deviation of the independently calculated tract inequality measure is similar to that of the block-group averaged measure of tract inequality, .07 and .06 respectively.

However, variation in city-wide inequality is a good deal larger than variation in city means of block-group inequality; the standard deviation of the independently calculated city inequality measure is twice the size of the standard deviation of the block-group averaged measure of city inequality: .04 compared to .02. Therefore, measuring city inequality independently, as I do for my multivariate analyses, reveals that city inequality has more potential importance than suggested by city-level means of block-group inequality, which correspond to the residual variance estimates from the null model.

The variances of the two crime outcomes are more evenly spread across levels. About 40% of the variance in robbery is at the block-group level, while 36% is at the tract level, and 24% is at the city level. Similarly, almost 36% of the variance in burglary is at the block-group level, with 49% at the tract level, and just under 15% at the city level.

Taken together, these results reveal that there is a sizeable amount of variance at the block-group, tract, and city level for inequality, robbery, and burglary. This suggests that there is enough variation in city inequality to explain a moderate amount of city variation in robbery and burglary, though it will probably not be the primary driver. Further, there is enough variation in robbery and burglary across all three levels to merit testing for a multilevel explanation.

MULTIVARIATE ANALYSES

Tables 3.3 and 3.4 present results of multilevel models for robbery, while tables 3.5 and 3.6 present results for burglary. The *b* coefficients presented are unstandardized Poisson regression coefficients, which represent the difference in the log of the expected robbery/burglary count per unit increase in the independent variable. Standard errors are in parentheses. I present the exponentiated coefficients in the columns labeled "e^b," and to aid in interpretation, I calculate the percent change in the robbery/burglary rate per standard deviation increase in the independent variable using the following formula:

$$\% \, Change = ((e^{b})^{SD} - 1) * 100$$

where *b* is the unstandardized coefficient, and *SD* is the standard deviation of the independent variable in question. These values are included in the column labeled "%Δ" in each model.

As in the previous chapter, all independent variables in all models are grand-mean centered. Therefore, when only one measure of inequality is included in the model, the coefficient for it corresponds to the between-unit effect of inequality on robbery/burglary at that level. But when all three measures of inequality are included simultaneously, I can interpret the tract-level and city-level effects of inequality as context effects on block-group robbery/burglary.

Robbery

Main Effects of Inequality

Model 1 of Table 3.3 indicates that, adjusting for all control variables, when block-group inequality is the only measure of inequality included to predict robbery, it is not a significant predictor (b = .40, p = .118). However, when tract inequality is the only measure of inequality included, as in Model 2, it has a positive and significant association with robbery (b = 1.46, p < .001). A standard deviation (.07) increase in tract inequality is associated with an 11.4% increase in the tract robbery rate. Model 3 reveals that when city inequality is included without block-group or tract inequality, it is not a significant predictor of robbery (b = –.19, p = .905). Therefore, Hypothesis 1, that all three measures increase crime when the other two are not controlled, is only partially supported.

In Model 4, all three measures of inequality are included. The coefficient for block-group inequality is negative but not significant ($b = -.21$, $p = .107$). Similarly, the coefficient for city inequality is negative but not significant ($b = -.75$, $p = .644$). In fact, tract inequality is the only measure of inequality that has a significant association with block-group robbery when all three are controlled. These results are supportive of Hypothesis 2, but not hypotheses 3 and 4. Interestingly, the magnitude of the association for tract inequality is larger when all three inequality measures are included than when tract inequality was included without controlling for block-group or city inequality ($b = 1.59$, $p < .001$). As a result, controlling for block-group and city inequality, a standard deviation (.07) increase in tract inequality is associated with a 12.5% increase in the block-group robbery rate.

Interaction Effects

Table 3.4 introduces the three cross-level interactions. Note that all three measures of inequality are included in all models, regardless of which two are being interacted. As shown in Model 5, there is a negative and significant interaction between block-group and tract inequality ($b = -5.97$, $p < .01$). The interaction indicates that the association between block-group inequality and block-group robbery becomes weaker (i.e., more negative) as tract inequality increases, and that the association between tract inequality and block-group robbery becomes weaker (i.e., less positive) as block-group inequality increases. The significant interaction here suggests that although the main effect of block-group inequality is not significant (Table 3.3, Model 4), block-group inequality may have a significant association with robbery under certain conditions (e.g., at certain values of tract inequality).

To understand the cross-level inequality interaction better, I calculated predicted block-group robbery rates at varying amounts of block-group and tract inequality. All other variables are held constant at their means. Using these predicted robbery rates, Figure 3.2 shows the association between block-group inequality and robbery in tracts with low, medium, and high tract inequality. The "low," "medium," and "high" values correspond to one standard deviation below the mean, the mean, and one standard deviation above the mean of tract inequality. To make interpretation of the figure more realistic, the predicted rates are only graphed for the range of block-group inequality that actually exists in the data for tracts with the corresponding amount of inequality. For example, the amount of block-group inequality for block groups in low inequality tracts ranges from 0 to .66, while it ranges from 0 to .77 in high inequality tracts. Therefore, predicted rates of block-group robbery for low inequality tracts are only plotted for block groups with block-group inequality scores ranging from 0 to .66.

In supplementary analyses, I re-centered the tract inequality measure using the low, medium, and high values and re-estimated the interaction models using these variables instead of the original one (results from the full models appear in Appendix D, Table D3.1). I use the conditional effect of block-group inequality from these models to determine whether each of the three plotted trend lines is significantly increasing or decreasing. For example, in a model interacting block-group inequality (grand-mean centered) and tract inequality (centered on low inequality), the coefficient for block-group inequality represents the association between block-group inequality and robbery for low inequality tracts. In the figure, asterisks next to trend lines in the figure legend correspond to the statistical significance of that trend line.

The negative interaction between block-group and tract inequality depicted in Figure 3.2 reveals positive, but non-significant associations between block-group inequality and block-group robbery in low and medium inequality tracts. However, the association between block-group inequality and robbery is actually negative and significant in tracts with high inequality. Therefore, while block-group inequality has a null association with robbery on average, it has a negative association with robbery in high inequality tracts. This result was unexpected and is addressed in more detail in the discussion section.

Model 6 in Table 3.4 reveals a negative interaction between block-group and city inequality as well ($b = -10.95$, $p < .05$), which suggests that the association between block-group inequality and robbery becomes weaker (i.e., more negative) as city inequality increases and vice versa. Again, although the main effect of block-group inequality in Model 4 of Table 3.3 is not significant, the significant negative interaction here suggests that block-group inequality may have an association with robbery under certain conditions (e.g., in cities with a certain amount of inequality). The interaction between block-group and city inequality is depicted in Figure 3.3, with predicted block-group robbery rates calculated using low, medium, and high values of city inequality. Predicted robbery rates for each value of city inequality are only plotted for the range of block-group inequality existing in the data for the corresponding cities. Table D3.2 in Appendix D contains results from supplementary analyses using city inequality re-centered at low, medium, and high values. Asterisks in the figure legend indicate which of the three trend lines are significant.

The negative interaction between block-group and city inequality in Figure 3.3 is similar to the previous interaction. As seen in the figure, the association between block-group inequality and robbery is positive in low and medium inequality cities, but these associations are not significant. In cities with high inequality, on the other hand, the association between block-group inequality and robbery is negative, such that block groups with high inequality have lower robbery rates than block groups with low inequality. Therefore, block-group inequality has no association with robbery in a low inequality city like Virginia Beach, but has a negative association with robbery in a high inequality city like Miami. Again, this result was unexpected, and I return to it in the discussion section.

Model 7 in Table 3.4 reveals that the interaction between tract and city inequality is only marginally significant ($b = -15.59$, $p = .080$). Although this interaction should be interpreted with caution it suggests that the association between tract inequality and block-group robbery becomes weaker (i.e., less positive) as city inequality increases and vice versa. In other words, while greater tract inequality is associated with higher block-group robbery rates on average, it is associated with even higher robbery rates in cities with low inequality, like Virginia Beach than in cities with high inequality, like Miami. Figure 3.4 depicts the negative interaction between tract and city inequality, using the same low, medium, and high values of city inequality as in Figure 3.3. Again, predicted rates are plotted for the range of tract inequality existing in cities with the given amount of city inequality. The supplementary analyses used to determine the significance of each trend line appear in Table D3.3 in Appendix D.

As seen in Figure 3.4, the interaction between tract and city inequality has a different pattern than the prior two interactions. Tract inequality is positively associated with block-group robbery rates in low, medium, and high inequality cities. Therefore, while the significant interaction indicates that tract inequality increases block-group robbery rates *more* in cities with low inequality (e.g., Virginia Beach) than in cities with high inequality (e.g., Miami), the significant slopes for all three trend lines in the figure reveal that tract inequality significantly increases block-group robbery rates in cities regardless of their amount of inequality.

To facilitate interpretation of the two-way interactions, Model 8 in Table 3.4 includes all three cross-level interactions at once. In this model, only the interaction between block-group and tract inequality remains significant ($b = -5.3$, $p < .05$). Additionally, in supplementary analyses (see Appendix D, Table D3.4), I also estimated a three-way cross-level interaction between block-group, tract, and city inequality but the interaction was not significant ($b = 18.84$, $p = .726$). Taken together, the interaction results for burglary are consistent with Hypothesis 5, that the association between inequality and crime at one level is dependent on the amount of inequality at the other levels.

Control Variables

Although the magnitudes of the coefficients fluctuate across models in tables 3.3 and 3.4, most of the control variables have consistent associations with robbery throughout. For example, at the block-group level, disadvantage, proportion Black, proportion Hispanic, and the spatial lag of robbery are all positive and significant predictors of robbery in all models. Additionally, the size of the young male population is a negative and significant predictor of robbery in all models. At the tract level, residential instability and immigrant concentration are positively and significantly related to robbery in all models. And at the city level, black-white segregation is positively and significantly associated with robbery in all models. The only control variable that shows some inconsistency is block-group racial diversity, which is only marginally significant when tract inequality is controlled for.

Burglary

Main Effects of Inequality

Table 3.5 presents results of the main effects of the three measures of inequality predicting burglary. As shown in Model 1, after controlling for all control variables, when block-group inequality is the only inequality measure included, it is a positive and significant predictor of burglary (b = .35, $p < .05$). This corresponds to a 3.2% increase in the burglary rate per standard deviation (.09) increase in block-group inequality. Model 2 reveals that tract inequality is also positively and significantly related to burglary rates when it is the only measure of inequality included (b = .83, $p < .001$). Tract burglary rates increase by 6.4% per standard deviation (.07) increase in tract inequality. Finally, when city inequality is the only measure of inequality included, it has a positive and significant association with burglary as well (b = 2.93, $p < .05$). A standard deviation (.04) increase in city inequality corresponds to a 12.1% increase in the city burglary rate. In contrast to robbery, then, results for burglary support Hypothesis 1 that each measure of inequality increases crime when included without the other two.

In Model 4, with all three measures of inequality included simultaneously, the block-group inequality coefficient becomes almost zero and is no longer significant (b = .004, p = .976), discounting Hypothesis 3. Additionally, the coefficient for city inequality is reduced by about 12% and becomes only marginally significant (b = 2.57, p = .057), providing only minor support for Hypothesis 4. This association should be interpreted with caution, but controlling for block-group and tract inequality, a standard deviation (.04) increase in city inequality corresponds to a 10.5% increase in the block-group burglary rate. Interestingly, tract inequality has almost the exact same association with burglary rates even after controlling for block-group and city inequality (b = .82, $p < .001$). Therefore, in support of Hypothesis 2, controlling for block-group and city inequality, a standard deviation (.07) increase in tract inequality corresponds to a 6.3% increase in the block-group burglary rate.

Interaction Effects

Cross-level interactions between the three inequality variables are found in Table 3.6. The interaction between block-group and tract inequality shown in Model 5 is significant and negative ($b = –4.75$, $p < .01$), indicating that the association between block-group inequality and burglary becomes weaker (i.e., less positive) as tract inequality increases in magnitude and the association between tract inequality and burglary becomes weaker (i.e., less positive) as block-group inequality increases. In other words, although the main effect of block-group inequality on burglary was not significant when controlling for tract and city inequality, block-group inequality may have a significant association with burglary under certain conditions (e.g., in tracts with a certain amount of inequality).

The interaction between block-group and city inequality in Model 6 is not significant, which suggests that the effect of block-group inequality on burglary does not depend on the amount of city inequality and the effect of city inequality on burglary does not depend on the amount of block-group inequality ($b = –4.54$, $p = .189$). Finally, Model 7 reveals a negative and significant association between tract and city inequality ($b = -15.27$, $p < .05$), signifying that the association between tract inequality and block-group burglary becomes weaker (i.e., less positive) as city inequality increases and that the association between city inequality and burglary becomes weaker (i.e., less positive) as tract inequality increases. In other words, tract inequality may have a positive association with block-group burglary on average, but the association may be larger in cities with low inequality than in cities with high inequality.

I calculated predicted rates of block-group burglary at varying values of inequality to ease interpretation of the interactions. To do so, I followed the same procedures as for robbery.. The interaction between block-group and tract inequality from Model 5 is depicted in Figure 3.5, the interaction between block-group and city inequality from Model 6 is depicted in Figure 3.6, and the interaction between tract and city inequality from Model 7 is depicted in Figure 3.7. (see Appendix D, tables D3.5 – D3.7 for full results of analyses with re-centered inequality variables).

As seen in Figure 3.5, the association between block-group inequality and burglary is not significant in tracts with medium or high inequality. However, the association is significant and positive in low inequality tracts. Although the interaction between block-group and city inequality was not significant in Model 6 of Table 3.6, I graphed the interaction in Figure 3.6 to see what it would look like if it were. Not surprisingly, none of the trend lines are significant. Finally, Figure 3.7 reveals that, as suggested by the negative interaction between tract and city inequality, the association between tract inequality and block-group burglary is larger in magnitude in low inequality cities (e.g., Virginia Beach) than in high inequality cities (e.g., Miami), but it is nonetheless significant and positive at all three values of city inequality.

I included all three two-way cross-level interactions simultaneously in Model 8 of Table 3.6 and found that both the interaction between block-group and tract inequality and the interaction between tract and city inequality are significant and negative. The interaction between block-group and tract inequality is somewhat smaller than it was in Model 5 ($b = -4.15$, $p < .05$), and the interaction between tract and city inequality is somewhat larger than in Model 7 ($b = -16.04$, $p < .05$). In supplementary analyses, I included a three-way interaction between block-group, tract, and city inequality, and the interaction was not significant ($b = -23.50$, p =

.536) (see Appendix D, Table D3.8 for full model). Similar to results for robbery, the results from models with interactions are supportive of Hypothesis 5 for burglary.

Control Variables

As with models predicting robbery, the control variables in models predicting burglary are relatively consistent across models. At the block-group level, disadvantage, proportion Black, proportion Hispanic, and the spatial lag of burglary are always positive and significant predictors of burglary, and the size of the young male population is always negatively associated with burglary. At the tract level, residential instability always has a positive and significant association with burglary.

Block-group racial diversity and immigrant concentration at the tract level, and Black-White segregation at the city level are less consistent. Racial diversity is a positive and significant predictor of burglary only when tract inequality is controlled, while immigrant concentration is only significantly related to burglary when tract inequality is *not* controlled and the relationship is marginally significant when all three measures of inequality are included. Finally, Black-White segregation is positively and significantly related to burglary when block-group inequality is the only inequality measure included, and the association is marginally significant when tract inequality is the only inequality measure.

DISCUSSION

Research examining the association between inequality and crime has produced inconsistent findings, with some research having found that greater inequality brings about higher rates of crime (Blau and Blau 1982; Hipp 2007b; Hipp and Yates 2011; Kovandzic et al.

1998; Peterson and Bailey 1988) while other research has found no association (Bailey 1984; Messner 1983; Pridemore 2008, 2011; Sampson 1985). I have argued that an explanation for this inconsistency is omitted level bias, whereby prior studies have neglected to examine the relationship between inequality and crime at every level at which it exists. Most prior research has estimated the association between inequality and crime at only one level of analysis, without consideration of how the association might operate differently at different levels. Omitted level bias has the potential to hide relationships between inequality and crime at multiple levels, which may cause researchers to draw incorrect or unsupported claims about the nature of the association. Additionally, while some of the earliest work on inequality and crime used cities as their level of analysis (Bailey 1984; Blau and Blau 1982; Sampson 1985), recent research has moved away from cities, focusing instead on neighborhoods and smaller units of aggregation (Boessen and Hipp 2015). This approach ignores the possibility that city characteristics may contribute to crime rates.

In this study I have contributed to the study of inequality and crime in four important ways. First, I established a theoretical framework for explaining how the association between inequality and crime may depend on level of aggregation. Second, I tested this theoretical framework, and the potential for omitted level bias, by measuring the association between inequality and crime at multiple levels simultaneously. Third, I included cities as a level of analysis to be able to look for city-level effects. Finally, I tested for dependencies between effects of inequality at different levels of analysis to see whether the association between inequality and crime at one level of aggregation alters the effect of inequality at another level of aggregation. My results are supportive of three main findings, and I discuss their implications here.

First, the separate associations between inequality and crime at each level of analysis, prior to controlling for the other two levels, were not as expected. While for burglary, inequality was found to increase crime whether measured at just the block-group, just the tract, or just the city level, only tract-level inequality was found to increase robbery. These findings are inconsistent with those of Boessen and Hipp (2015). They found that block-group inequality was a significant predictor of both robbery and burglary. However, as previously mentioned, their analyses included nine structural characteristics at multiple levels simultaneously. Therefore, the significant effect of block-group inequality on robbery may be due to the particular combination of variables in their study. Additionally, their sample included only seven cities, which may not be a representative sample.

Although the findings from the first part of my analyses were somewhat unexpected, they still do not reveal whether the associations at each level are resulting from processes at each level because the analyses do not separate effects by level. For example, the association between tract inequality and burglary could result from a tract-level process, but it could also result from a block-group-level process which shows up as a tract-level result when block-group inequality is not accounted for. Even though tract inequality was the only inequality measure with a significant relationship to robbery before controlling for inequality at other levels, a block-group- or city-level effect might have emerged as a suppression effect after controlling for all three levels. To determine whether each association found in the first part of the analyses resulted from processes occurring at the corresponding level, I included all three measures of inequality at once.

My second main finding is that for burglary, the associations between inequality and crime at each level of analysis changed when all three were estimated simultaneously. Block-group inequality was no longer related to burglary, and city inequality was only marginally related. Further, for robbery, tract inequality remained the only significant inequality measure. Taken together, these results suggest that the primary reference group through which inequality increases crime is the neighborhood, whether this is due to strain or social disorganization.

It is not possible for me to distinguish which theory is the best explanation for the associations that I found because both predicted a context effect of tract-level inequality. If the mechanism through which tract-level inequality increases robbery and burglary is strain, then my results suggest that the primary reference group that people use to assess their comparative position is people in their neighborhood. This would be supportive of Baumer's (2007) multilevel theory that macro-level inequality influences individual offending. Alternatively, if social disorganization is the explanation for the effect of tract inequality, then neighborhoods may indeed be the best unit of aggregation for measuring social distance. It should be noted that while both theories predicted a tract-level context effect, that type of effect was the *only* prediction from social disorganization because of its emphasis on neighborhoods. Given that inequality was the only significant main effect of inequality, social disorganization theory closely fits with the results without needing to make any assumptions about the level at which it applies.

The lack of a city-level effect of inequality for robbery, both before and after accounting for all three levels, was surprising. The analysis of variance that I conducted suggested that city inequality would not be the primary influence on crime rates, but I still expected it to have some effect on robbery. It should be noted that in preliminary analyses that I estimated before settling on my final models, I did not control for Black-White segregation. In those analyses, the results for block-group and tract inequality were similar to results reported in tables 3.3 and 3.4, but city inequality was a positive and significant predictor of robbery, both when included as the only measure of inequality and when all three measures of inequality were controlled. The correlation between city inequality and city Black-White segregation is high and highly significant ($r = .60$; $p < .001$). In other words, cities with greater inequality tend to be more segregated.

On the one hand, this may suggest that any relationship between city inequality and robbery is spurious, and is actually the result of the distribution of people of different races across the city, which coincides with the distribution of income. Alternatively, segregation and income inequality may both be aspects of a broader inequality that increases crime. In this case, the two would better be measured as a composite of inequality and segregation, rather than as separate indicators. In other words, both income inequality and segregation increase crime, but they overlap to the extent that inclusion of either diminishes the effect of the other.

To distinguish between these two alternatives, I re-estimated a model with city inequality but not segregation and a model with segregation but not city inequality. For both of these models, I included all control variables and the block-group and tract measures of inequality. Therefore, these models are best assessed in comparison to Model 4 of Table 3.3. If the standard errors of segregation and city inequality remain consistent with either configuration, but the coefficients for one or both variables change, then the first alternative is probably accurate. If, however, the standard errors are smaller when each is included without the other, but the coefficients are relatively similar across models, then the second explanation is more likely.

In comparison to the main results, city inequality is a strong and significant predictor of block-group robbery when segregation is not controlled for ($b = 5.12$, SE = 1.84, $p < .01$). This corresponds to a 22.7% increase in the block-group robbery rate per standard deviation increase in city inequality. Therefore, the magnitude of the coefficient for city inequality is much larger when not controlling for segregation, but the standard error is similar. When city inequality is not controlled for, the coefficient for segregation is actually a bit smaller, with a similar standard error and significance level as in the main results of this study ($b = 2.29$, SE = .51, $p < .001$). Therefore, it is more likely that any influence of city inequality on block-group robbery is spurious, and is explained by the distribution of people across space. It may also suggest that a measure of interracial inequality rather than general inequality would be a better measure of inequality at the city level, which is an idea that has been suggested before (Blau and Blau 1982; Hipp 2007b). Nonetheless, the lack of a city-level context effect of inequality should not be taken as evidence that city characteristics do not matter, since it was a city-level characteristic that explained its effect.

As an aside, Hipp (2007b) has also suggested that routine activities theory can be used to explain an association between inequality and crime. Because inequality is based on the range and variation in the income distribution, areas with high inequality should have a combination of suitable targets (i.e., those on the high end of the income distribution) and motivated offenders (i.e., those on the low end of the income distribution). I did not include routine activities theory in my theoretical framework because it requires making a strong assumption about offender motivation being tied to income that I did not feel comfortable making. Additionally, as routine activities theory is primarily about a convergence in time and space (Cohen and Felson 1979), any theorizing about how it links to level of aggregation requires being able to take into account the distance that offenders are willing to travel for victims. Therefore, it would be more applicable here if I had offender addresses in addition to offense location. Future research should investigate the potential relevance of routine activities theory for understanding the multilevel association of inequality.

Beyond the main effects of inequality, I found several interactions between the different measures of inequality. As this portion of my analyses was exploratory, the interaction results should be interpreted with caution. Additionally, the interaction between tract and city inequality for robbery is only marginally significant. Further, the interactions between block-group and city inequality for robbery and between tract and city inequality for burglary are only significant at the $p < .05$ level. While this is considered significant by conventional standards, it is less meaningful in exploratory analysis. Therefore, while several cross-level interactions were significant, they are less revealing and less trustworthy than the cross-level interactions of disadvantage in the prior chapter.

With that caveat in mind, the general pattern of the interactions suggests that while on average, block-group inequality does not affect robbery or burglary, there are conditions in which it does. The figures plotting the interactions revealed that greater block-group inequality actually *decreased* crime in tracts and cities with high inequality. In other words, within tracts and cities with high inequality, block groups with low inequality actually have higher rates of robbery and burglary than block groups with high inequality.

While I can only speculate on the reason for this counter-intuitive finding, it suggests that within cities and tracts with high inequality, there is something special about block groups with high inequality. Perhaps they represent intentionally mixed income housing areas, which are expected to reduce crime rates because they are characterized by a mixture of disadvantaged residents and more affluent households who may "demand a stricter and better enforced set of ground rules for the community" (Brophy and Smith 1997:6). Alternatively, high inequality block groups within high inequality tracts and cities may be experiencing population turnover through gentrification. Such turnover may result in reductions in crime rates as disadvantaged residents are replaced by more affluent ones. I control for residential instability at the tract level, but not the block-group level because the data to do so were not available. Additionally, the characteristics of those moving in and out may matter more than the turnover itself. Future research should examine these and alternative explanations of the interactions more closely.

This study has important theoretical and methodological implications for future research. While inequality and crime had the strongest association at the tract level, as argued in Chapter 2, there may not be just one "correct" level of analysis for measuring community characteristics and crime. Instead the magnitude and even direction of influence can differ by level of analysis, so different mechanisms may be driving each association. The framework I laid out here demonstrated that each theory could be used to derive predictions about inequality across levels of analysis. It is important to remember, however, that strain theory was not explicit about the levels of aggregation at which it applies, so this is a matter of interpretation. It will be important to develop new theory that is explicit about level of analysis.

Scholarship about social disorganization has focused on neighborhoods, and the main results from this study support the contention that the primary level at which inequality matters for crime is the neighborhood level (measured here using tracts). Therefore, it seems appropriate to continue using neighborhoods to measure inequality in studies of social disorganization. However, while tracts have generally been the census designation used to represent neighborhoods, as I have done here, others have suggested that social disorganization may also predict an influence of block-group inequality on crime as well (Boessen and Hipp 2015). Yet the effect of block-group inequality here was wiped out by the inclusion of tract-inequality. Therefore, social disorganization scholars should develop the theory further to be more explicit about what constitutes a neighborhood. Additionally, there is also evidence that city characteristics matter in the way that they influence lower-level relationships. Therefore, as discussed in the prior chapter, social disorganization scholars would do well to incorporate the potential influence of city characteristics on the mechanisms associated with social disorganization.

In contrast to social disorganization, I argued that strain theory could be used to explain the influence of inequality on crime at any level, depending on how closely each level matches people's reference groups. My findings suggest that if strain theory explains the association between inequality and crime, then its influence is at the tract level. This suggests that strain theorists should seek more direct evidence that census tracts match the social comparison groups that people use to assess their comparative position. Further, strain theory should develop Baumer's (2007) arguments about context effects on individual offending further to address the specific level of analysis at which the macro-level influence of inequality on crime exists.

Progress in research will also depend on the collection of more multilevel data of the kind employed in this study. Prior research has been largely unable to do multilevel communities and crime research with both cities and smaller units of aggregation included as levels because the data necessary to do this kind of analyses are rare. As explained in Chapter 2, most datasets either contain county- or city-level measures across a broad range of counties or cities, or measures at a smaller level like blocks or block groups but only within one or a few cities. As a result, most studies have not separated effects by level or estimated city-level effects on lower-level crime rates. At the same time, however, previous studies using block-group measures have missed the opportunity to conduct multilevel analyses to separate effects at multiple levels, using just two levels (i.e., block groups and tracts). Boessen and Hipp (2015) did this, but theirs is the only study that I am aware of that does so. As we await further data collection, researchers should begin to do this sort of analysis with the data that are already available.

Peterson and Krivo's (2010) National Neighborhood Crime Study was a huge step forward in terms of data for communities and crime research because they collected crime data at the tract level for 91 cities. However, the data used in the current analyses are even more exceptional because they use crime-incident information about where each individual crime occurred. This allows for aggregation to whatever level of analysis the researcher desires. I aggregated crime to the block-group level because it is the lowest level of analysis for which the ACS releases the demographic information necessary for this project, but the possibilities with this data seem endless. More data of this kind should be collected.

LIMITATIONS

Although this study addresses a major limitation of prior research, it has its own limitations. I make predictions about level of analysis based on theory, but I do not measure the mechanisms through which the theories hypothesize inequality would increase crime. So while on the one hand, my findings revealed that the tract level was the primary level of aggregation of the processes that connect inequality with crime, my findings cannot determine whether this process is the result of strain theory or social disorganization theory. As I discussed in my theoretical framing, both of these theories could have predicted a tract-level association between inequality and crime, even after controlling for block-group and city inequality. Future research should incorporate measures of the intervening mechanisms between inequality and crime to determine whether different processes are at work at the tract level and the city level, and at the block-group level when tract and city inequality are high.

Further, I have included each control variable at the lowest available level of aggregation. As more research of the sort conducted here is produced, it will be more feasible to incorporate relationships of multiple variables at multiple levels simultaneously. Relatedly, although this study addresses omitted level bias, this study may still be at risk of omitted variable bias if there are consequential community characteristics that I have failed to include.

Finally, while the data used in this study cover a span of five years (2005 – 2009), the analyses were conducted cross-sectionally. As a result, my findings are associations between variables rather than causal. Future research should aim to combine this data with data from an earlier or later time period to conduct longitudinal analyses.

CONCLUSION

Despite the limitations just outlined, the current study makes an important contribution to the field of communities and crime. My findings have shown the importance of separating the effects of inequality in particular for avoiding omitted level bias. Specifically, my analyses revealed that the relationship between inequality and crime is more complex than prior work has allowed for in modeling. While city inequality may not influence crime rates as much as tract inequality, it still contributed to the overall association between inequality and crime by shaping the association between block-group inequality and crime and between tract inequality and crime. Future research should extend my work here and in the previous chapter by distinguishing the effects of other community characteristics at different levels of analysis, while also including cities as an influential level.

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Table 3.1. Descriptive Statistics

	Robbery Sample[a]		Burglary Sample[b]	
	Mean/%	SD	Mean/%	SD
Block Group Level				
Burglary Count	75.94	71.47	75.67	70.66
Burglary Rate (per 100)	7.89	24.99	7.88	24.57
Robbery Count	24.59	32.38	24.59	32.38
Robbery Rate (per 100)	3.04	9.27	3.04	9.27
Spatial Lag of Burglary Rate	8.30	13.54	8.29	13.32
Spatial Lag of Robbery Rate	3.31	5.69	3.31	5.69
Inequality (Gini)	.39	.09	.39	.09
Disadvantage	.06	.66	.05	.67
% in Low Wage Sector Jobs	25.37%		25.25%	
% Unemployed	42.39%		42.08%	
% Female-Headed Household	17.95%		17.79%	
% in Poverty	17.48%		17.41%	
% Not in Professional or Managerial Occupation	68.98%		68.61%	
% with Less than HS Degree	18.32%		18.11%	
Racial Diversity	.42	.24	.43	.24
% White	45.03%		45.71%	
% Black	29.86%		29.41%	
% Hispanic	18.90%		18.55%	
% Asian	3.90%		3.95%	
% Other Race	2.30%		2.38%	
% Young Men	7.36%		7.37%	
Population	1420.85	1428.83	1404.54	1408.82
Tract Level				
Inequality (Gini)	.42	.07	.42	.07
Residential Instability	.10	.95	.11	.96
Immigrant Concentration	13.07%		13.14%	
Population	4522.22	3176.67	4478.02	3144.53
City Level				
Inequality (Gini)	.46	.04	.46	.04
Black-White Segregation	.52	.15	.52	.15
Population	444534.60	411042.40	442676.50	405101.80

ABBREVIATION: SD = standard deviation; HS = high school
[a]$N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34
[b]$N_{BLOCK\ GROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35

Table 3.2. Analysis of Variance

	Variance per Level		
Variable	Block Group	Tract	City
Inequality	84%	9%	6%
Robbery	40%	36%	24%
Burglary	36%	49%	15%

[a]$N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34
[b]$N_{BLOCK\ GROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35

Table 3.3. Multilevel Poisson Models (with Variable Exposure and Overdispersion) Predicting Block Group Robbery with Inequality Measured at Three Levels

	Model 1				Model 2				Model 3				Model 4			
	b	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ
Block Group Level																
Inequality	.40	(.26)	1.49	3.6									-.21	(.13)	.81	-1.9
Disadvantage	.28 ***	(.04)	1.32	20.5	.26 ***	(.04)	1.30	18.9	.28 ***	(.04)	1.33	20.7	.26 ***	(.04)	1.30	19.1
Proportion Black	.91 ***	(.12)	2.48	37.1	.95 ***	(.13)	2.58	39.0	.91 ***	(.12)	2.48	37.1	.94 ***	(.13)	2.57	38.7
Proportion Hispanic	.81 ***	(.09)	2.25	21.9	.87 ***	(.09)	2.38	23.5	.81 ***	(.10)	2.24	21.7	.86 ***	(.08)	2.37	23.4
Racial Diversity	.07	(.08)	1.07	1.6	.13 †	(.07)	1.13	3.0	.07	(.08)	1.07	1.7	.13 †	(.07)	1.14	3.1
% Young Men	-.66 **	(.22)	.52	-4.2	-.76 ***	(.20)	.47	-4.9	-.71 **	(.23)	.49	-4.6	-.72 ***	(.19)	.49	-4.6
Spatial Lag of Outcome	.02 *	(.01)	1.02	11.3	.02 *	(.01)	1.02	11.1	.02 *	(.01)	1.02	11.4	.02 *	(.01)	1.02	11.1
Tract Level																
Inequality					1.46 ***	(.37)	4.31	11.4					1.59 ***	(.33)	4.92	12.5
Residential Instability	.26 ***	(.02)	1.29	27.7	.23 ***	(.02)	1.26	24.3	.27 ***	(.02)	1.31	29.0	.23 ***	(.02)	1.26	24.6
Immigrant Concentration	.51 *	(.22)	1.67	6.3	.63 **	(.22)	1.88	7.8	.46 *	(.21)	1.59	5.7	.62 **	(.22)	1.86	7.6
City Level																
Inequality									-.19	(1.58)	.83	-.7	-.75	(1.61)	.47	-2.9
Black-White Segregation	2.34 ***	(.52)	10.37	42.9	2.27 ***	(.51)	9.69	41.4	2.40 ***	(.62)	11.07	44.3	2.40 ***	(.61)	11.05	44.3
Intercept	.19 **	(.06)	1.21		.20 **	(.06)	1.22		.20 **	(.06)	1.22		.20 **	(.06)	1.23	
Residual Variance	*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)		
City Level	.14 ***	(.37)			.14 ***	(.37)			.14 ***	(.37)			.14 ***	(.37)		
Tract Level	.04 *	(.20)			.04 ***	(.21)			.07 ***	(.26)			.06 ***	(.24)		
Block Group Level	38.30	(6.19)			37.07	(6.09)			34.34	(5.86)			35.47	(5.96)		

NOTES: $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Table 3.4. Multilevel Poisson Models (with Variable Exposure and Overdispersion) Predicting Block Group Robbery with Cross-Level Inequality Interactions

	Model 5				Model 6				Model 7				Model 8			
	b	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ
Block Group Level																
Inequality	.08	(.18)	1.08	.7	.05	(.17)	1.05	.5	-.22 †	(.13)	.80	-1.9	.15	(.21)	1.17	1.4
Disadvantage	.26 ***	(.04)	1.30	18.7	.26 ***	(.04)	1.30	19.1	.26 ***	(.04)	1.30	19.1	.26 ***	(.04)	1.30	18.8
Proportion Black	.95 ***	(.13)	2.58	38.9	.94 ***	(.13)	2.57	38.7	.94 ***	(.13)	2.56	38.5	.94 ***	(.13)	2.57	38.8
Proportion Hispanic	.87 ***	(.08)	2.39	23.6	.86 ***	(.08)	2.37	23.3	.86 ***	(.08)	2.36	23.2	.86 ***	(.08)	2.37	23.4
Racial Diversity	.14 †	(.07)	1.15	3.3	.13 †	(.07)	1.14	3.2	.13 †	(.07)	1.14	3.2	.14 †	(.08)	1.15	3.4
% Young Men	-.73 ***	(.18)	.48	-4.7	-.74 ***	(.19)	.48	-4.7	-.74 ***	(.19)	.48	-4.8	-.75 ***	(.18)	.47	-4.8
Spatial Lag of Outcome	.02 *	(.01)	1.02	11.1	.02 *	(.01)	1.02	11.1	.02 *	(.01)	1.02	11.1	.02 *	(.01)	1.02	11.1
Tract Level																
Inequality	1.65 ***	(.32)	5.22	13.0	1.58 ***	(.34)	4.84	12.4	1.96 ***	(.36)	7.10	15.6	1.88 ***	(.33)	6.57	14.9
Residential Instability	.23 ***	(.02)	1.26	24.4	.23 ***	(.02)	1.26	24.4	.23 ***	(.02)	1.26	24.3	.23 ***	(.02)	1.26	24.2
Immigrant Concentration	.61 **	(.21)	1.83	7.5	.61 **	(.22)	1.84	7.5	.61 **	(.22)	1.84	7.5	.60 **	(.21)	1.82	7.4
City Level																
Inequality	-.80	(1.62)	.45	-3.1	-.65	(1.60)	.52	-2.5	-.69	(1.58)	.50	-2.7	-.71	(1.60)	.49	-2.7
Black-White Segregation	2.38 ***	(.62)	10.81	43.8	2.37 ***	(.61)	10.68	43.5	2.37 ***	(.60)	10.65	43.5	2.34 ***	(.61)	10.43	43.0
Inequality Interactions																
Block Group x Tract	-5.97 **	(2.17)	.00										-5.33 *	(2.24)	.00	
Block Group x City					-10.95 *	(4.98)	.00						-4.68	(2.95)	.01	
Tract x City									-15.59 †	(8.89)	.00		-9.96	(8.09)	.00	
Intercept	.22 **	(.06)	1.24		.21 **	(.06)	1.23		.22 **	(.06)	1.24		.23 ***	(.06)	1.25	
Residual Variance	*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)		
City Level	.14 ***	(.37)			.14 ***	(.37)			.14 ***	(.37)			.13 ***	(.36)		
Tract Level	.03 ***	(.18)			.05 ***	(.22)			.05 ***	(.23)			.03 ***	(.17)		
Block Group Level	38.74	(6.22)			36.23	(6.02)			35.52	(5.96)			38.87	(6.23)		

NOTES: $N_{\text{BLOCK GROUPS}}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Table 3.5. Multilevel Poisson Models (with Variable Exposure and Overdispersion) Predicting Block Group Burglary with Inequality Measured at Three Levels

	Model 1				Model 2				Model 3				Model 4			
	b	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ	*b*	(SE)	e^b	%Δ
Block Group Level																
Inequality	.35 *	(.17)	1.42	3.2									.00	(.13)	1.00	.0
Disadvantage	.23 ***	(.04)	1.26	16.7	.22 ***	(.04)	1.24	15.7	.23 ***	(.04)	1.26	16.7	.22 ***	(.04)	1.25	16.1
Proportion Black	.75 ***	(.09)	2.11	29.3	.77 ***	(.09)	2.17	30.5	.75 ***	(.08)	2.11	29.3	.76 ***	(.09)	2.14	29.9
Proportion Hispanic	.42 ***	(.08)	1.52	10.7	.45 ***	(.09)	1.57	11.5	.41 ***	(.08)	1.50	10.3	.44 ***	(.08)	1.56	11.3
Racial Diversity	.07	(.06)	1.08	1.8	.11 *	(.06)	1.12	2.6	.07	(.06)	1.08	1.7	.11 *	(.05)	1.12	2.7
% Young Men	-.80 ***	(.19)	.45	-5.1	-.89 ***	(.17)	.41	-5.7	-.86 ***	(.18)	.42	-5.5	-.83 ***	(.18)	.44	-5.4
Spatial Lag of Outcome	.01 **	(.00)	1.01	8.7	.01 **	(.00)	1.01	8.8	.01 **	(.00)	1.01	9.0	.01 **	(.00)	1.01	8.8
Tract Level																
Inequality					.83 ***	(.25)	2.30	6.4					.82 ***	(.24)	2.28	6.3
Residential Instability	.12 ***	(.02)	1.13	12.4	.11 ***	(.02)	1.11	10.9	.13 ***	(.02)	1.14	13.2	.11 ***	(.02)	1.11	10.9
Immigrant Concentration	-.34 *	(.16)	.71	-3.9	-.27	(.17)	.76	-3.2	-.34 *	(.16)	.71	-4.0	-.28 †	(.17)	.76	-3.3
City Level																
Inequality									2.93 *	(1.30)	18.65	12.1	2.57 †	(1.30)	13.04	10.5
Black-White Segregation	.69 *	(.33)	1.99	10.9	.65 †	(.33)	1.92	10.3	.24	(.42)	1.27	3.7	.25	(.42)	1.29	3.9
Intercept	1.69 ***	(.05)	5.40		1.69 ***	(.05)	5.42		1.68 ***	(.04)	5.39		1.69 ***	(.04)	5.41	
Residual Variance	*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)		
City Level	.08 ***	(.27)			.07 ***	(.27)			.07 ***	(.26)			.07 ***	(.26)		
Tract Level	.02	(.14)			.03 *	(.16)			.03 *	(.17)			.02 †	(.16)		
Block Group Level	62.59	(7.91)			60.16	(7.76)			59.79	(7.73)			60.38	(7.77)		

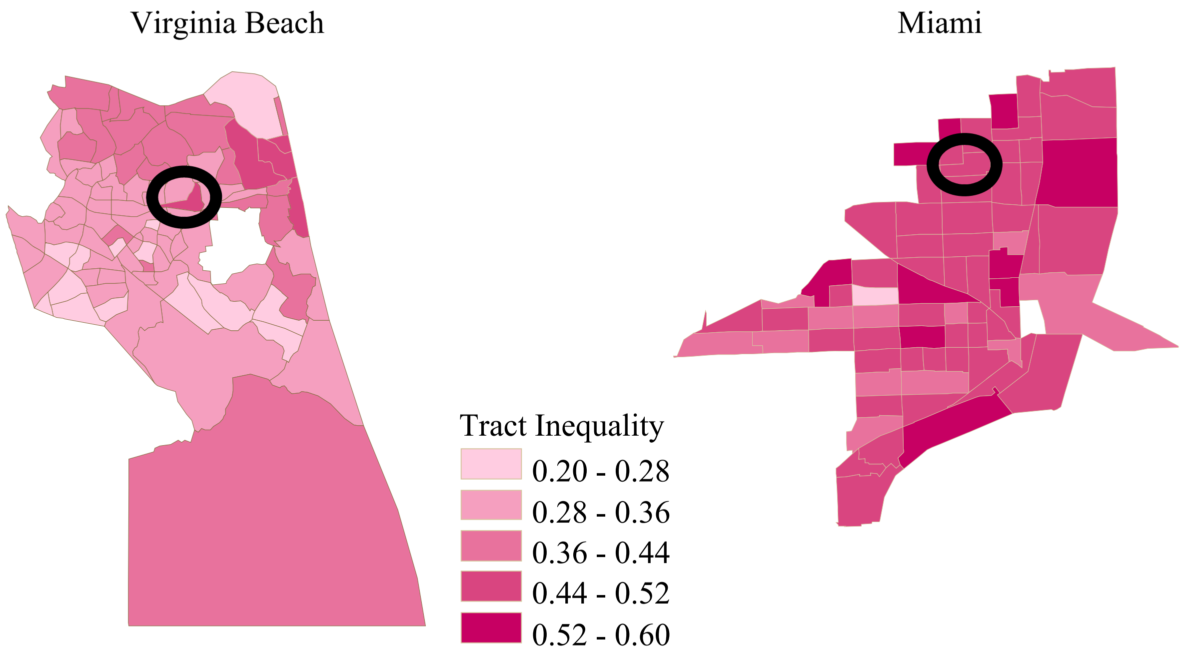
NOTES: $N_{\text{BLOCK GROUPS}}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Table 3.6. Multilevel Poisson Models (with Variable Exposure and Overdispersion) Predicting Block Group Burglary with Cross-Level Inequality Interactions

	Model 5				Model 6				Model 7				Model 8			
	b	(SE)	e^b	%Δ	b	(SE)	e^b	%Δ	b	(SE)	e^b	%Δ	b	(SE)	e^b	%Δ
Block Group Level																
Inequality	.20	(.15)	1.22	1.8	.11	(.18)	1.11	1.0	.00	(.13)	1.00	.0	.06	(.21)	1.06	.6
Disadvantage	.22 ***	(.04)	1.25	16.0	.23 ***	(.04)	1.25	16.2	.22 ***	(.04)	1.25	16.1	.22 ***	(.04)	1.25	15.9
Proportion Black	.77 ***	(.09)	2.15	30.1	.76 ***	(.09)	2.14	30.0	.76 ***	(.09)	2.13	29.8	.76 ***	(.09)	2.14	29.9
Proportion Hispanic	.46 ***	(.09)	1.58	11.7	.45 ***	(.08)	1.56	11.4	.44 ***	(.08)	1.55	11.1	.45 ***	(.09)	1.56	11.4
Racial Diversity	.12 *	(.06)	1.13	2.9	.11 *	(.06)	1.12	2.7	.12 *	(.05)	1.12	2.8	.12 *	(.06)	1.13	2.9
% Young Men	-.84 ***	(.18)	.43	-5.4	-.84 ***	(.18)	.43	-5.4	-.85 ***	(.18)	.43	-5.5	-.85 ***	(.18)	.43	-5.5
Spatial Lag of Outcome	.01 **	(.00)	1.01	8.6	.01 **	(.00)	1.01	8.6	.01 **	(.00)	1.01	8.7	.01 **	(.00)	1.01	8.7
Tract Level																
Inequality	.87 ***	(.23)	2.39	6.7	.82 ***	(.24)	2.27	6.3	1.13 ***	(.25)	3.11	8.8	1.20 ***	(.25)	3.32	9.3
Residential Instability	.11 ***	(.02)	1.11	10.8	.11 ***	(.02)	1.11	10.8	.11 ***	(.02)	1.11	10.6	.11 ***	(.02)	1.11	10.7
Immigrant Concentration	-.31 †	(.16)	.73	-3.7	-.29 †	(.16)	.75	-3.4	-.29 †	(.16)	.75	-3.4	-.31 †	(.16)	.73	-3.6
City Level																
Inequality	2.53 †	(1.31)	12.51	10.4	2.58 †	(1.30)	13.23	10.6	2.53 †	(1.28)	12.50	10.4	2.47 †	(1.29)	11.84	10.1
Black-White Segregation	.24	(.42)	1.27	3.7	.24	(.42)	1.27	3.6	.22	(.41)	1.24	3.3	.22	(.41)	1.25	3.4
Inequailty Interactions																
Block Group x Tract	-4.75 **	(1.80)	.01										-4.15 *	(1.87)	.02	
Block Group x City					-4.54	(3.46)	.01						4.59	(3.45)	98.65	
Tract x City									-15.27 *	(5.90)	.00		-16.04 *	(6.24)	.00	
Intercept	1.70 ***	(.04)	5.47		1.69 ***	(.04)	5.42		1.70 ***	(.04)	5.48		1.71 ***	(.04)	5.53	
Residual Variance	*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)			*Var.*	(SD)		
City Level	.07 ***	(.26)			.07 ***	(.26)			.07 ***	(.26)			.07 ***	(.26)		
Tract Level	.01	(.12)			.02	(.14)			.02	(.15)			.02	(.13)		
Block Group Level	63.98	(8.00)			62.01	(7.87)			60.48	(7.78)			62.05	(7.88)		

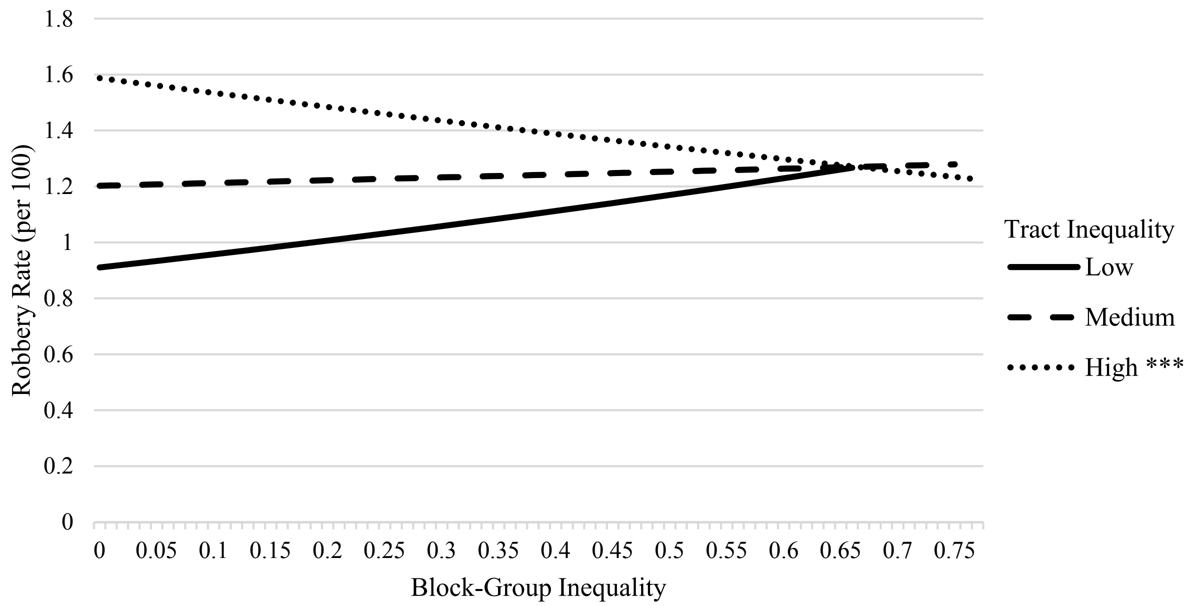
NOTES: $N_{\text{BLOCK GROUPS}}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Figure 3.1. Spatial Distribution of Inequality Across Tracts in Virginia Beach and Miami



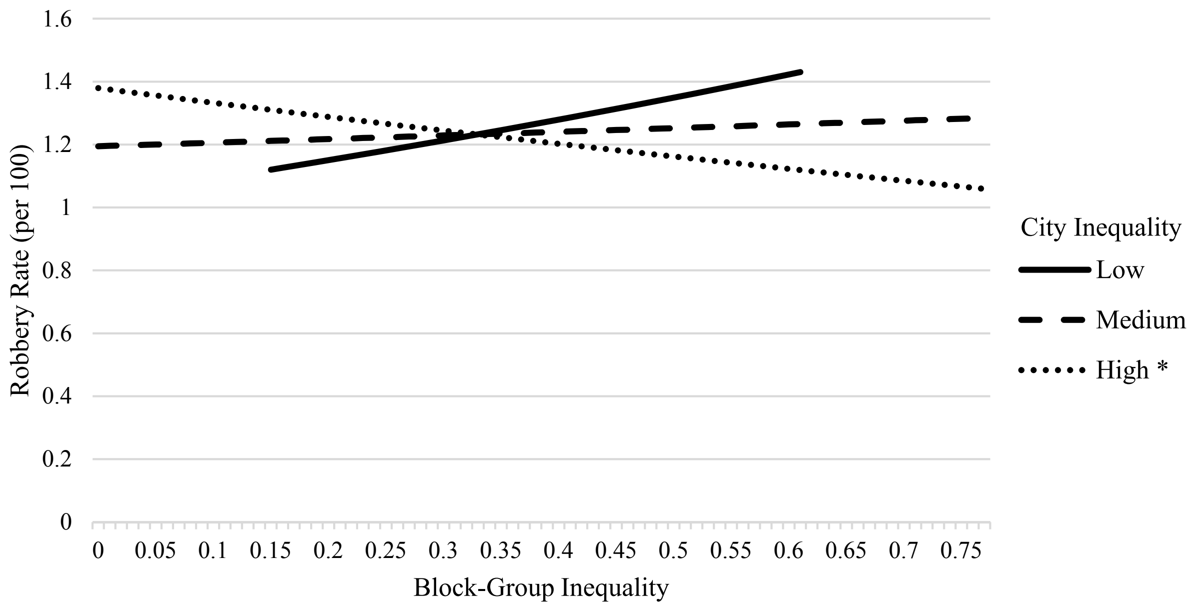
NOTE: The black circles highlight tracts in each city with nearly identical amounts of inequality (.491)

Figure 3.2. Predicted Robbery Rates at Varying Amounts of Block-Group and Tract Inequality



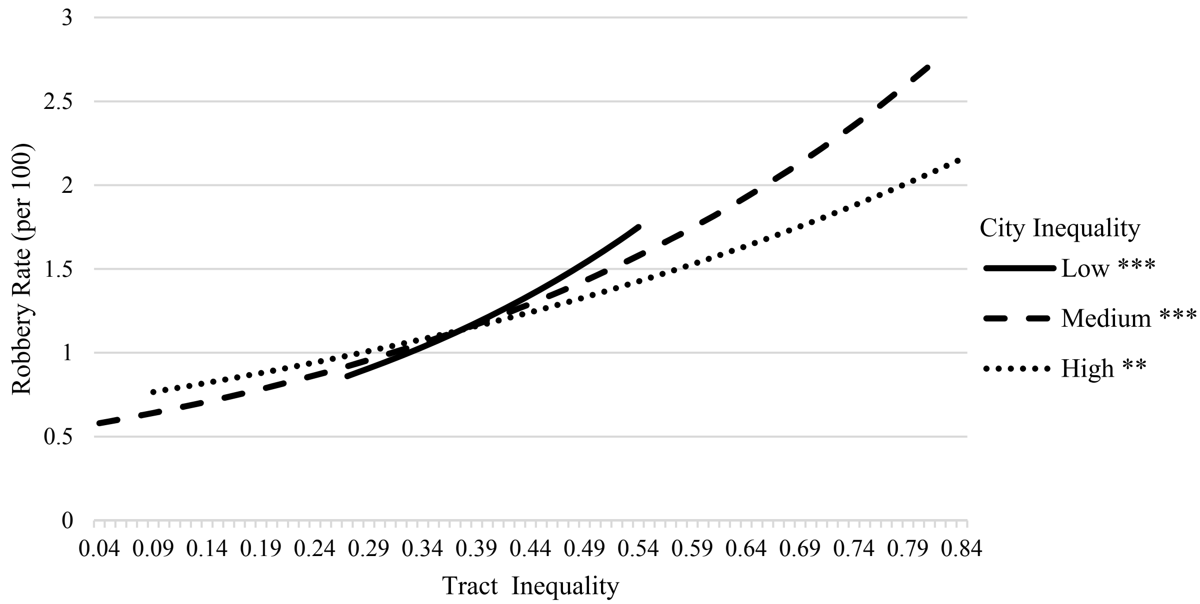
*** p < .001 for separate trend lines

Figure 3.3. Predicted Robbery Rates at Varying Amounts of Block-Group and City Inequality



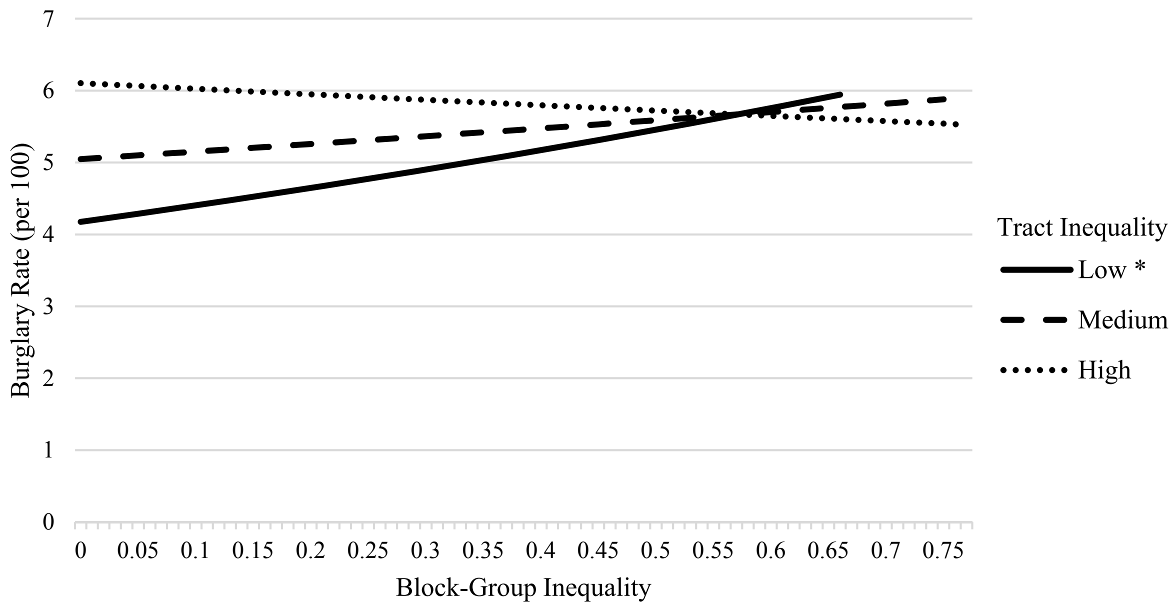
* p < .05 for separate trend lines

Figure 3.4. Predicted Robbery Rates at Varying Amounts of Tract and City Inequality



*** p < .001 for separate trend lines

Figure 3.5. Predicted Burglary Rates at Varying Amounts of Block-Group and Tract Inequality



* p < .05 for separate trend lines

Figure 3.6. Predicted Burglary Rates at Varying Amounts of Block-Group and City Inequality

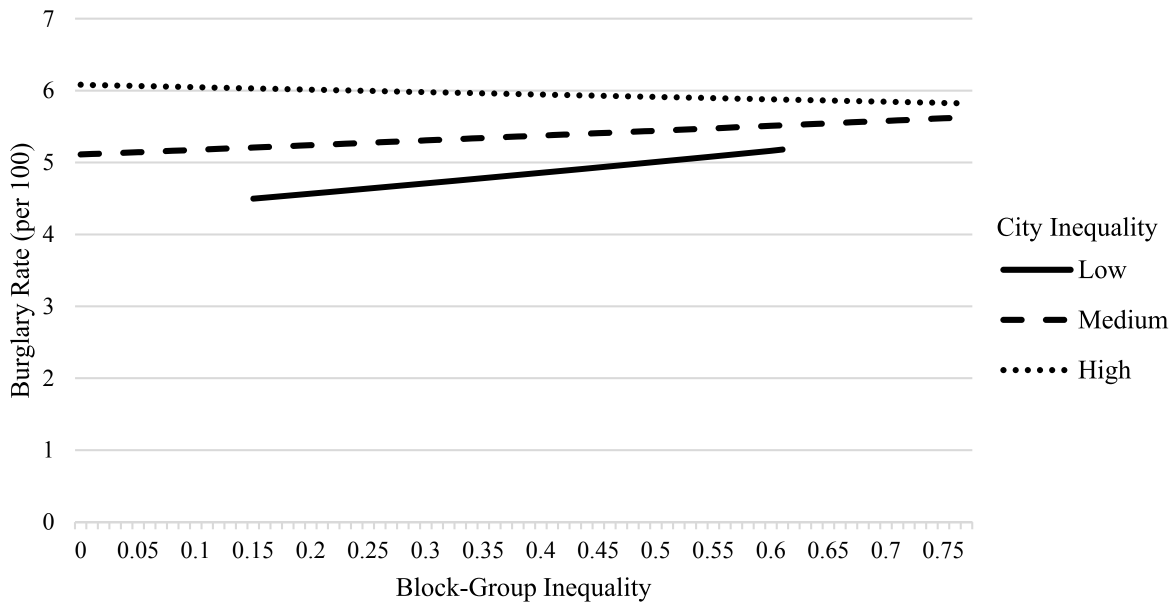
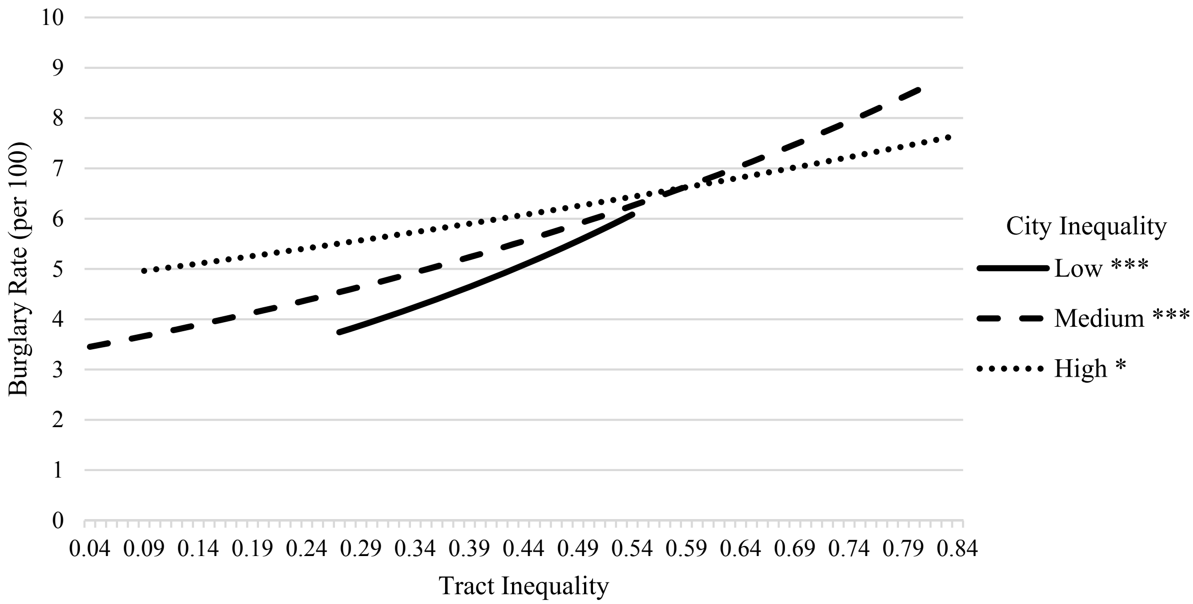


Figure 3.7. Predicted Burglary Rates at Varying Amounts of Tract and City Inequality



* p < .05; *** p < .001 for separate trend lines

APPENDIX C: LIST OF CITIES

City	Block Groups	Tracts
Akron, Ohio	247	71
Arlington, Texas	199	65
Atlanta, Georgia	274	111
Austin, Texas	447	165
Carrollton, Texas	63	24
Chandler, Arizona	109	42
Charlotte, North Carolina	321	127
Chula Vista, California	107	39
Cincinnati, Ohio	313	125
Cleveland, Ohio	525	213
Evansville, Indiana	126	41
Fort Collins, Colorado	103	38
Fort Wayne, Indiana	164	67
Fort Worth, Texas	476	148
Glendale, Arizona	183	52
Greensboro, North Carolina	155	66
Houston, Texas	1,238	439
Las Vegas, Nevada	350	107
Lexington, Kentucky	143	60
Lincoln, Nebraska	169	53
Memphis, Tennessee	592	179
Milwaukee, Wisconsin	592	223
Minneapolis, Minnesota[a]	399	121
Newport News, Virginia	111	34
Oklahoma City, Oklahoma	428	172
Orlando, Florida	144	76
Philadelphia, Pennsylvania	1,762	362
Plano, Texas	158	48
Raleigh, North Carolina	134	69
Sacramento, California	326	111
St. Petersburg, Florida	196	65
Tampa, Florida	309	91
Tempe, Arizona	103	34
Tucson, Arizona	417	120
Waco, Texas	102	36

[a]Excluded from robbery analyses.

APPENDIX D. SUPPLEMENTARY TABLES

Table D3.1. Multilevel Poisson Models of Cross-Level Interaction between Block Group and Tract Inequality Predicting Block Group Robbery with Tract Inequality Re-Centered at Low, Medium, and High Values

	Model 1			Model 2			Model 3		
	Low			Medium			High		
	b	(SE)	e^b	*b*	(SE)	e^b	*b*	(SE)	e^b
Block Group Level									
Inequality	.50	(.32)	1.6	.08	(.18)	1.1	-.34 ***	(.10)	.7
Disadvantage	.26 ***	(.04)	1.3	.26 ***	(.04)	1.3	.26 ***	(.04)	1.3
Proportion Black	.95 ***	(.13)	2.6	.95 ***	(.13)	2.6	.95 ***	(.13)	2.6
Proportion Hispanic	.87 ***	(.08)	2.4	.87 ***	(.08)	2.4	.87 ***	(.08)	2.4
Racial Diversity	.14 †	(.07)	1.1	.14 †	(.07)	1.1	.14 †	(.07)	1.1
% Young Men	-.73 ***	(.18)	.5	-.73 ***	(.18)	.5	-.73 ***	(.18)	.5
Spatial Lag of Outcome	.02 *	(.01)	1.0	.02 *	(.01)	1.0	.02 *	(.01)	1.0
Tract Level									
Inequality (re-centered)	1.65 ***	(.32)	5.2	1.65 ***	(.32)	5.2	1.65 ***	(.32)	5.2
Residential Instability	.23 ***	(.02)	1.3	.23 ***	(.02)	1.3	.23 ***	(.02)	1.3
Immigrant Concentration	.61 **	(.21)	1.8	.61 **	(.21)	1.8	.61 **	(.21)	1.8
City Level									
Inequality	-.80	(1.62)	.5	-.80	(1.62)	.5	-.80	(1.62)	.5
Black-White Segregation	2.38 ***	(.62)	10.8	2.38 ***	(.62)	10.8	2.38 ***	(.62)	10.8
Inequality Interaction									
Tract x Block Group	-5.97 **	(2.17)	.0	-5.97 **	(2.17)	.0	-5.97 **	(2.17)	.0
Intercept	.10	(.07)	1.1	.22 **	(.06)	1.2	.33 ***	(.06)	1.4

NOTES: $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table D3.2. Multilevel Poisson Models of Cross-Level Interaction between Block Group and City Inequality Predicting Block Group Robbery with City Inequality Re-Centered at Low, Medium, and High Values

	Model 1			Model 2			Model 3		
	Low			Medium			High		
	b	(SE)	e^b	*b*	(SE)	e^b	*b*	(SE)	e^b
Block Group Level									
Inequality	.52	(.34)	1.7	.08	(.18)	1.1	-.35 *	(.17)	.7
Disadvantage	.26 ***	(.04)	1.3	.26 ***	(.04)	1.3	.26 ***	(.04)	1.3
Proportion Black	.94 ***	(.13)	2.6	.94 ***	(.13)	2.6	.94 ***	(.13)	2.6
Proportion Hispanic	.86 ***	(.08)	2.4	.86 ***	(.08)	2.4	.86 ***	(.08)	2.4
Racial Diversity	.13 †	(.07)	1.1	.13 †	(.07)	1.1	.13 †	(.07)	1.1
% Young Men	-.74 ***	(.19)	.5	-.74 ***	(.19)	.5	-.74 ***	(.19)	.5
Spatial Lag of Outcome	.02 *	(.01)	1.0	.02 *	(.01)	1.0	.02 *	(.01)	1.0
Tract Level									
Inequality	1.58 ***	(.34)	4.8	1.58 ***	(.34)	4.8	1.58 ***	(.34)	4.8
Residential Instability	.23 ***	(.02)	1.3	.23 ***	(.02)	1.3	.23 ***	(.02)	1.3
Immigrant Concentration	.61 **	(.22)	1.8	.61 **	(.22)	1.8	.61 **	(.22)	1.8
City Level									
Inequality (re-centered)	-.65	(1.60)	.5	-.65	(1.60)	.5	-.65	(1.60)	.5
Black-White Segregation	2.37 ***	(.61)	10.7	2.37 ***	(.61)	10.7	2.37 ***	(.61)	10.7
Inequality Interaction									
Block Group x City	-10.95 *	(4.98)	.0	-10.95 *	(4.98)	.0	-10.95 *	(4.98)	.0
Intercept	.24 *	(.09)	1.3	.21 **	(.06)	1.2	.18 *	(.09)	1.2

NOTES: $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table D3.3. Multilevel Poisson Models of Cross-Level Interaction between Tract and City Inequality Predicting Block Group Robbery with City Inequality Re-Centered at Low, Medium, and High Values

	Model 1				Model 2				Model 3			
	Low				Medium				High			
	b		(SE)	*e* *b*	*b*		(SE)	*e* *b*	*b*		(SE)	*e* *b*
Block Group Level												
Inequality	-.22	†	(.13)	.8	-.22	†	(.13)	.8	-.22	†	(.13)	.8
Disadvantage	.26	***	(.04)	1.3	.26	***	(.04)	1.3	.26	***	(.04)	1.3
Proportion Black	.94	***	(.13)	2.6	.94	***	(.13)	2.6	.94	***	(.13)	2.6
Proportion Hispanic	.86	***	(.08)	2.4	.86	***	(.08)	2.4	.86	***	(.08)	2.4
Racial Diversity	.13	†	(.07)	1.1	.13	†	(.07)	1.1	.13	†	(.07)	1.1
% Young Men	-.74	***	(.19)	.5	-.74	***	(.19)	.5	-.74	***	(.19)	.5
Spatial Lag of Outcome	.02	*	(.01)	1.0	.02	*	(.01)	1.0	.02	*	(.01)	1.0
Tract Level												
Inequality	2.63	***	(.58)	13.8	2.00	***	(.37)	7.4	1.38	**	(.43)	4.0
Residential Instability	.23	***	(.02)	1.3	.23	***	(.02)	1.3	.23	***	(.02)	1.3
Immigrant Concentration	.61	**	(.22)	1.8	.61	**	(.22)	1.8	.61	**	(.22)	1.8
City Level												
Inequality (re-centered)	-.69		(1.58)	.5	-.69		(1.58)	.5	-.69		(1.58)	.5
Black-White Segregation	2.37	***	(.60)	10.7	2.37	***	(.60)	10.7	2.37	***	(.60)	10.7
Inequality Interaction												
Tract x City	-15.59	†	(8.89)	.0	-15.59	†	(8.89)	.0	-15.59	†	(8.89)	.0
Intercept	.25	**	(.09)	1.3	.22	**	(.06)	1.2	.19	*	(.09)	1.2

NOTES: $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table D3.4. Multilevel Poisson Models (with Variable Exposure and Overdispersion) predicting Block Group Robbery with Three-Way Cross-Level Interaction

	Robbery				
	b		(SE)	e^b	%Δ
Block Group Level					
Inequality	.16		(.20)	1.18	1.5
Disadvantage	.26	***	(.04)	1.30	18.8
Proportion Black	.94	***	(.13)	2.57	38.7
Proportion Hispanic	.86	***	(.08)	2.37	23.4
Racial Diversity	.14	†	(.08)	1.15	3.4
% Young Men	-.76	***	(.18)	.47	-4.9
Spatial Lag of Outcome	.02	*	(.01)	1.02	11.1
Tract Level					
Inequality	1.88	***	(.33)	6.57	14.9
Residential Instability	.23	***	(.02)	1.26	24.1
Immigrant Concentration	.60	**	(.21)	1.82	7.4
City Level					
Inequality	-.76		(1.61)	.47	-2.9
Black-White Segregation	2.34	***	(.61)	10.43	43.0
Inequality Interactions					
Block Group x Tract	-5.75	**	(2.15)	.00	
Block Group x City	-5.38		(4.23)	.00	
Tract x City	-10.12		(8.32)	.00	
Block Group x Tract x City	18.84		(53.86)	152579184.92	
Intercept	.23	***	(.06)	1.25	
Residual Variance	*Var.*		(SD)		
City Level	.13	***	(.36)		
Tract Level	.03	***	(.17)		
Block Group Level	38.88		(6.24)		

NOTES: $N_{BLOCK\ GROUPS}$ = 11,086; N_{TRACTS} = 3,676; N_{CITIES} = 34. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

Table D3.5. Multilevel Poisson Models of Cross-Level Interaction between Block Group and Tract Inequality Predicting Block Group Burglary with Tract Inequality Re-Centered at Low, Medium, and High Values

	Model 1			Model 2			Model 3		
	Low			Medium			High		
	b	(SE)	e^b	*b*	(SE)	e^b	*b*	(SE)	e^b
Block Group Level									
Inequality	.54 *	(.24)	1.7	.20	(.15)	1.2	-.13	(.15)	.9
Disadvantage	.22 ***	(.04)	1.2	.22 ***	(.04)	1.2	.22 ***	(.04)	1.2
Proportion Black	.77 ***	(.09)	2.2	.77 ***	(.09)	2.2	.77 ***	(.09)	2.2
Proportion Hispanic	.46 ***	(.09)	1.6	.46 ***	(.09)	1.6	.46 ***	(.09)	1.6
Racial Diversity	.12 *	(.06)	1.1	.12 *	(.06)	1.1	.12 *	(.06)	1.1
% Young Men	-.84 ***	(.18)	.4	-.84 ***	(.18)	.4	-.84 ***	(.18)	.4
Spatial Lag of Outcome	.01 **	(.00)	1.0	.01 **	(.00)	1.0	.01 **	(.00)	1.0
Tract Level									
Inequality (re-centered)	.11 ***	(.02)	1.1	.11 ***	(.02)	1.1	.11 ***	(.02)	1.1
Immigrant Concentration	-.31 †	(.16)	.7	-.31 †	(.16)	.7	-.31 †	(.16)	.7
Tract Inequality	.87 ***	(.23)	2.4	.87 ***	(.23)	2.4	.87 ***	(.23)	2.4
City Level									
Inequality	2.53 †	(1.31)	12.5	2.53 †	(1.31)	12.5	2.53 †	(1.31)	12.5
Black-White Segregation	.24	(.42)	1.3	.24	(.42)	1.3	.24	(.42)	1.3
Inequality Interaction									
Block Group x Tract	-4.75 **	(1.80)	.0	-4.75 **	(1.80)	.0	-4.75 **	(1.80)	.0
Intercept	1.64 ***	(.05)	5.1	1.70 ***	(.04)	5.5	1.76 ***	(.05)	5.8

NOTES: $N_{BLOCKGROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table D3.6. Multilevel Poisson Models of Cross-Level Interaction between Block Group and City Inequality Predicting Block Group Burglary with City Inequality Re-Centered at Low, Medium, and High Values

	Model 1				Model 2				Model 3			
	Low				Medium				High			
	b		(SE)	e^b	*b*		(SE)	e^b	*b*		(SE)	e^b
Block Group Level												
Inequality	.31		(.31)	1.4	.13		(.19)	1.1	-.06		(.12)	.9
Disadvantage	.23	***	(.04)	1.3	.23	***	(.04)	1.3	.23	***	(.04)	1.3
Proportion Black	.76	***	(.09)	2.1	.76	***	(.09)	2.1	.76	***	(.09)	2.1
Proportion Hispanic	.45	***	(.08)	1.6	.45	***	(.08)	1.6	.45	***	(.08)	1.6
Racial Diversity	.11	*	(.06)	1.1	.11	*	(.06)	1.1	.11	*	(.06)	1.1
% Young Men	-.84	***	(.18)	.4	-.84	***	(.18)	.4	-.84	***	(.18)	.4
Spatial Lag of Outcome	.01	**	(.00)	1.0	.01	**	(.00)	1.0	.01	**	(.00)	1.0
Tract Level												
Inequality	.82	***	(.24)	2.3	.82	***	(.24)	2.3	.82	***	(.24)	2.3
Residential Instability	.11	***	(.02)	1.1	.11	***	(.02)	1.1	.11	***	(.02)	1.1
Immigrant Concentration	-.29	†	(.16)	.7	-.29	†	(.16)	.7	-.29	†	(.16)	.7
City Level												
Inequality (re-centered)	2.58	†	(1.30)	13.2	2.58	†	(1.30)	13.2	2.58	†	(1.30)	13.2
Black-White Segregation	.24		(.42)	1.3	.24		(.42)	1.3	.24		(.42)	1.3
Inequality Interaction												
Block Group x City	-4.54		(3.46)	.0	-4.54		(3.46)	.0	-4.54		(3.46)	.0
Intercept	1.58	***	(.08)	4.8	1.68	***	(.05)	5.4	1.78	***	(.06)	6.0

NOTES: $N_{BLOCKGROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table D3.7. Multilevel Poisson Models of Cross-Level Interaction between Tract and City Inequality Predicting Block Group Burglary with City Inequality Re-Centered at Low, Medium, and High Values

	Model 1				Model 2				Model 3			
	Low				Medium				High			
	b		(SE)	e^b	*b*		(SE)	e^b	*b*		(SE)	e^b
Block Group Level												
Inequality	.00		(.13)	1.0	.00		(.13)	1.0	.00		(.13)	1.0
Disadvantage	.22	***	(.04)	1.3	.22	***	(.04)	1.3	.22	***	(.04)	1.3
Proportion Black	.76	***	(.09)	2.1	.76	***	(.09)	2.1	.76	***	(.09)	2.1
Proportion Hispanic	.44	***	(.08)	1.5	.44	***	(.08)	1.5	.44	***	(.08)	1.5
Racial Diversity	.12	*	(.05)	1.1	.12	*	(.05)	1.1	.12	*	(.05)	1.1
% Young Men	-.85	***	(.18)	.4	-.85	***	(.18)	.4	-.85	***	(.18)	.4
Spatial Lag of Outcome	.01	**	(.00)	1.0	.01	**	(.00)	1.0	.01	**	(.00)	1.0
Tract Level												
Inequality	1.80	***	(.40)	6.0	1.19	***	(.25)	3.3	.58	*	(.29)	1.8
Residential Instability	.11	***	(.02)	1.1	.11	***	(.02)	1.1	.11	***	(.02)	1.1
Immigrant Concentration	-.29	†	(.16)	.7	-.29	†	(.16)	.7	-.29	†	(.16)	.7
City Level												
Inequality (re-centered)	2.53	†	(1.28)	12.5	2.53	†	(1.28)	12.5	2.53	†	(1.28)	12.5
Black-White Segregation	.22		(.41)	1.2	.22		(.41)	1.2	.22		(.41)	1.2
Inequality Interaction												
Tract x City	-15.27	*	(5.90)	.0	-15.27	*	(5.90)	.0	-15.27	*	(5.90)	.0
Intercept	1.59	***	(.08)	4.9	1.69	***	(.05)	5.4	1.79	***	(.06)	6.0

NOTES: $N_{BLOCKGROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors. Residual variance estimates not shown.
ABBREVIATION: SE = standard error
† p < .10; * p < .05; ** p < .01; *** p < .001

Table D3.8. Multilevel Poisson Models (with Variable Exposure and Overdispersion) predicting Block Group Burglary with Three-Way Cross-Level Interaction

	Burglary				
	b		(SE)	e^b	%Δ
Block Group Level					
Inequality	.06		(.21)	1.06	.5
Disadvantage	.22	***	(.04)	1.25	15.9
Proportion Black	.76	***	(.09)	2.14	29.9
Proportion Hispanic	.45	***	(.09)	1.56	11.4
Racial Diversity	.12	*	(.06)	1.13	2.9
% Young Men	-.84	***	(.17)	.43	-5.4
Spatial Lag of Outcome	.01	**	(.00)	1.01	8.7
Tract Level					
Inequality	1.20	***	(.25)	3.33	9.3
Residential Instability	.11	***	(.02)	1.11	10.7
Immigrant Concentration	-.31	†	(.17)	.73	-3.6
City Level					
Inequality	2.55	†	(1.27)	12.75	10.4
Black-White Segregation	.22		(.41)	1.25	3.4
Inequality Interactions					
Block Group x Tract	-3.69	†	(2.02)	.02	
Block Group x City	5.28		(3.80)	195.81	
Tract x City	-15.87	*	(6.24)	.00	
Block Group x Tract x City	-23.50		(37.98)	.00	
Intercept	1.71	***	(.05)	5.52	
Residual Variance	*Var.*		(SD)		
City Level	.07	***	(.26)		
Tract Level	.02		(.14)		
Block Group Level	61.43		(7.84)		

NOTES: $N_{BLOCK\ GROUPS}$ = 11,485; N_{TRACTS} = 3,797; N_{CITIES} = 35. All estimates are based on population-average models with robust standard errors.
ABBREVIATIONS: SE = standard error, %Δ = percent change in outcome per standard deviation increase in predictor, SD = standard deviation, Var. = variance component
† p < .10; * p < .05; ** p < .01; *** p < .001

CHAPTER 4:

CONCLUSION

In this dissertation I have argued that communities and crime research to date has been limited by the standard of estimating the association between community characteristics and crime at only one level of analysis per study. I have referred to this limitation as omitted level bias, which I defined as the failure to measure and include constructs at all levels of analysis at which they have an association with the outcome. Within the realm of communities and crime research, omitted level bias results when researchers include a community construct, like disadvantage or inequality, at only one level of analysis even though the process through which the construct influences crime is at a different level or at multiple levels. The only way to determine whether omitted level bias is a problem for any given study and to avoid the bias in research is to jointly analyze relationships at multiple levels.

As I argued in the conceptual chapter, and showed by example in the empirical chapters, relationships at different levels are distinct phenomena. The influence of a neighborhood-level variable on crime may not be the same as the influence of a city-level variable. When a study includes the variable at only one level, the researcher may reach incorrect conclusions. For example, when I included disadvantage and inequality at only the block-group level, both were found to be significant predictors of burglary. If I had stopped there and made this study a block-group level study, as many studies are, I would have concluded that block-group disadvantage and block-group inequality increase crime. However, when tract and city disadvantage were controlled for, block-group disadvantage was no longer a significant predictor, and when tract and city inequality were controlled for, block-group inequality no longer had an association with crime. Therefore, both disadvantage and inequality have their effect on crime at a larger unit of aggregation than the block group, and my conclusion based on only the block-group level effect would have resulted in erroneous and misleading claims about the importance of block-group disadvantage and inequality.

Beyond the necessity of separating effects by level of analysis, I argued for the importance of considering the potential influence of cities. I suggested that cities may have context effects on crime, such that city characteristics influence crime in all neighborhoods of a city, regardless of the characteristics of the neighborhoods themselves. Additionally, I proposed that city characteristics may also influence lower-level associations, by interacting with lower-level characteristics. In the empirical chapters, I found that indeed, city-level disadvantage increased crime, in addition to any effect of block-group or neighborhood disadvantage. Further, the amount of disadvantage at the city level influenced the associations between block-group disadvantage and crime and between tract disadvantage and crime. Similarly, city inequality influenced the association between block-group inequality and crime and between tract inequality and crime. Therefore, studies that omit city characteristics miss part of the communities and crime bigger picture.

IMPLICATIONS FOR THEORY

Although I was able to document separate effects of disadvantage and inequality by level of analysis, I was unable to determine the specific mechanism operating at each level. For example, tract and city disadvantage were found to increase robbery and burglary when adjusting for all three measures of disadvantage, but both social disorganization theory and strain theory could have been used to explain this finding. Relatedly, tract inequality was found to increase robbery and burglary, but social disorganization theory and strain theory could have both been used to make that prediction as well.

Regarding social disorganization theory, most theorizing is about neighborhood processes (Peterson and Krivo 2005; Sampson 2012). Therefore, social disorganization's strongest predictions are about tract-level influences. Both tract disadvantage and tract inequality increased robbery and burglary rates, after accounting for their counterparts at the block-group and tract level. Therefore, my results are supportive of the theory. However, city disadvantage also increased crime rates, in addition to the effect of tract disadvantage. I argued that this effect could partially be explained by social disorganization, even though it is a neighborhood theory, because city disadvantage affects the amount and quality of resources available to neighborhood residents. However, the theory does not address cities in particular, and it needs to be able to account for their influence.

Strain theory, on the other hand, is ambiguous about level of analysis. The theory has been used to explain how individual-level factors lead to individual offending (Agnew 1987) and how macro-level factors lead to variation in crime rates across places (Bernard 1987; Messner and Rosenfeld 1994). Alternatively, it has been suggested as a multilevel theory about how macro-level factors influence individual offending (Baumer 2007). Therefore, my predictions about level of analysis based on the theory were more about what each association would imply if it were significant, and my conclusions were based on the implications of each association, assuming that strain was the underlying mechanism. I argued that my finding that tract inequality increased crime suggested that the primary reference group that individuals use to assess their comparative position was the tract, rather than the city as a whole or just their most immediate contacts. Further, I argued that my findings that tract and city disadvantage both increased crime, but block-group disadvantage did not, suggest that macro-level factors indeed lead to variation in crime rates beyond their influence on individual offending.

In contrast to both social disorganization theory and strain theory, subcultural theories are not specific about level of analysis but they are not entirely ambiguous either. I theorized that disadvantaged areas may be more likely to promote subcultures which encourage or endorse criminal behavior, thereby increasing criminal activity (Anderson 1990, 1999). Further, I argued that this influence was most likely to occur at a small level of analysis like the block group because it relies on socialization through everyday interactions. Therefore, since block-group disadvantage was not associated with crime once tract and city disadvantage were controlled, I concluded that subcultural theories were not the best explanation for the connection between disadvantage and crime. However, my hypothesis using subcultural theory was based on my own interpretation of the theory's connection to level of analysis rather than an explicit claim made by the theory itself.

Although I interpreted my results in terms of how each theory would have explained them, it was difficult to specify the mechanisms at work for each association. Social disorganization theory is the most explicit about level of analysis, but "neighborhood" is still a somewhat ambiguous term. By contrast, strain theory is not explicit about whether the theory is even a macro-level theory. And those theorists who argue that it is a macro theory do not specify the particular aggregate level of analysis to which it should apply. The current project revealed that associations are limited to some levels and not others, and that the level of influence can differ by characteristic. Therefore, it is problematic that theories are not clear about level. Developing theories to make level of analysis less ambiguous would strengthen their applicability.

IMPLICATIONS FOR POLICY

Findings from this dissertation have important policy implications. Efforts to curtail criminal activity through community change would be more effective with knowledge about the level(s) of analysis at which each community characteristic matters. Programs that intend to target problematic conditions of communities, like disadvantage or residential instability, would benefit from documentation of how these conditions influence crime at different levels. Without such information, these programs might waste valuable resources by mistakenly targeting a problem at a level of aggregation which is not relevant for the crime rate.

For example, a reduction in block-group disadvantage no doubt would benefit residents in many ways, but my results showed that block-group disadvantage had no influence on crime once tract and city disadvantage were accounted for. Thus, efforts to reduce disadvantage in any given block group may not reduce the crime rate if they are not also combined with an effort to reduce disadvantage at a larger scale, like the tract or the city. Therefore, knowledge about the level of aggregation at which each community characteristic matters can provide valuable guidance about which geographic areas to target and about the types of programs and policy changes that would actually lead to reductions in crime rates.

FUTURE DIRECTIONS AND CONCLUSIONS

In addition to focusing on the mechanisms driving the associations found here, future work should extend this research by conducting similar analyses with characteristics of communities. The results of the empirical chapters show that relationships between community characteristics and crime are more nuanced than generally acknowledged, even when only looking at one characteristic at a time. For example, inequality at the tract level had the strongest relationship with crime, but inequality at the other two levels influenced the extent to which tract inequality increased crime. As the separation of the effect of inequality did not mirror the separation of disadvantage, the separation of effects by level can differ for each construct. In other words, discovering how the effects of disadvantage and inequality separate at different levels does not reveal how the effects of other variables will separate; it only reveals that they can. Therefore, research that jointly analyzes relationships at multiple levels of aggregation for the other major explanatory variables in the study of communities and crime is needed to see how other characteristics vary in their associations with crime across level of analysis.

Additionally, there is potential for different characteristics to interact with each other both within and across levels, and this will become more and more possible to research as knowledge grows about each characteristic's association with crime. For example, it would be worth exploring whether the association between block-group inequality and crime may depend not only on the amount of inequality at the tract level, but also on the amount of disadvantage at either the block-group or tract level.

An additional avenue for future research would involve conducting similar analyses with longitudinal data. The cities represented in the National Neighborhood Crime Study (NNCS; Peterson and Krivo 2010) overlap with the cities used in the analyses presented in this dissertation. Therefore, I plan to join the two data sets, using changes in community characteristics between the two studies (1999 – 2001 for the NNCS, 2005 – 2009 for the data in this project) to predict changes in crime rates over the same time period. Another avenue of future research, which I plan to pursue, is to account for other city-level mechanisms which may directly impact crime rates or shape lower-level associations. For example, I hope to incorporate information about police resources, the role of elected officials, and transportation systems to see how each impacts crime.

The purpose of this dissertation was to document the problem of omitted level bias and to expose the influence that the bias can have on the interpretation of results. Results specific to disadvantage and inequality revealed that not only do the associations with crime change for each predictor when effects are separated by level of aggregation, but also that a construct can be found to be a significant correlate of crime at a certain level, even though the process producing the effect occurs at a different level. As explained in the discussion sections of chapters 2 and 3, scholars should adapt theory to account for specific levels of aggregation. And further, future work on communities and crime must incorporate multiple levels of aggregation or avoid drawing conclusions about how an association operates at a certain level. Separating the effects of levels of analysis is crucial for the advance of research on crime and ecological context, and cities must be brought back into focus as an influential level of aggregation.

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