Social Distance and Social Change: How Neighborhoods Change over Time

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A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Sociology

Chapel Hill
2006

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Abstract

John R. Hipp: Social Distance and Social Change: How Neighborhoods Change over Time
(Under the direction of Kenneth A. Bollen)

Two key theoretical themes guided my exploration of neighborhood change. First, I utilized the classic sociological notion of social distance in testing its determinants and viewing its effect on neighborhood change over time. I measured social distance in various manners: 1) racial/ethnic differences, 2) a composite of several characteristics (including racial/ethnic, socio-economic, and demographic), or 3) the consolidated inequality created by difference along both racial/ethnic and socio-economic differences simultaneously. Second, I built an explicit micro-level theory of household residential mobility decisions to explain the *generation* of the structural characteristics that theories posit cause neighborhood crime.

I found that social distance had important implications for neighborhoods. Using a multi-level, longitudinal sample of the American Housing Survey (AHS) I found that individual-level social distance along multiple characteristics helps explain neighborhood satisfaction: this suggests the importance of focusing on the *fit* of the household with the neighborhood. Dynamic analyses using this same sample showed that racial/ethnic heterogeneity explains crime rates four years later. Fixed effects analyses using a sample of census tracts in eleven cities found that changing ethnic heterogeneity over the decade is positively related to changing crime rates. These same fixed effects analyses showed that increasing inequality between African-Americans and whites is positively related to the change in various official crime rates.

My theoretical model helped explain the change in neighborhood structural characteristics. Using the AHS sample, I found that perceived crime in a block increases general residential mobility. This theoretical model also predicted and found that the presence of more homeowners on a block reduces perceived crime four years later in dynamic models. While residential instability had no effect on crime four years later in cross-lagged models, more vacant units in the block are positively related to perceived crime four years later. This suggests a possible manner in which residential mobility may affect neighborhood crime rates. I also found using the AHS sample that higher levels of block perceived crime creates racial/ethnic residential transformation by increasing the likelihood that African-Americans and Latinos will move *into* the block, and reducing the likelihood that whites will move in.

In memory of my father, and to my mother.

The spirit I inherited from him and the sisu I inherited from her helped me through this process

ACKNOWLEDGEMENTS

My years in the graduate program at UNC have been the most rewarding of my life to date. This time period has combined intellectual stimulation, with research exploration, with friends and colleagues who are genuinely wonderful people. Most important for my intellectual growth and stimulation has been the guidance of my advisor, Ken Bollen. I feel deeply fortunate to have had him as an advisor: he provided the perfect balance of allowing me the freedom to pursue intellectual interests along with the safety net of an intellectual resource to turn to in times of uncertainty. Ken has the unusual combination of incredible brilliance and knowledge, along with a generosity to always be available to impart that knowledge, along with an ironic sense of humor and a genuine warmth and compassion that make him both a wonderful teacher as well as person. Thank you, Ken.

I also feel privileged to have had an esteemed dissertation committee, and they provided amazing intellectual input. Barbara Entwisle always went the extra mile to provide suggestions and insight throughout my time here: whether it was feedback during courses, insight and suggestions during the master's thesis, or comments and challenges during the dissertation process. Ken Land provided key insights into methodological strategies, as well as substantive suggestions regarding criminology and demographic issues. Tom Mroz provided key insight from an econometric perspective, and challenged me to think in new and useful ways. Francois Nielsen challenged me to think carefully about conceptual issues, and provided useful suggestions regarding measurement issues.

My years at UNC were made particularly memorable by the close ties I fostered with my fellow cohort members—all of them provided intellectual stimulation as well as warm friendship. Of particular importance is Kraig Beyerlein, my fellow “pedestrian intellect”! We have grown in a parallel fashion as academics, and also together as a research team. We have gone from stumbling along blindly learning to do research, to learning our craft to the point of accomplishing several rewarding research projects while here, to now envisioning a future in which we embark on many more research enterprises together. Jeff Edmeades has been a wonderful colleague who has repeatedly helped in various manners, ranging from providing detailed feedback on drafts of chapters, to the more mundane tasks of dissertation formatting! While not a member of our cohort, Jeff’s wife Sunny provided many intellectual discussions of statistical issues from an econometric perspective. Cheol-Sung Lee was always a source of intellectual ideas and good humor, and provided feedback on drafts of chapters. Finally, Ben Fletcher was a colleague for several years who provided amazing intellectual insight and an ability to challenge conventional ways of thinking. While academia is likely not the path of choice for Ben, I will always cherish the conversations we had. But even more important than the intellectual stimulation these cohort members provided me is the wonderful friendship they provided.

I have also benefited from intellectual stimulation and friendships from numerous other sources. Sharon Christ provided feedback on drafts of chapters, as well as many hours of interesting discussions of various statistical issues. Kammi Schmeer likewise provided insightful feedback on early drafts of chapters. Bob Faris was a fun lunch companion, provided theoretical insight, and, perhaps most importantly, began and cultivated my appreciation of Tar Heel basketball! Heather Krull was an always-cheery presence as we

whiled away the hours working in Odum. Phil Kim and I shared many interesting conceptual discussions over coffee, not to mention stimulating discussions about Tar Heel baseball. Several other fellow graduate students provided both intellectual stimulation and enjoyable companionship, including Kristin Kenneavy, Lynn Owens, Jeremy Pienik, Darci Powell, Jeff Rosenthal and Steve Vaisey.

I also experienced wonderful encounters with several faculty members not part of my committee. The tidbits of intellectual exchange I enjoyed with Howard Aldrich when he frequently stopped to chat with me at the coffee shop were a constant boost. Andy Perrin provided numerous opportunities to share theoretical and conceptual ideas, as well as the opportunity to collaborate on projects. Likewise, Guang Guo was a project collaborator who also provided numerous discussions of statistical issues.

My time as a member of the Carolina Structural Equation Modeling group provides some particularly fond memories. While all the members of the group were brilliant and funny—including Ken, my advisor—two others particularly stand out. First, Patrick Curran was an amazingly generous source of information for me. Besides being a collaborator, Patrick was always generous with his time to counsel me on negotiating the perils and joys of the academic endeavor. Second, Dan Bauer was also a collaborator, but was also incredibly generous in his time and effort. Dan spent countless hours guiding me in learning how to write and how to do research.

Several others have been important to me in this process. Kirk White helped me to negotiate the census bureau while doing my research work at the Triangle Census Research Data Center (TCRDC). Rodney Hodson was always generous in helping me with computer issues—now that I'm leaving, perhaps his lab computers will finally stop smoking! Amanda

Henley's generous help in tracking down various shape files has helped the geocoding involved in this dissertation. I have benefited from the geocoding wizardry of Bev Wilson and Karl Lauff at the Odum Institute. Sharon Morris at the Johns Hopkins University library provided data useful for geocoding the neighborhoods of Baltimore. I also benefited financially from the graduate school's funding my final year of research with a dissertation fellowship, as well as a financial grant provided by the TCRDC allowing me to access the data there. I even benefited from my favorite coffee shops that provided a pleasant refuge to work: the Daily Grind, Caribou, and the resplendent Caffe Driade!

A special word of thanks goes to my longtime friend, Jim Garrett, whose simple comment ten years ago "I don't know why you don't consider going back to school" sent me careening off on this intellectual journey. His keen insight provided a new direction to my life that has brought me fulfillment and joy.

Finally, while Chapel Hill has provided an intellectual direction to my life and the training to pursue it, my years in Chapel Hill most importantly allowed me to meet Cynthia, the love of my life. Cynthia provided a spark and joy to my life that provided balance to the rigors of academia. I will always cherish the moments we shared together here—from the simple joys of our favorite restaurants (such as Sal's and Los Potrillos), to the splendor of our favorite natural spots (such as Estes Trail), to the pleasure of exploring neighborhoods together. The fond memories of this time period are a wonderful backdrop to the many more moments we will create as we share the rest of our lives together.

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I. Introduction

Social scientists have long been confronted by the empirical puzzle of why some neighborhoods undergo a period of disorder and decline while others seemingly avoid this fate. Given that neighborhoods are such important parts of people's lives, this is no trivial question. The quality of neighborhoods are important for the social relations they provide adults, for the environment and education they provide children growing up, and for the investment they represent to many home owners for whom the value of their home represents much of their net worth. As neighborhoods worsen, all of these dimensions are negatively impacted. I explore this question here by both measuring the quality of neighborhoods through reported satisfaction and by using crime rates as an objective measure of neighborhoods to trace how neighborhoods change over time.

Two key theoretical themes guide my exploration of neighborhood change. First, I utilize the classic sociological notion of social distance in testing its determinants and utilizing it to view its effect on neighborhood change over time. While early theoretical models viewed social distance along a single characteristic—economic class—that would eventually lead to a full-scale revolt (Marx 1978), later formulations included other socio-economic dimensions (Weber 1968). In the twentieth century, race/ethnicity difference has sometimes been viewed synonymously with social distance (Bogardus 1947). Common to all of these formulations is the hypothesis that social distance inhibits interaction among individuals and can affect social cohesion (Durkheim 1952 [1897]). I therefore take into account in my theoretical model how this social distance may affect household decisions in neighborhoods, and how these decisions may affect changes in neighborhoods over time.

Second, I build an explicit micro-level theory of household decisions and incorporate this into theories positing that neighborhood change occurs due to structural characteristics of neighborhoods. While sociological scholarship often posits that neighborhood change occurs due to structural characteristics of neighborhoods, less attention is given to the *generation* of these structural characteristics. My household level model attempts to explain the existence of neighborhood structural characteristics through household residential mobility decisions. That is, household decisions to leave a neighborhood will affect the aggregated measure of residential stability; similarly, to the extent that certain types of households are more likely to leave a neighborhood with increasing crime (based on economic resources or racial/ethnic background) aggregated economic and racial/ethnic measures of the neighborhood will be affected by such activity. Additionally, I use the construct of social distance to explain some household decisions.

My approach nesting a household-level model within theories positing that structural characteristics of neighborhoods such as social distance affect neighborhood change is inherently a two-level problem requiring two-level data: information on both households and their neighborhoods. While national surveys provide information on individual attitudes, they infrequently provide information on the neighborhood in which these individuals are embedded. Conversely, aggregate-level data for communities allow us to view the change in neighborhoods over time but do not provide information on the decision-making processes of the individuals within those neighborhoods. However, the restricted-use version American Housing Survey (AHS) provides me a unique opportunity to address these questions since it allows me to link household level respondents with the census tract in which the household resides. In addition, the AHS allows me to follow housing units over a period of time, allowing for longitudinal tests.

This research question is also an inherently longitudinal one as I wish to view how neighborhoods change over time. While panel studies occasionally provide access to the neighborhood characteristics of the respondents (i.e., the Panel Study of Income Dynamics), these studies usually follow *individuals* over time. In such studies, once the household leaves a neighborhood there is no longer information on the neighborhood: not only has the respondent abandoned the neighborhood, but the researcher effectively has as well. In contrast, the AHS allows me to view individuals before they leave the neighborhood, as well as the individuals who replace them in the event that they choose to leave. Understanding these new people in the neighborhood and the attitudes they hold provides a new insight not available from studies following individuals over time.

Chapter two

In chapter two I use a national data set of 660 blocks to explore the determinants of neighborhood satisfaction. I build on the residential mobility literature to suggest that, broadly speaking, there are two key components of neighborhood satisfaction: the degree to which the neighborhood is desirable in general, and 2) the degree of fit of the household with the neighborhood (that is, the extent to which the neighborhood fits the household's lifestyle at their particular point in the life course). By using multilevel data, I aim to disentangle neighborhood-level effects from household-level effects. In this sense, neighborhood-level effects tend to capture differences across neighborhoods (their overall desirability), whereas individual-level effects capture the degree to which the household fits with the neighborhood. While some studies have used multilevel data to explore the determinants of neighborhood satisfaction, nearly all of these studies only have data for respondents in neighborhoods within a single city (or in some instances, only a subset of the neighborhoods in a city) (Bolan 1997; Sampson 1991; Woldoff 2002). This raises the question of whether such findings can be generalized from a particular city to all cities.

Second, whereas past studies have suggested that certain aggregate demographic characteristics of neighborhoods are related to overall satisfaction, less studied is *why* such characteristics would lead to more satisfaction. I build on the insights of the social disorganization model (Shaw and McKay 1942)to test whether the crime and disorder of a neighborhood mediate the effect of these demographic characteristics on neighborhood satisfaction. While it is certainly plausible that aggregate levels of crime and disorder reduce aggregate neighborhood satisfaction, studies have generally been limited to testing whether an *individual* who perceives more crime and disorder reports less *individual* neighborhood satisfaction (Adams 1992; Davis and Fine-Davis 1981; Parkes, Kearns, and Atkinson 2002; Woldoff 2002). Taylor (2001) provided a strong critique of such an approach, suggesting that while in his study of Baltimore those who perceived more crime or disorder were less satisfied, there were few aggregate level effects for neighborhoods.

A third key feature of this chapter is that in focusing on the degree of fit of the household with the neighborhood, this naturally introduces the possibility that households prefer to move to neighborhoods in which there is minimal *social distance* between themselves and their neighbors. Whereas studies have tested the effect of individual-level racial/ethnic social distance on neighborhood satisfaction (Harris 2001; Stipak and Hensler

1983), generally finding little effect, virtually none have viewed the effects of social distance along a number of categories simultaneously. I do so here by employing a unique sample that allows me to view the demographic composition of a block of eleven households. Thus, we might expect that an individual household more socially distant from their neighbors will experience less 'fit' with the neighborhood, and hence express less satisfaction. I am also able to test whether the average social distance on the block has an aggregate effect on neighborhood satisfaction.

Chapter three

In chapter three I test for possible reciprocal effects between three structural characteristics (residential instability, ethnic composition, and poverty) and crime rates. Past studies using the social disorganization perspective have discovered cross-sectional relationships between these neighborhood structural characteristics and higher rates of crime, and have posited that these structural neighborhood characteristics *cause* higher crime. However, I test here whether causal direction is reversed due to the mobility decisions of households giving rise to these neighborhood structural characteristics.

A key feature of this chapter is that I build on the work of Lyons and Lowery (1986) who elaborated the view of Hirschman (1970) to build a household level model in which households respond to neighborhood problems either with: 1) voice (by getting involved in either formal or informal means to affect the neighborhood); 2) exit (by moving out of the neighborhood); 3) loyalty (by failing to acknowledge these as problems); or 4) neglect (by withdrawing from social life). While research in the social disorganization perspective often assumes that neglect is the only option available to households, I build a theoretical model in which households may respond to higher crime rates by choosing to move out of the neighborhood. Thus, I explicitly focus on the problem of crime, as fear for one's own safety is a very salient concern that may influence decisions to leave an area (Cullen and Levitt 1996; Dugan 1999). I employ the notion of social distance in this model to predict when households will respond to crime through voice rather than exit.

I perform three key tests in this chapter using longitudinal data. First, I test whether the household level model I construct explains household decisions to leave an area in response to higher rates of crime. The model attempts to explain which households are more likely to leave in such an instance, and tests whether social distance moderates these effects by increasing the likelihood of choosing exit instead of voice. Second, a key implication of the model that I test here is that households choosing exit give rise to these structural neighborhood characteristics that the social disorganization model suggests *cause* crime. Thus, household decisions to leave a neighborhood that is struggling can change various structural characteristics of a neighborhood: a) moving out will increase the residential instability in a neighborhood (by definition, since this is a mathematical relationship); b) if those with higher income are more likely to leave, this will change the economic structure if they are replaced by households with lower income levels; and c) if those who leave are replaced by households of a different racial background this will change the ethnic composition of the neighborhood. Third, I test the social disorganization hypothesis that these neighborhood structural characteristics will cause changes in crime rates. This hypothesis has generally been tested using cross-sectional data despite the causal nature of the proposed relationship. Thus, I develop and test various hypotheses for a household-level model that can undergird the aggregate-level hypotheses of the social disorganization model using multi-level longitudinal data.

Chapter four

In chapter four I test whether two key dimensions of social distance—income inequality and ethnic heterogeneity—increase crime rates in neighborhoods. While several different theoretical models postulate that crime will be increased by inequality and/or ethnic heterogeneity (or a combination of the two leading to inequality *within* ethnicity or inequality *across* ethnicities), virtually no studies have simultaneously tested these constructs using neighborhood-level data. Since inequality and ethnic heterogeneity are fundamentally aggregate level constructs, they can have different manifestations at different levels of analysis. I explore the mechanisms posited by six theoretical models, and point out that these differing theories suggest mechanisms working at differing levels of aggregation.

Thus, past studies of this general question are limited in one or more of the following ways: 1) several studies in the 1980's measured these constructs at large levels of aggregation, such as metropolitan areas or counties. I point out below that since the posited mechanisms generally work at smaller levels of aggregation, this is rarely an appropriate strategy. 2) Studies have generally failed to consider the geographic level at which the mechanisms of inequality or heterogeneity should work for the particular theory being tested. I adopt a strategy of carefully considering the mechanisms of each theory, and show how this suggests constructing measures at particular levels of aggregation. I also show that past studies failing to take this approach often do not construct appropriate measures for capturing the proposed theoretical mechanisms. 3) Studies often fail to take into account more than one theory at a time. Since more than one theory posits some of these relationships, finding a particular relationship does not adjudicate between these competing theories. 4) Related to #3, studies often fail to take into account more than one of these inequality/ethnic heterogeneity constructs in their studies. Since these constructs are highly related both conceptually and empirically as I discuss below, this leaves open the possibility that the empirical relationship observed contains omitted confounding effects. 5) Studies using data for small units of analysis often only have data for neighborhoods in a single city. Such an approach has a) limited ability to generalize its findings, since it requires the assumption that the city being studied is representative of all U.S. cities, b) limited power to find effects due to the relatively small sample size, and c) possibly limited variability due to using neighborhoods from a single city. 6) Studies rarely utilize longitudinal data. As a result, causal claims are more difficult to establish.

I address all of these issues by testing these relationships using neighborhood level data for eleven cities over several decade periods. Thus, I not only measure these effects at the more theoretically appropriate level of small neighborhoods, but by using a fixed effects design, I test whether the change in these inequality and heterogeneity measures affect the change in crime within a neighborhood. By taking into account unchanging characteristics of neighborhoods, fixed effects models utilize longitudinal data to provide a more stringent test of the hypotheses under study (Halaby 2004).

The overarching theme throughout this dissertation is the role of social distance in fostering neighborhood change. The following chapters measure this social distance in various manners: either simply as racial/ethnic differences in a block or tract, as a composite of several characteristics (including racial/ethnic, socio-economic, and demographic characteristics) measured both at the individual- and block-level, or as the consolidated inequality created by difference along both racial/ethnic and socio-economic characteristics simultaneously (Blau 1977) measured at the tract level. In these chapters I explore the role of social distance for fostering neighborhood satisfaction, as well as neighborhood crime and disorder. In the concluding chapter I synthesize the findings, point out policy implications, and suggest future directions for research.

II. Neighborhood Networks of Social Distance: Do they Explain Neighborhood Satisfaction?

Even in an era of increasing globalization, neighborhoods have important implications for their residents. They are the sites for many of the daily activities of their residents: whether shopping, engaging in recreational activities with family and friends, chatting with neighbors, experiencing crime and disorder, or sending their children to nearby schools. For these and other reasons, neighborhoods are important to households, and while a particular household may simply abandon an undesirable neighborhood, there is reason to suspect that many households lack the resources to move away from such a neighborhood, or feel a strong emotional tie that precludes simply moving away (Massey and Denton 1993; Massey, Gross, and Shibuya 1994). As a result, considerable scholarship has focused on the determinants of greater reported neighborhood satisfaction by residents (Adams 1992; Bolan 1997; Connerly and Marans 1985; Hartnagel 1979; Lee, Campbell, and Miller 1991; McHugh, Gober, and Reid 1990; Woldoff 2002). However, not always acknowledged by these studies is the complication that the neighborhood satisfaction reported by any household has two components: 1) the difference in the quality of neighborhoods *across* neighborhoods, and 2) the degree of fit of any household *within* a neighborhood. The notion of a household's degree of fit with the neighborhood comes from the residential mobility literature in which an individual (or household) desires different types of housing units and neighborhoods as they move through the life course. Thus, young singles generally prefer an area with a vibrant nightlife, while couples with children generally prefer tree-lined suburbs perceived to be safe with quality schools. This complication has important implications for the results of prior studies.

While early neighborhood satisfaction studies adopted the strategy of using individual-level data and regressing an individual's reported neighborhood satisfaction on the individual's report of neighborhood characteristics or their demographic characteristics, such an approach suffers from two key limitations. First, is it reasonable to assume that the respondent can provide error-free assessments of various neighborhood characteristics? Second, how do we interpret any observed relationship between a particular demographic characteristic and reported satisfaction? As to the first issue, if certain types of respondents exhibit systematic bias in how they respond to such queries, we will not get an accurate portrayal of the neighborhood. Additionally we don't know if any observed relationship is simply a psychological one: that is, an individual who perceives more problems in the neighborhood is less satisfied than their neighbors who perceive fewer problems, suggesting no neighborhood effects (Taylor 2001). As to the second issue, what does a positive relationship between, say, one's level of education and neighborhood satisfaction mean in such studies? This finding cannot distinguish between various competing explanations: 1) it might measure the degree to which households with high education are better able to move into the most desirable neighborhoods, 2) it might measure the degree to which households with high education 'fit' in the neighborhood and hence are more satisfied, 3) it might simply be a psychological effect where those with more education report more satisfaction, 4) it might indeed capture a compositional effect where the presence of more highly educated households brings about more overall satisfaction. Such indeterminacy suggests a need for data containing households nested in neighborhoods.

For these reasons, recent scholarship has employed a multilevel approach by viewing respondents nested within neighborhoods (Sampson 1988; Sampson 1991). An advantage of this approach is that it does not assume that residents are infallible evaluators of the neighborhood, but rather takes into account that any individual's responses may contain error and systematic bias, and therefore uses the responses of multiple respondents in the neighborhood when constructing neighborhood-level measures (Bollen 1989; Raudenbush and Bryk 2002; Speizer and Bollen 2000). While studies using nested data have made important advances, there remain unanswered questions. For instance, nearly all of these studies have data for respondents in neighborhoods within a single city (or in some instances, only a subset of the neighborhoods in a city) (Bolan 1997; Sampson 1991; Woldoff 2002). This raises the question of whether such findings can be generalized from a particular city to all cities. Even more important are two additional key under-explored questions in the current literature: 1) while studies have found a relationship between various demographic compositions of neighborhoods and satisfaction, few have attempted to explain *why* such relationships exist; 2) studies have paid little attention to whether the *social distance* between residents (as measured by various demographic characteristics) reduces satisfaction. I discuss each of these issues next.

Given the insights of the social disorganization model (Shaw and McKay 1942), it is reasonable to ask whether the crime and disorder of a neighborhood helps explain the relationship between neighborhood demographic composition and overall neighborhood satisfaction. The social disorganization model posits that particular neighborhood social structures (poverty, racial/ethnic heterogeneity, and residential instability) lead to a lack of cohesiveness that diminishes guardianship capability, leading to higher levels of crime and disorder. This crime and disorder then likely reduces the desirability of the neighborhood. To test such a possible mediating effect of crime/disorder on satisfaction requires three tests: 1) whether the neighborhood demographic composition affects the level of crime/disorder; 2) whether neighborhood-level crime/disorder affects overall satisfaction; 3) whether the effect of neighborhood demographics is reduced when including measures of crime/disorder. While numerous studies have performed test 1, surprisingly few have performed test 2 and none have performed test 3. Regarding test 2, while it is certainly plausible that aggregate levels of crime and disorder reduce aggregate neighborhood satisfaction, studies have generally been limited to testing whether an *individual* who perceives more crime and disorder reports less *individual* neighborhood satisfaction (Adams 1992; Davis and Fine-Davis 1981; Parkes, Kearns, and Atkinson 2002; Woldoff 2002). Note that this may simply represent a psychological finding, as Taylor (2001) found in his study of Baltimore that while those who perceived more crime or disorder were less satisfied, there were few aggregate level effects for neighborhoods. And while studies have occasionally tested whether crime victimization in the neighborhood affects satisfaction (Sampson 1991), studies have failed to test whether this might mediate the effects of neighborhood demographic composition. For instance, Sampson's (1991) finding that ethnic heterogeneity led to less reported satisfaction leaves unanswered the question why this relationship exists. Is this because such ethnic heterogeneity is inherently undesirable? Or is it because this ethnic heterogeneity increases the amount of crime and disorder in the neighborhood, which then reduces the satisfactoriness of the neighborhood?

A second key limitation of past work in the neighborhood satisfaction and attachment literature is its focus on the differences across neighborhoods, with subsequently little focus on the degree of 'fit' of the household with the neighborhood. While different households may prefer different neighborhood amenities, there is also reason to suspect that households prefer to move to neighborhoods in which there is minimal *social distance* between themselves and their neighbors. The notion of *social distance* is a fundamental concept in sociology (Poole 1927), and is based on difference in statuses among individuals. Sometimes referred to as "Blau-space" (McPherson and Ranger-Moore 1991), it is caused by such categories as race/ethnicity, economic resources, life course stage, and social background. For instance, a household with children may well prefer a neighborhood with many other children. Although there is reason to suspect that in the neighborhood-context social distance will result in less social interaction, less cohesion, and a subsequent reduction in neighborhood satisfaction, few studies have tested these possible effects. Whereas studies have tested the effect of individual-level racial/ethnic social distance on neighborhood satisfaction (Harris 2001; Stipak and Hensler 1983), generally finding little effect, virtually none have viewed the effects of social distance along a number of categories simultaneously. I do so here by employing a unique sample that allows me to view the demographic composition of a block of eleven households. Thus, we might expect that an individual household more socially distant from their neighbors will experience less 'fit' with the neighborhood, and hence express less satisfaction.

While the social distance of a particular household from their neighbors may reduce the fit with the neighborhood for that household and create dissatisfaction, there may also be compositional effects in which greater social distance in a neighborhood affects all of the residents, not just those more socially distant. This social distance might work through various mechanisms: it might reduce the perceived closeness of the neighborhood in a sort of Durkheimian mechanical solidarity fashion; it could reduce social interaction among residents, therefore reducing neighborhood satisfaction if social interaction is inherently desirable; it might work indirectly by reducing interaction, which then results in increased crime and disorder, which then reduces neighborhood satisfaction. While studies have tested whether neighborhood-level social distance based on the category of race/ethnicity impacts crime and disorder (Bellair 1997; Roncek and Maier 1991; Rountree and Warner 1999; Sampson and Groves 1989; Smith, Frazee, and Davison 2000; Warner and Pierce 1993; Warner and Rountree 1997), and other studies have tested whether it reduces the satisfaction of all residents (Adams 1992; Connerly and Marans 1985; Harris 2001), studies have not tested for the effect of social distance along a number of categories beyond race/ethnicity upon crime and disorder. Additionally, they have not tested whether social distance based on race/ethnicity has a direct effect on neighborhood satisfaction, or whether its effect is mediated by increasing the level of crime and disorder in a neighborhood.

In this paper, I begin by discussing the mechanisms through which social distance should work. I then discuss four possible determinants of social distance suggested by past scholarship. I then explain how these determinants of social distance can be combined into a single measure of social distance between neighbors on a block. Following that, I develop my theoretical model of neighborhood satisfaction by first discussing the determinants of quality *between* neighborhoods, and then discussing the determinants of the degree of fit of any household with a neighborhood. I then introduce the data and methods I will employ, and present the findings of a structural equation model. I close with conclusions and implications.

Theoretical Model of Social Distance

The notion of *social distance* is a fundamental concept in sociology (Poole 1927), and was expressed by Marx as a dichotomy between two distinct groups based on the single determinant of economic class that would eventually lead to a full-scale revolt (Marx 1978). That is, there is minimal social distance between any two members *within* a particular class, but considerable social distance between any two members of *different* classes. In the twentieth century, the importance of racial/ethnic differences has come to dominate and define measures of social distance, and is posited to cause such outcomes as racism, group conflict, and segregation (Green, Strolovitch, and Wong 1998; Massey and Denton 1987; Sampson 1984; South and Deane 1993; Tajfel and Turner 1986). Social distance can also be created by various other characteristics such as religion, social background, or stage of the life course, and Blau (1977; 1987) built on the work of Simmel (1955) to focus on the degree of overlap between individuals in these various categories, or *cross-cutting circles.* This perspective focuses on the distance between individuals in *social* space, rather than *physical* space. This general notion of social distance—as measured by the social positions individuals occupy—has been key to understanding solidarity, cohesion, and conflict (Durkheim 1984 [1933]), under the general assumption that individuals prefer homophily.[1] Homophily is the notion that "birds of a feather flock together," and posits that social

[1] In early broad theories of historical change in cities, Simmel (1908) viewed the impersonality of cities increasing social distance and leading to anomie, while Wirth (1956b) focused on the groups based on common interests that formed in cities. More recently, Fischer (1975) pointed out that subcultures existing within the city contained minimal social distance *within* them, and were accompanied by considerable social distance *between* the subcultures.

distance is inherently undesirable to individuals, often leading to mistrust and a lack of communication (Ross and Jang 2000).

Mechanisms of Social Distance

Past theory and research suggests four reasons why social distance might be important for fostering neighborhood satisfaction: 1) social distance can decrease the similarity in attitudes between two individuals; 2) social distance can decrease the chances of creating a shared group identity; 3) social distance can decrease the likelihood of interaction; 4) social distance as exemplified by social statuses creates role differences. I consider each of these next.

First, Bourdieu (1984: 476-77) argued that the social position of individuals affects their attitudes and cultural preferences. An individual's social origin shapes their views and attitudes throughout life, what Bourdieu referred to as *habitus*, creating social distance from those with different social origins. Thus, the awareness of others' different social background will discourage interaction based on the expectation of a lack of common social ground.

Second, a long line of social psychology literature suggests that individuals with even superficial similarities can come to categorize themselves and others as members of the same group (Friedkin 1999; Hogg 1992; Simon, Hastedt, and Aufderheide 1997; Turner 1987). Once an individual self-categorizes into a particular group, self-categorization theory (Tajfel and Turner 1986) posits that: 1) individuals will expect to agree with those who are functionally identical; 2) failing to agree with similar others will increase subjective uncertainty; 3) the views of similar others will be influential as they provide feedback on the social validity of one's own views (Fleming and Petty 2000). This suggests that groups fostered by similarity on social categories are important for providing self-validation and order to the world (Lau 1989). Again, greater social distance will inhibit this formation of a group identity.

Third, social distance may have an important effect on the likelihood of social interaction, due to the principle of *homophily*, which suggests that people will tend to prefer associating with those close in *social* space (McPherson and Ranger-Moore 1991). The principle of homophily dates to Aristotle and Plato, and suggests that individuals will prefer to interact with others similar to themselves (McPherson, Smith-Lovin, and Cook 2001).[2] As a result, individual networks are homogeneous along many socio-demographic and behavioral characteristics. This is partially due to choosing similar others with whom to interact, but also because pairs that are more similar are more likely to remain connected over time (Kandel 1978; McPherson, Smith-Lovin, and Cook 2001). One viewpoint suggests conceptualizing this social distance as a cost to interacting with those more socially distant (Mayhew, McPherson, Rotolo, and Smith Lovin 1995).

Finally, in social status theory (Merton 1968) individuals inhabit social positions (or *social statuses*) that are accompanied by appropriate social roles. There are then various role expectations associated with each position, and we might expect these to lead to differences in the actions and attitudes of an individual in one position compared to someone in another position. Many statuses are categorical, bringing about social distance. For instance, consider marital status: membership in the social position of "married" precludes simultaneous membership in the social position of "single."

[2] However, it is interesting to note that they both also suggested that opposites might attract. This suggests that simply looking at a single social position at a time may not capture the entire effect. In such an instance, viewing the overall social distance between two individuals may be important. For instance, difference on a particular social position may be appealing as long as it is accompanied by similarity along other social positions.

All four of these theories suggest that social distance can limit or enhance social interaction. While the preference for homophily clearly impacts social interaction, Bourdieu's concept of habitus suggests that the differing interests of those in different social positions will limit the ability and desire to interact. Tajfel's self-categorization theory suggests that the interaction of group members will foster group identity, leading to even more interaction among those closer socially. And social status theory argues that the roles associated with these positions lead to different lifestyles that will sometimes minimize interaction between those in different statuses.

Determinants of Social Distance

Given these mechanisms of social distance, the question then is what social characteristics might be particularly important for fostering distance.[3] Theoretical models have suggested four key determinants of social distance: 1) economic class; 2) racial/ethnic differences; 3) life course position; 4) social upbringing. While gender would also be a key determinant for many outcomes, it has less meaning in a neighborhood context given that most households are mixed in terms of gender.[4] Thus, there is little reason for it to create social distance among households in neighborhoods. Figure 2.1 presents this conceptual

[3] Given the amorphous definitions of 'social distance,' being able to determine its proper determinants on first principles seems unlikely. That is, social distance is fundamentally based on the social structure of a particular society, and hence its determinants will be created by the structure of that society. Given that, a more reasonable goal is to construct a measure of social distance based on modern industrial societies. While some general categories can be drawn from these societies, empirical observation seems most likely to provide additional insight. The question then becomes how general can these measures of social distance be within: 1) different outcomes; 2) different contexts; 3) different time periods.

[4] Of course, some households have only one head, and therefore it is possible to create some distance based on gender. But consider a neighborhood in which half the units are single parent families headed by women, and the other half are married couples. The single parent households will nonetheless have minimal social distance with the *wives* of the married households. In addition, the social distance measure I create below likely captures any possible difference between such households by measuring distance based on marital status.

model, and highlights that these various determinants *create* social distance. We can then view what effects social distance has: while I view its effect on neighborhood satisfaction in this study, its effect on the formation of ties, marriage patterns, and other outcomes could be studied as well. I consider each of these determinants of social distance next.

Arguably the most fundamental sociological determinant of social distance is economic class. While Marx (1978) articulated this as a dichotomous measure of differing classes, Weber (1968) expanded this to include a broader conception of social class that functioned more like a continuous measure. Weber's conceptualization included one's education level and the prestige of one's occupation. Recent work in this tradition has viewed economic inequality as social distance between individuals that leads to strain and hostility (Morenoff, Sampson, and Raudenbush 2001).

The twentieth century saw the theoretical extension of social distance to include racial/ethnic differences as a determinant. This view has blossomed to the point that many social distance measures are synonymous with racial/ethnic difference (Aldrich, Cater, Jones, McEvoy, and Velleman 1985; Bogardus 1947; Jargowsky 1996; Jones 1991; Payne, York, and Fagan 1974; Rosenbaum 1992). A large literature has shown how race/ethnicity can lead to social distance: for instance, studies have found that high school students exhibited strong tendencies towards selecting same race friends (Mouw and Entwisle 2006). Another study using a survey of teachers for the 1992-3 school year found that those of the same race, gender, and subject field are more likely to be in the same subgroup (Frank 1996). And a range of research has viewed the effects of social distance on ethnic intermarriage (Gray 1987; Jones 1991; South and Messner 1986).

The life course perspective has advanced the view that social positions fundamental to most societies—age, marital status, and presence of children—are important for creating social distance and reducing interaction (Elder 1985; Elder 1998; La Gory and Pipkin 1981; Michelson 1976). Age is particularly important for creating social distance, as birth cohorts experience different life events that create social distance in attitudes and viewpoints (Elder 1999). Additionally, children are grouped in classrooms based on age, while "homogamy on age in marriage is so taken for granted that it is seldom even studied" in research of the U.S. (McPherson, Smith-Lovin, and Cook 2001). Studies of factory workers (Feld 1982) and persons aged 60 and over (Ward, LaGory, and Sherman 1985) also found age homophily effects. Besides age, marital status and the presence of children are important determinants of social distance. Marital status leads to lifestyle differences from those who are single (Fischer 1982), while the presence of children creates a host of role expectations that result in considerable lifestyle differences from those without children (Fischer 1982; Stueve and Gerson 1977).

A fourth possible determinant of social distance comes from Bourdieu (1984), who suggested that early life histories imprint individuals into a social class that creates social distance throughout life from others without that social background. As a result, two individuals raised in different cultures or sub-cultures will have different attitudes and viewpoints. For instance, growing up in an urban area may lead to a different outlook from someone raised in a rural area (Wirth 1956a; Wirth 1956b), or the perception of such differences (Simon, Hastedt, and Aufderheide 1997). Likewise, being raised in a different society, or even a particular part of the country, may lead to social distance between individuals (Breton 1964; Logan, Alba, and Zhang 2002; Quillian 1995). Bourdieu also argued that obtaining more education will lead to different views from those with less education, creating social distance. As a result, those occupying different social positions will have little in common and hence interact infrequently.

Measuring Social Distance between Neighbors

Utilizing these different determinants of social distance, we can then construct a measure of overall social distance between households in a block or neighborhood. Building on the work of Peter Blau (1977; 1987), the overlap in various characteristics among individuals will minimize the social distance between them. For instance, focusing only on marital status and the presence of children for expositional purposes, an individual who is married with children will have most in common with someone else who is married with children. However, this person will only have a moderate amount in common with someone who is married *without* children: they will have married life in common, but not the issues dealing with children. Likewise, they would have a moderate amount in common with an unmarried person with children: they would have the commonality of children, but very different experiences regarding married life. Finally, this person will have very little in common with someone who is single with no children. These various social statuses should lead to differing attitudes and interests, and work has formalized Blau's model to take into account in-group preferences (Skvoretz 1983). It is straightforward to generalize the concept of social distance to continuous measures. In such instances, we can talk about the *degree* of difference between two individuals based on a particular status, rather than an absolute difference as is the case for categorical determinants.

Given this framework, we can determine the amount of overlap in social positions (or *cross-cutting circles*) among individuals in a neighborhood. For instance, consider a simple example with just two determinants (X and Y) that are each characterized by just two categories (high and low). Assume that preference for in-group associations (τ) = 1: that is, individuals will only associate with others that they share at least one social characteristic with. Thus we can construct a 2x2 table of possible cells to place individuals in, as shown in Table 2.1.

Table 2.1. Hypothetical table for social distance on a block based on two dimensions

	Y- high	Y –low
X- high	A	B
X- low	C	D

Consider two hypothetical neighborhoods, each containing twelve residents. In the first hypothetical neighborhood there is perfect correlation between X and Y. Here, there are six individuals each in cells A and D, but no individuals in cells B and C. In this neighborhood, there is greater social distance as individuals are split into two distinct groups: those who are high on X and Y, and those who are low on X and Y. Those in cell A have nothing in common with other residents in the neighborhood, and thus only associate with each other. Therefore, an individual in this group will associate with 5 of the other 11 neighborhood residents (5 / 11 = .45).

In the second hypothetical neighborhood of twelve individuals there is no correlation between X and Y. This neighborhood will contain three individuals in each of the cells. Here there will be more overlap in relations: those in cell A will have a high value of X in common with those in cell B, and high values of Y in common with those in cell C. Thus, they have the commonality to interact with 8 of the other eleven neighborhood members (73%). A similar value can be constructed for each of the other three cells.

There are important consequences of the structures of social distance in these two neighborhoods. In the first neighborhood, there is the potential to create two strongly interlinked groups that each frequently interact only with fellow group members. However, these two groups will have no interlinkages with each other, therefore creating an overall network structure in the neighborhood that is bifurcated. Thus, we can extract a *social distance structure* of a neighborhood. On the other hand, the second neighborhood will not create any strong small groups, but should lead to an overall network structure creating more interlinkages. Changing the value of the preference for in-group associations (τ) will modify these results but not change the broader implications. This notion of distance naturally generalizes to more determinants. Finally, after measuring the social distance between pairs of individuals within a neighborhood, these can be combined into a matrix of neighborhood social distances. I can then test whether the social distance structure of a particular block affects overall neighborhood satisfaction. I next develop a general model of neighborhood satisfaction based on both the overall quality of the neighborhood as well as the fit of a particular household with that neighborhood, and incorporate the notion of social distance into this model.

Neighborhood satisfaction theoretical model

While studies have viewed many determinants of neighborhood satisfaction, these determinants can be grouped into two broad categories: 1) those measuring the overall quality of a neighborhood, and 2) those measuring the degree of fit with the neighborhood.

This suggests viewing the quality differences *between* neighborhoods, and the degree to which the individual household 'fits' with the neighborhood. I incorporate the perspective of the burgeoning social disorganization literature to test whether: 1) the difference in crime/disorder between neighborhoods impacts overall satisfaction with the neighborhood; 2) whether individual *perceptions* of crime and disorder impact an individual's reported neighborhood satisfaction. Figure 2.2 presents the theoretical model that I will elaborate here. In this figure, the ovals represent the latent constructs at the neighborhood level (crime, disorder, neighborhood satisfaction): these constructs are "latent" since we do not have perfect measures of them, and instead must rely on several indicators (or, approximations) to tap these variables. The arrows from these latent constructs point to assessments by individuals within the neighborhood: thus, several residents within the same block are all treated as "expert witnesses" in assessing the level of crime or disorder in the neighborhood. Note that each of these "expert witnesses" is characterized by particular characteristics that may systematically affect their report of neighborhood disorder/crime; thus, these individual characteristics have arrows pointing from them to the individual report of crime/disorder to take these systematic biases into account. Finally, the two rectangles at the left represent neighborhood-level measures of physical characteristics and demographic composition or social distance. While below I make a distinction between physical and social disorder, here I represent them as a single construct simply for clarity purposes.

Differences between neighborhoods in overall quality

When comparing across neighborhoods to determine more desirable ones, researchers primarily have focused on 1) the physical characteristics and 2) the social demographic characteristics.[5] The physical features of the neighborhood include such generally desirable amenities as the presence of parks, recreational activities, and general economic dynamism as measured by the presence of numerous restaurants and shops. Studies have also frequently pointed to the importance of quality schools, showing them to be related to higher home values (Clark and Herrin 2000; Kain and Quigley 1975), higher neighborhood attachment (Greenberg 1999) and higher neighborhood satisfaction (Harris 2001; Parkes, Kearns, and Atkinson 2002).[6] These possible effects are represented by path A in Figure 2.2. The physical characteristics also include ostensibly undesirable features such as the presence of toxic waste sites, or bars and liquor stores. High rates of pollution and the nearby placement of toxic sites may also pose a health risk, particularly for pregnant mothers and infants (Berry and Bove 1997; Croen, Shaw, Sanbonmatsu, Selvin, and Buffler 1997; Knox and Gilman 1997; Shaw, Schulman, Frisch, Cummins, and Harris 1992). Bars and liquor stores may reduce satisfaction in two ways: 1) they may do so simply because bars and liquor stores are inherently undesirable; 2) they may create more crime and disorder (Sampson and Raudenbush 2004). This implies a possible indirect effect on neighborhood satisfaction, and is represented by path B in Figure 2.2.

Besides the physical characteristics of a neighborhood, numerous studies have also tested whether the structural demographic characteristics of a neighborhood are related to overall satisfaction (Adams 1992; Connerly and Marans 1985; Harris 2001; Sampson 1991;

[5] There are two key methodological strategies in the literature for comparing the quality of neighborhoods qua neighborhoods: 1) the community attachment/satisfaction literature relies on respondent assessments of their attachment to, or satisfaction with, the neighborhood and then regresses these perceptions on neighborhood amenities; 2) the hedonic modeling approach regresses home values on neighborhood and housing amenities under the assumption that home values are a measure of more desirable neighborhoods.

[6] Of course, this feature is most important to those who have or are planning to have children of school age. I discuss at length below this notion of different preference structures among households for various features of neighborhoods.

Stipak and Hensler 1983). This is represented by path F in Figure 2.2. Note that the source of the relationship represented by path F is ambiguous. In part, such a relationship may simply represent a selection effect in which those with the most resources are able to move into the most desirable neighborhoods. If this is the case, areas with a greater concentration of higher socio-economic status households (i.e., higher levels of income or education) will have greater neighborhood satisfaction. And if certain racial/ethnic groups in the U.S. have limited options when choosing neighborhoods (Cutler, Glaeser, and Vigdor 1999; Kain and Quigley 1975; Rosenbaum 1994; South and Crowder 1997a; South and Deane 1993), neighborhoods with a larger concentration of minorities will report less satisfaction. Thus suggests that these positive relationships would disappear if we could appropriately model all the determinants of a desirable neighborhood. Failing a perfectly specified model, this relationship would persist to capture these unmeasured neighborhood characteristics.

A second possibility is that certain demographic characteristics have a direct causal effect on the overall neighborhood satisfaction. For instance, the systemic model suggests that neighborhoods with a greater level of residential stability create a greater level of attachment and satisfaction among their residents (Kasarda and Janowitz 1974). Thus, greater stability increases satisfaction by increasing social interaction among residents (Connerly and Marans 1985; Logan and Spitze 1994; Ross and Jang 2000; Rountree and Warner 1999; Sampson 1988; Sampson 1991; Warner and Rountree 1997). Of course, the reverse may be true, as lack of residential satisfaction may cause residential stability given that Speare (1974; 1982) argued that neighborhood satisfaction plays a key role in mobility decisions.

A third possibility is that the demographic characteristics of a neighborhood affect neighborhood satisfaction indirectly through their effect on neighborhood crime and disorder. This naturally suggests a mediating relationship, though studies have failed to explore this possibility. The social disorganization model comes from the pioneering work of Shaw and McKay (1942), and argues that particular social structures of neighborhoods (poverty, racial/ethnic heterogeneity, and residential instability) lead to a lack of cohesiveness that diminishes guardianship capability, leading to higher levels of crime and disorder. Disorder can be characterized by both physical disorder (e.g., the presence of litter, abandoned cars, and broken windows), and social disorder (the presence of undesirable persons and/or engaging in undesirable activities). Recent work by Sampson and colleagues (Sampson 1991; Sampson and Groves 1989; Sampson and Raudenbush 1999) has tested the mechanisms linking such neighborhood structures to crime/disorder using cross-sectional data. Paths C1 and C2 in Figure 2.2 represent these possible effects.

While researchers have frequently explored this relationship between neighborhood demographic characteristics and crime/disorder, there is less evidence that this neighborhood-level crime/disorder then reduces overall neighborhood satisfaction. Despite the plausibility of such a relationship, few studies have tested this as a *neighborhood-level* construct, as represented by paths D1 and D2 in Figure 2.2. Instead, studies have tested whether an individual's *perception* of crime/disorder leads to less individual satisfaction with the neighborhood (Adams 1992; Harris 2001; Lu 1999a). Note that in the context of my theoretical model, these studies are testing paths E1 and E2 in Figure 2.2. For instance, Lu (1999a) found a relationship between the perceived level of disorder on the part of individuals and neighborhood satisfaction. In a series of studies surveying 3,500 people in mostly upper-middle-income neighborhoods, Greenberg (1999) found that perceived crime and physical deterioration were the most critical factors associated with individual assessment of poor neighborhood quality.[7] Numerous studies in the community attachment literature have probed the relationship between perceived physical disorder—measured by such things as abandoned houses, litter and trash, and rundown buildings–and neighborhood attachment or satisfaction (Arguea and Hsiao 2000; Christakopoulou, Dawson, and Gari 2001; Perkins, Florin, Rich, Wandersman, and Chavis 1990; Sampson and Raudenbush 1999). And studies have asked whether perceived social problems in the community such as vandalism, graffiti, drug/alcohol use, and gangs/winos hanging out on streets affect neighborhood satisfaction (Jang and Johnson 2001; Ross and Mirowsky 1999; Simcha-Fagan and Schwartz 1986). However, an individual-level approach does not tell us whether there are any true "neighborhood effects" present. For instance, Taylor (2001) in a study of Baltimore found that there were minimal aggregate level effects of disorder/crime on satisfaction, but rather that individuals *who perceived more* disorder were less satisfied; he concluded that the relationship might simply be a psychological one. This strong critique highlights the need to test these possible neighborhood effects with a national dataset.

If there are indeed neighborhood-level effects of crime and disorder on overall neighborhood satisfaction, this suggests an important mechanism through which aggregate demographic characteristics may affect neighborhood satisfaction. For instance, residential stability may have an additional indirect effect on neighborhood satisfaction since the social disorganization model argues that the increase in interaction due to this stability will decrease crime (Sampson and Groves 1989; Shaw and McKay 1942). Likewise, studies in the social

[7] Besides being limited to the individual respondent's perception, Greenberg acknowledges that these studies are also hampered by the limited variability in the neighborhoods sampled: all were conducted in upper-middle-income neighborhoods. This suggests that even these findings may not generalize to all neighborhoods.

disorganization perspective have found a positive relationship between single parent families and crime and disorder even controlling for poverty rates (Rountree and Warner 1999; Warner and Pierce 1993). And to the extent that homeowners' greater investment in the community leads them to get more involved in neighborhood associations that then reduce the amount of crime, neighborhoods with a higher proportion of owners would have less crime and hence be more desirable.

While the demographic composition of a neighborhood may be important for fostering satisfaction, the *distribution* of demographic characteristics in a neighborhood—that is, the aggregate level of social distance—may also be important, for the reasons outlined above. Although social distance is created by numerous social categories, studies have focused only on the relationship between racial/ethnic distance and neighborhood satisfaction, as represented by path F in Figure 2.2. For instance, studies using such varied samples as the 1975 Detroit survey (N=1194) (Connerly and Marans 1985), a sample of 99 small Iowa towns (Rice and Steele 2001), and a 1984 sample of 11,030 residents of 500 localities in Great Britain found a negative relationship between neighborhood ethnic heterogeneity and reported satisfaction or attachment (Sampson 1991). Note that, as highlighted above, these studies cannot determine why this ethnic heterogeneity reduces satisfaction: is it because it is inherently undesirable, or is it because it increases the level of crime/disorder in the neighborhood? Additionally, studies have rarely tested whether other determinants of social distance directly affect neighborhood satisfaction. One study viewed the relationship between age homogeneity and neighborhood satisfaction (Ward, LaGory, and Sherman 1985), highlighting the possible importance of social distance along characteristics other than race/ethnicity.

Social distance may instead indirectly affect neighborhood satisfaction by increasing the amount of crime/disorder. If social distance reduces interaction between neighbors, which the social disorganization model posits will increase the amount of crime/disorder, social distance may impact neighborhood satisfaction through this indirect path (paths C1 and C2, and then through D1 and D2 in Figure 2.2). For instance, a study employing the 1975 Detroit survey (N=1194) that found no significant relationship between ethnic heterogeneity and neighborhood satisfaction may suggest an indirect effect on satisfaction since they included both perceived crime, and proportion of friends in the area, in the model (Adams 1992). That is, social distance (as measured by racial/ethnic heterogeneity in this instance) may simply work through paths C1 and C2, and then through paths D1 and D2 to affect neighborhood satisfaction indirectly. This implies no direct effect for path F. While studies have tested the effect of racial/ethnic heterogeneity for the creation of neighborhood ties and hence disorder (Connerly and Marans 1985; Rountree and Warner 1999; Warner and Rountree 1997), studies have generally not tested whether social distance as measured by *a number of determinants* affects crime/disorder.

Furthermore, while nearly all studies have tested a linear relationship between social distance and neighborhood satisfaction, there is reason to suspect a nonlinear relationship. That is, small amounts of social distance may be acceptable or even desirable, but beyond a certain point increasing social distance results in dissatisfaction. For instance, a study of New York City neighborhoods from 1830 to 1875 observed:

> that densely connected networks apparently thrived only in the very poorest of neighborhoods suggests that their absence elsewhere may have been socially beneficial. Ironically, the more closed a community was socially, the more it showed signs of social pathology rather than of mutual support. By contrast, the new loosely structured community constructed out of weak ties, while rooted in the local area, was geographically unbounded and thus better suited to inure New Yorkers to the

> emerging world of transiency and constant neighborhood change. (Scherzer 1992: 204)

Such nonlinear social distance may also have indirect effects through crime and disorder: for instance, Bellair (1997) suggested that weak ties are more effective at reducing crime than strong ties. The logic builds on the ideas of bridging versus bonding social capital (Bellair 2000; Beyerlein and Hipp 2005; Putnam 2000), and posits that the presence of numerous weak ties for residents allow time to foster ties with others in the broader community beyond their local block. These broader ties are hypothesized to allow linking in to the broader resources of the neighborhood, making crime fighting more effective. In contrast, blocks with numerous strong ties take considerable time, and hence inhibit the formation of broader-based ties, leading to a bonding social capital that is not as effective in obtaining broader community resources. This suggests a possible curvilinear relationship between the amount of social distance in a neighborhood and crime, and hence in overall satisfaction.

Finally, if networks are indeed important fostering neighborhood satisfaction, the structure of social distance in a block—beyond a simple average of social distance—may affect satisfaction. For instance, a neighborhood such as the one in Figure 2.3a in which two distinct groups are present with little social distance *within* them but considerable difference *between* them may have a different impact on neighborhood satisfaction than would a neighborhood with similar total social distance but a different overall structure, such as the neighborhood in Figure 2.3b. This latter neighborhood has a small amount of social distance between all households, but no groups are present to cause a bifurcated network structure. Differing predictions are possible here: on the one hand, the closeness of the subgroup might increase satisfaction for its members, who would then be unconcerned about their large difference from the other subgroup. On the other hand, it may be that the presence of a very different subgroup would be perceived in a very negative fashion. I test these possibilities down below.

Differences between individuals in fit with the neighborhood

While some neighborhoods are inherently more desirable than others as judged by nearly all persons, an important component of neighborhood satisfaction is the *degree of fit* between the household and the particular neighborhood. For instance, whereas some may prefer an area with a large number of high-end retail establishments, others may prefer "funky" neighborhoods lined with coffee shops and bookstores. These considerations suggest possible differences between individuals *within the same neighborhood* in their degree of neighborhood satisfaction. There are several reasons why we might see differences in neighborhood satisfaction between residents of the same block.

First, similar to the previous consideration of differences in quality between neighborhoods, there may be a *selection* effect in which those with the most resources are best able to attain residence in a neighborhood that suits them. Again, the SES of the household would be an important determinant of this ability, and race/ethnicity would be important if certain groups have more limited residential choices. This suggests that households with higher levels of income or education in a neighborhood would be more satisfied. Similarly, minority racial/ethnic households in the neighborhood would be less satisfied than their neighbors. This is represented by the G3 paths in Figure 2.2: the individual's characteristics have a direct effect on his or her reported neighborhood satisfaction.

In contrast, a *social injustice model* suggests the opposite effect (Jasso 1980; Markovsky 1985). Building on the reference group theory of Merton (1968), those in the block with higher SES might feel relatively deprived. The logic is as follows: in the U.S. one's home is a major measure of wealth and hence one's economic achievement. Consider two households living on the same street, hence having achieved a similar level of locational attainment (Alba and Logan 1992; Alba, Logan, and Bellair 1994; Logan, Alba, and Leung 1996): the household with greater educational attainment or higher income level would have expected to achieve a better neighborhood than the other household, and will therefore be *less* satisfied. This is analogous to work in the status inconsistency literature suggesting a similar outcome (Bauman 1968). Note that this model assumes that finding a neighborhood with a good fit is equally feasible regardless of one's economic resources. Likewise, to the extent that racial/ethnic minorities are limited to living in more undesirable areas (Cutler, Glaeser, and Vigdor 1999; Kain and Quigley 1975; Rosenbaum 1994; South and Crowder 1997a; South and Deane 1993), they may have limited expectations for their neighborhood and hence express greater satisfaction. Sampson and Raudenbush (2004) made an analogous argument regarding expectations, suggesting that the prior life experiences of racial/ethnic minorities explain why they appear less sensitive to perceiving disorder in their neighborhoods than whites (this suggests the G1 and G2 paths in Figure 2.2).

Another reason why residents in the same neighborhood may differ in degree of satisfaction is that some may have a greater psychic attachment to the neighborhood. Two key theories make differing predictions of who will develop this attachment. The systemic model argues that greater length of residence in a neighborhood increases the number of informal social ties a resident will have (Adams 1992; Austin and Baba 1990; Bolan 1997;

Campbell and Lee 1992; Kasarda and Janowitz 1974; Logan and Spitze 1994; Sampson 1988; Sampson 1991). These additional social ties will then increase the attachment of the individual with the neighborhood, and hence their satisfaction (Sampson 1988; Sampson 1991). On the other hand, the community of limited liability model (Janowitz 1952) focuses on the degree of investment in the neighborhood the resident feels. This investment can be both economic and social. Thus, an important source of economic investment in the neighborhood is homeownership, which should increase attachment and thus satisfaction. A key source of social attachment is the presence of children, who's activity sphere increases the household's feeling of attachment, and hence satisfaction, with the neighborhood.

Finally, beyond the demographic characteristics of the individual household, it may be important is how much the individual *differs* along those characteristics from their neighbors. This is the notion of social distance described above, and may reduce satisfaction by reducing social interaction (Connerly and Marans 1985; Rountree and Warner 1999; Warner and Rountree 1997), which then may decrease neighborhood satisfaction (Adams 1992; Connerly and Marans 1985; Lee, Campbell, and Miller 1991). Alternatively, it may be that simple difference from one's neighbors is undesirable. That is, a sense of perceived closeness to others may be more likely to develop to the extent that the individual perceives those others as similar to oneself; indeed, one of the questions used by studies constructing neighborhood cohesion scales is the degree to which residents perceive others to have similar values (Browning and Cagney 2002; Browning, Feinberg, and Dietz 2004; Morenoff, Sampson, and Raudenbush 2001; Sampson, Morenoff, and Earls 1999; Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997). Another possibility is that those who are socially distant from their neighbors perceive more crime and disorder: studies have found racial/ethnic distance to increase perceived crime (Quillian and Pager 2001) and disorder (Sampson and Raudenbush 2004). This might occur because such social differences reduce social interaction and hence increase suspicion and mistrust (Ross and Jang 2000). To the extent that greater perception of crime and disorder leads to less individual satisfaction (Adams 1992; Parkes, Kearns, and Atkinson 2002; Taylor 2001; Woldoff 2002), this suggests a possible indirect effect of social distance from one's neighbors on neighborhood satisfaction.

But while there are numerous determinants of social distance, studies have generally focused only on racial/ethnic distance. Interestingly, studies testing whether those differing from their neighbors based on race/ethnicity report less satisfaction with the neighborhood have generally found little effect (Harris 2001; Stipak and Hensler 1983). Instead, these studies simply found that an increasing percentage of African-Americans in the neighborhood leads to lower overall satisfaction for both whites and African-Americans. Thus, it is an open question whether a more broad-based measure of social distance can better explain the satisfaction of residents with their neighborhood.

Data and Methodology

Data for analyses

I employ a unique sub-sample of the American Housing Survey (AHS) to address these research questions. In this sub-sample, my units of analysis are 660 blocks across the United States, in which approximately eleven residents were sampled in each block in the years 1985, 1989, and 1993. The AHS is a national sample of about 60,000 housing units conducted every other year in odd-numbered years.[8] For this special neighborhood sub-sample, the AHS initially randomly selected about 660 housing units from the full AHS that were located in either urban or suburban locations. They then interviewed the ten closest neighbors of the initial respondent.

A challenge confronting all community/urban studies is that despite the ubiquitous use of the term *neighborhood*, defining it is difficult. Building on Hunter (1974), Bursik and Grasmick (1993) suggested that a neighborhood is characterized by: 1) a small physical area embedded within a larger area in which people inhabit dwellings; 2) a collective life that emerges from the social networks that have arisen among the residents and the institutional arrangements overlapping these networks; 3) some tradition of identity and continuity over time. Nonetheless, various spheres can create a "neighborhood": 1) the local shopping center may foster interaction among individuals in its service area; 2) schools create social ties as well as fostering a sense of common interests; 3) the area bounded by larger streets

[8] The American Housing Survey sampling strategy uses 401 primary sampling units (PSU's). Of these, 177 were self-representing strata, that is, the PSU is selected with certainty. The other 224 come from non self-representing strata, constructed by use of a multivariate clustering algorithm based on race of householder, tenure, change in the population from 1970 to 1980, and value of the housing. Selection within these strata was with probability proportionate to the 1985 projected number of housing units within the PSU. Within PSU's, the national average sampling rate was about 1 in 1,900. There are two types of enumeration districts (ED's): address and area ED's. In the address ED's of sample PSU's, systematic sample units were selected from the 1980 Census Sample Housing Unit Record File. A Housing Unit Coverage Study was performed to locate units missed by the 1980 census, and an additional sample was selected from the units located by this study (such as non-residential to residential units, new mobile home parks, etc). In area ED's of each sample PSU, four housing units were drawn from each sample area segment. Area ED's were so classified if the ED did not lie within a jurisdiction which issued building permits for new construction, or if more than 4 percent of the addresses within the ED were incomplete. Units receiving the census long form were the sampling frame for area ED's. Building permits are also sampled to represent newly constructed housing since the 1980 census. To construct the frame for building permits: clusters of four new construction units were formed using information from sample building permit offices; one construction unit was subsampled from each cluster. They used the 1980 characteristics of the units in these ED's as stratifiers based on: 1) geographic location (central city, urbanized area outside of central city, urban outside of urbanized area, rural); 2) tenure; 3) number of rooms; 4) value of unit or gross rent. The survey design described here is the current one, and was changed beginning with the 1985 sample (compared to the 1972-84 samples), leading the AHS to conclude that "with respect to variance, the unclustered, stratified, systematic sample of the new design will produce survey estimates with lower variances than the clustered sample of the old design" (Hadden and Leger 1995). For the special neighborhood subsample that I use, 566 were located within address ED's, 63 were located within area ED's, and 51 were located in new construction developments.

and containing only small neighborhood streets (tertiary streets) may foster a sense of neighborhood (Grannis 1998).[9]

In this study I used blocks as my unit of analysis. The reasoning is several-fold. First, research has suggested that while individuals will interact with neighbors from neighboring blocks, most interaction takes place between residents on the same block (Caplow and Forman 1950). Second, all households on a particular block are certainly part of the same neighborhood. Thus, I am able to use household assessments of neighborhood satisfaction as measures of the *same* neighborhood, allowing me to take into account individual variability in neighborhood satisfaction. Third, even if the block only represents a subset of the larger neighborhood, the respondents are still all assessing the *same* neighborhood. Given that the initial household was selected randomly (with the other households selected deterministically from the same block), this can be viewed as a block selected randomly from the larger neighborhood. Using these respondents as measures of the larger neighborhood would only be problematic if a) the social or physical composition of the block is considerably different than the larger area, and b) I do not include various measures accounting for the characteristics of the larger area. In instances where the block is considerably different than the larger area, the characteristics of the larger neighborhood might affect reported neighborhood satisfaction by respondents on the block. Therefore, I explicitly take this into account by placing these blocks into their respective census tracts using special access to data at the Triangle Census Research Data Center.[10]

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[9] Grannis found that his measured construct was strongly related to census block groups: 90% of his communities were census block groups or exact combinations of them. Note that this suggests an area smaller than a census tract.

[10] I estimated models similar to those presented here, but also including these tract-level measures. The key substantive results are unchanged in these additional models. To retain focus on the theoretical questions posed here, I present just the results using the block level measures.

My key outcome measure is a single question asking the respondents their satisfaction with the neighborhood (on a 0 to 10 scale). Thus I have several respondents from each block reporting their individual level of satisfaction: I use these as separate indicators of block level neighborhood satisfaction.[11] Thus, for each of the neighborhood constructs I am estimating the following equation:

$$y_{ik} = \Lambda_1 \eta_k + \varepsilon_{ik} \tag{1}$$

where y_{ik} is the combined ten-point response in the AHS regarding the level of satisfaction with the neighborhood reported by the *i*-th respondent of *M* respondents in the *k*-th block, η_k is the latent variable of common perception of neighborhood satisfaction in the block, Λ_1 measures the impact of perceived neighborhood satisfaction on the respondent's report of neighborhood satisfaction (since the ordering of respondents in neighborhoods is random, these λ's are constrained equal to unity), and ε_{ik} is a disturbance term (with the variances of the ε's constrained to be equal).[12] I can assess the reliability of these individual reports by viewing the R^2's for each of these equations.

[11] One of the rare studies to adopt a somewhat similar approach to that taken in this paper was a study that used latent variables to estimate market values of amenities (Arguea and Hsiao 2000). This also allowed taking into account measurement errors. The study used the AHS for four metro areas in the southeast: Tampa, Miami, New Orleans, and Atlanta. While they used a MIMIC model, their unit of analysis was 808 respondents. Their latent variable of neighborhood satisfaction included indicators of 1) junk; 2) crime; 3) noise; 4) litter. However, it also included measures of whether the respondent was nonwhite and the level of education. There seems little justification for including these latter two measures.

[12] I tested the appropriateness of these constraints on the λ's and the ε's separately. I found no reduction in model fit when constraining the λ's equal, or when constraining the ε's equal, or both simultaneously.

I also included three intervening constructs of crime, physical disorder, and social disorder, which are also constructed using equation 1. For measuring perceived crime, the AHS asks respondents a series of three questions: is crime a problem, is it so much of a problem that it's a bother, and is it such a bother that the respondent wishes to move. I combine these responses into a four point response where the respondent either replies "no" to all questions, replies "yes" to one, "yes" to two, or "yes" to all three. The physical disorder concept is a single yes/no question asking whether "litter or housing deterioration is bothersome." The social disorder concept is a single yes/no question asking whether "people in the neighborhood are bothersome."[13]

Determinants Included in the Social Distance Measure

My key constructs of interest are the various measures of the social distance structure in the neighborhood. These are built on the underlying principle of measuring how different the respondent is to his/her neighbors on various demographic measures. The variables used to measure each of the social distance determinants are listed in Table 2.2.[14] I log transformed income since higher levels of income should create social distance at a diminishing rate. Homeownership places the household in the class of property-owners, leading to different economic interests and concerns. Education is a component of socio-

[13] To handle the ordinal nature of these measures, I created a polychoric correlation matrix and estimated the model using weighted least squares with a mean and variance adjustment for the chi square in the structural equation modeling software Mplus 3.0. This assumes that these ordinal measures have unobserved continuous measures underlying them that are normally distributed. Such an approach is analogous to simultaneously estimating each individual y_{ik} as a probit or ordered probit equation.

[14] Unfortunately, a few other possible important determinants are not available in this data set: occupation (class), membership in voluntary organizations, and religious affiliation (and type of religious tradition), are potentially important determinants. While including occupation as a determinant would be preferable, my inclusion of income, education, and home value likely take this determinant into account to some degree. The latter two determinants provide a fruitful direction for future research.

economic status, as well as being an important form of social distance in Bourdieu's model (1984), affecting attitudes and values (McPherson, Smith-Lovin, and Cook 2001).

Table 2.2. Variables used to measure each of the social distance determinants

Social Distance Determinant	Measure
Economic	Household Income (log transformed)
Economic	Home ownership
Economic	Home value (log transformed)
Economic	Size of home (sq. ft.)
Economic/Social Origin	Education
Race/ethnicity	White
Race/ethnicity	African-American
Race/ethnicity	Latino
Race/ethnicity	Other race
Life Course	Age
Life Course	Marital status (married/not)
Life Course	Children (under 18 in home)
Social Origin	Foreign-born
Social Origin	Raised in south at age 16
Social Origin	Size of community at age 16

Since those born in another country may have different cultural customs creating social distance from their neighbors, I included a measure of the birth country of the respondent.[15] Likewise, the southern region of the U.S. has long been identified for its unique culture (Ellison 1991; Reed 1972), and therefore may create social distance between someone raised in that region and someone who was not. Being raised in an urban area versus a rural area shapes an individual's attitudes and preferences; I therefore included a

[15] Simply including a measure of immigrant status would not be satisfactory, as we would expect two individuals who had emigrated from different countries to have different customs that created social distance. Therefore I take into account the country from which the respondent came.

measure of the type of community the respondent lived in at age 16.[16] I treated this variable as ordinal and determined the amount of distance between two individuals along this continuum: this assumes that someone who grew up in a large city will have some social distance from someone who grew up in a suburb, but much more social distance from someone who grew up on a farm.[17]

Constructing the Social Distance Measure

I then combined these determinants of social distance into a single measure of distance between dyads on the block. Past research has sometimes constructed a social distance measure based on a particular demographic variable, such as: START HERE

(2) $$sd_i = \frac{1}{M - 1}\sum_{j=1}^{M} | x_i - x_j |$$

where *sd* is the social distance on this variable for individual *i*, *M* is the number of individuals in an AHS neighborhood, *j* represents the other individuals in the neighborhood, and $i \neq j$.[18] This gives a measure of the social distance for the respondent from other individuals for a particular construct. If individual *i* is exactly like every other individual on

[16] This variable includes the following possible categories: 1) a large city; 2) suburb near a large city; 3) a medium sized city/suburb; 4) a small city; 5) a town or village; 6) open country but not a farm; 7) farm; 8) other.

[17] The constructs in this paragraph were only available in the 1985 sample, so I am unable to include this determinant of social distance in the two later waves.

[18] Various approaches can be taken with continuous variables. One approach for variables with non-negative values is to divide the variable by the maximum value to place it onto a zero-one metric before performing this calculation. Another approach is to standardize the variable by dividing it by its standard deviation. I adopted this latter approach with the additional constraint of providing a ceiling value of 2. While subsidiary analyses without this ceiling showed very similar results, I prefer the ceiling conceptually since: 1) it constrains differences to two standard deviations, beyond which difference likely has little effect; 2) this puts the variables on the same metric as the race variables (since the race variables all are zero-one, two persons of different race will get a value of two for difference: one for the race of the first respondent, and one for the race of the second respondent). This strategy minimizes the possibility of outliers on any particular determinant of social distance unduly influencing the measure.

this characteristic, sd_i will have a value of zero. The more people who differ from i on this construct, the higher the value of sd_i. In the extreme case where i is different from everyone else in the neighborhood, sd_i will be equal to one.

However, of more theoretical interest is comparing individuals on several determinants *simultaneously*. To compute the distance between two individuals along all determinants simultaneously, I used a dyadic social distance measure:

$$sd_{ij} = \frac{1}{K}\sum_{k=1}^{K} |(x_{ik} - x_{jk})\phi_k| \tag{3}$$

where sd_{ij} is the social distance between individuals i and j, k represents the K number of social determinants being measured, x_{ik} and x_{jk} are the values on social characteristic k for individuals i and j respectively, ϕ_k is the salience of social characteristic k (a weighting factor for its relative importance), and $i \neq j$. The question is then a value to choose for each ϕ_k in the model. The simplest assumption is to assign a value of one to each social characteristic, thus weighting them equally.[19]

Social network measures

Calculating this social distance value for each dyad in the neighborhood yields a matrix of social distances between dyads. By then treating this as a non-directional valued

[19] Another approach is to perform a subsidiary dyad-level analysis in which first, a fixed effects regression is run in which the outcome is neighborhood satisfaction and the predictors are the various individual-level characteristics. This conditions on these characteristics, and I then use the y-hats from this model in the second step in which a regression is run in which the outcome is the absolute value of the difference of these y-hats from the first step for the two respondents, and the predictors are their differences along these various social characteristics. The coefficients from this model are then used as the ϕ_k weights. I use the simpler approach here, and leave this alternative approach for future studies.

network, there are various social network measures that can then be constructed from this matrix to statistically characterize these network structures.[20]

A measure recommended by Blau (1977) to capture group cohesion and commonly used is the density of ties in a network. Here I measure the average social distance among all dyads in the neighborhood (Wasserman and Faust 1994: 181):

(5) $$sd = 1/(M*(M+1)/2)[\sum_{i=1}^{M}\sum_{j=1}^{M} \frac{1}{K}\sum_{k=1}^{K} |(x_{ik} - x_{jk})\phi_k|]$$

where all terms are defined as before, $i < j$ (we only need to compute the values below the diagonal of this symmetric matrix since the social distance between i and j is the same as that between j and i), [M*(M+1)/2] is the number of dyads in the neighborhood and sd is measuring the average social distance for the entire block. Thus the summed social distance values are divided by the total dyads; smaller values would indicate neighborhoods with very little social distance among the residents and hence more cohesion.

In addition to this measure of the central tendency of social distance on the block, the variance of these dyad distance measures give an indication of the amount of dispersion in the network (Wasserman and Faust 1994: 182). This is calculated by computing the variance of these distance measures for the block:

(6) $$sd_{\text{var}} = [\sum_{i=1}^{M}\sum_{j=1}^{M} (sd_{ik} - sd)^2]/[M*(M+1)/2]$$

where all terms are defined as before, and sd_{ik} and sd are computed as shown in equations 3 and 5 respectively. Low values for this variable indicate a neighborhood in which social

[20] To define these network terms: network ties can be either directional (where we know that A does something to B, e.g., provides help), or nondirectional (where we only know an association between A and B, e.g., they are friends). Network ties are often considered "nonvalued" (only a dichotomous measure of the presence or absence of a tie); in other instances when they are "valued" the strength of the tie is given (this can be as a count variable, as a proportion on a zero to one scale, or even a valence containing both positive and negative values) (Wasserman and Faust 1994).

distance is relatively equidistant between dyads (such as shown previously in Figure 2.3b), while large values indicate a neighborhood with considerable variability in the amount of social distance between dyads (such as in Figure 2.3a). Thus, higher variance suggests the possible presence of groups within the neighborhood.

While there are various strategies available for directly estimating the members of groups within a neighborhood (for a more complete discussion, see Wasserman and Faust 1994), I took the approach of using exploratory factor analysis of the individual distances of the individuals in the block for various numbers of factors, and then performed an oblique rotation on these factors using an algorithm developed by Bernaards and Jennrich (2005). This clusters individuals into subgroups in the block based on their social distance from each of the other households. While a noted limitation of factor analysis of sociometric data is the limitation that individuals are not necessarily assigned to a single group (Wasserman and Faust 1994: 290), I address this by assigning a household to the factor in which they have the highest loading. Since I found that for nearly all of the blocks two groups captured the degree of clustering in the block, and that only in rare instances were three groups needed, I used two-factor solutions for all blocks. Following this, I constructed measures of: 1) the number of individuals in the largest group; 2) the average social distance within each group; and 3) the average social distance *across* the two groups.

Measures of Social and Physical Characteristics of Neighborhoods

I also take into account several other characteristics of the neighborhood that may be important for fostering satisfaction. Since the presence of economic vitality is likely desirable, I included data from the U.S. economic census on the number of employees per capita working in restaurants or recreation services. I used the number of employees rather than the number of establishments since this likely provides a more accurate measure of the possible services available to the resident of a neighborhood. To maintain temporal precedence, I used data from the 1982 economic census for the 1985 AHS sample, data from the 1987 economic census for the 1989 AHS sample, and data from the 1992 economic census for the 1993 AHS sample. While this economic census data is reported for zip codes, I apportioned this zip code data into its constituent 1980 census tracts based on the proportion of the zip code contained within a given tract. For the 1992 data I additionally needed to then apportion the 1990 tracts into 1980 tracts (since the AHS respondents are placed into 1980 census tracts). Since bars and liquor stores are likely disamenities, I included a measure from the economic census of the employees per capita for bars and liquor stores constructed in a similar fashion. To capture the quality of local schools, I constructed a measure of the completion rate of students in the local school district. This information is taken from the Local Education Agency (School District) Universe Survey Longitudinal Data File: 1986-1997 (Education 2001). The appendix describes how I placed these data into tracts. Since the presence of a body of water may be desirable, I included a measure of the percentage of the tract that is water. To capture the effect of parks, I include a measure of the presence of open area within 300 feet as assessed by the AHS interviewer.

Finally, since the presence of toxic waste sites is likely undesirable, I included a measure of the pounds of toxic waste emitted in an area, weighted by the inhalation toxicity. The data for the presence of toxic waste sites was obtained from the Toxic Release Inventory (TRI), which contains information on the quantity of certain chemicals released into the environment (obtained at http://www.rtknet.org/triabout.html). The U.S. Environmental

Protection Agency (EPA) maintains this database. Facilities are required to file with the EPA each year if they exceed a particular threshold in release particulates (this is generally 25,000 pounds per calendar year for manufacture or processing activities, and 10,000 pounds per calendar year for "otherwise used" activities). For each site, I first geocoded its location based on its latitude and longitude. While it is well-known that the actual distance that such toxic waste can impact humans is variable based on the chemical involved and the wind patterns in the local area, I drew one-mile buffers around each site as an approximation of the geographic dispersion of its impact (for a study using both quarter mile and one mile buffers and finding similar results for the two cutoff values, see Pastor, Sadd, and Hipp 2001). While the limitations of the TRI database are well-known (i.e., it only captures emitters of large amounts of toxic chemicals), it does give a reasonable approximation of the amount of such activity in a neighborhood (Agency 2005). Another limitation is that the simple count of releases does not capture actual exposure of households: of additional importance is the actual toxicity of the chemical, as well as prevailing wind patterns. While I am unable to take into account wind patterns, I take into account the toxicity of the particular chemical being released by multiplying the pounds of the chemical released by an inhalation toxicity score constructed by the Risk Screening Environmental Indicators (RSEI) study conducted by the United States Environmental Protection Agency (Agency 2004).[21]

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[21] This toxicity score information provides an approximation of the degree of toxicity of various chemicals based on two types of weights: either inhalation scores or oral scores. The oral toxicity weight is used for releases or transfers to water, while the inhalation toxicity weight is used for releases or transfers to fugitive air, stack air, off-site incineration, and off-site incineration-no fuel value. While these toxicity scores are an approximation, as the toxicity of a chemical can vary based on the length of exposure, and the age and size of the individual, they provide an approximation of the degree of toxicity of chemical releases that is arguably better than using simple summed amounts of chemical release.

Individual Characteristics

I included several individual- and household-level demographic measures to determine their effect on reported neighborhood satisfaction. To take into account gender differences, I included a dichotomous measure coded one for females. I captured SES with measures of household income (logged) and years of education of the respondent. To account for racial/ethnic differences, I included dichotomous indicators for African-Americans, Latinos, and other race (with whites as the reference category). To measure community investment I included an indicator of whether the respondent owned their residence. To account for life course, I included a measure of the age of the respondent, dichotomous indicators for marital status (married, divorced) with single/widowed as the reference category, and an indicator of whether they have children less than 18 years of age at home. I include the length of time in the residence (log transformed), as well as an indicator for those who have lived less than a year in the residence (as there is theoretical reason to suspect that new residents may have preconceived notions of the neighborhood that color their evaluations of the neighborhood crime and disorder).[22] Finally, I included a measure of the persons per room (log transformed) to capture over-crowding that may color the respondent's assessment of the neighborhood. Note that these measures take into account the differences in individuals reporting on the same neighborhood. The summary statistics for the variables used in the analyses are shown in Table 2.3.

Methodology

I used structural equation modeling to evaluate the neighborhood assessments

[22] Further exploration of the length of residence variable by constructing a series of dummy variables indicating years of residence did not indicate any additional nonlinear effects in the model.

provided by AHS respondents. I began by using confirmatory factor analysis (CFA) (Bollen 1989) to assess whether the evaluations provided by approximately eleven neighbors in each of the 660 blocks in this sub-sample are reliable indicators of physical disorder, social disorder, crime, and overall neighborhood satisfaction. This approach assumes that there is an unobserved "latent" variable for each of these constructs—for instance, overall neighborhood satisfaction—of which we only have imperfect realizations in the form of the particular questions asked of each respondent in the block—for instance, "how satisfied are you with this neighborhood?" Recall that this was equation 1. The model is estimated using a maximum likelihood estimator. This results in an overidentified model in which these overidentifying restrictions can be tested by a likelihood ratio test that is chi-square distributed with degrees of freedom equal to the number of overidentifying restrictions. Speizer and Bollen (2000) adopted a similar approach for a different research question. This model allows me to assess the reliability of these measures: the R^2 for each indicator illustrates how much of the variance in each individual response is explained by the latent variable of neighborhood satisfaction, and is a measure of reliability.

Individual Characteristics

I then test whether various demographic predictors have a direct effect on my four key neighborhood constructs reported by respondents (Hipp 2003b; Sampson, Raudenbush, and Earls 1997). I am asking if individuals with a particular characteristic view *the same* neighborhood more or less favorably than someone without that characteristic. Conceptually, this is similar to a multilevel model where these individual characteristics are at level one and the neighborhood measures are at level two. For instance, while the *percent in poverty in the neighborhood* can be used as a predictor of overall neighborhood satisfaction (and therefore is a measure of neighborhood quality), an *individual's poverty status* can be used to predict an *individual's* assessment of satisfaction (and therefore is measuring the degree to which individuals in poverty are more or less satisfied with the neighborhood than individuals not in poverty who are living *in the same neighborhood*). With the addition of these individual-level characteristics, equation 1 is elaborated to:

(7) $$y_{ik} = \lambda\eta_k + \Gamma X_{ik} + \varepsilon_{ik}$$

where the previous model has been augmented by X_{ik}, a matrix of exogenous predictors with values for each individual i in neighborhood k, and Γ which shows the effect of these predictors on the subjective assessment.[23] Note that here the outcome measure is *each individual's assessment* of neighborhood satisfaction. The vector X will be constructed from responses to the AHS, and will include the several measures outlined above. I estimate this same equation also for the crime, physical disorder, and social disorder measures. After determining whether these responses can be used as indicators of these neighborhood-level constructs, I next model the determinants of neighborhood satisfaction, crime, physical disorder, and social disorder.

Characteristics of Neighborhoods

I incorporate both subjective and objective indicators of neighborhood characteristics as described above. Adding neighborhood predictors extends the initial model thusly:

(8) $$\eta_k = \beta Z_k + \varepsilon_k$$

where η_k represents the overall satisfaction with neighborhood k, Z represents a matrix of

[23] Note that by constraining the variances and covariances among the disturbances and the λ's to be equal, this approach is equivalent to a fixed effects model. By "fixed effects" model, I refer to the approach sometimes referred to as a least squares dummy variable model in which the second level units (neighborhoods in this instance) can be taken into account by including K-1 dummy variables for the K second level units in the study. More commonly such models are estimated by simply centering the variables around the neighborhood means and performing OLS estimation.

variables measured at the level of neighborhood k, β shows the effect of these measures on overall satisfaction, and ε_k is a disturbance for neighborhood k. This equation is estimated simultaneously with the equation predicting individual satisfaction, as well as individual perceived crime, physical disorder, and social disorder.[24]

Finally, I took into account the possibility of correlations between constructs and correlations between respondents' assessments. To accomplish the first task, I allowed the disturbances of neighborhood-level physical disorder, social disorder, and crime to freely covary. Such covariances between these disturbances can be due to omitted variables that affect these outcomes similarly—indeed, the correlations between these disturbances ranged between .31 and .48. To accomplish the second task, I freely estimated the covariances between the responses to the questions regarding perceived crime, physical disorder, and social disorder provided by the same household. This takes into account the possibility that a household reporting more crime also perceives more social and physical disorder—indeed, these correlations were significant and generally between .09 and .15.

While this model includes indicator variables to distinguish neighborhoods for the three waves of data, this assumes that the coefficients are equal over the three years. I tested this assumption by creating a data set where each row represents one block (rather than one block year). I then estimated two models: one allowing the coefficients to vary over the three waves, and one constraining them equal. The estimated coefficients for the different years in the first model tended to be very similar over years. To assess this more formally, the results for each of these multiply imputed data sets showed that constraining these coefficients equal did not reduce the fit of the various approximate fit indices; in addition, I

[24] For some of the constructs measured I also have an interviewer response that I can use as an additional indicator.

used the combchi program of Paul Allison (2000) to perform an F-test combining the chi-square differences of these five datasets and found that constraining the coefficients equal did not reduce the model fit (F = .564, df= 204, ddf = .088, p = .816) (this test is discussed on page 115 in Schafer 1997).

Results of structural equation models

Confirmatory Factor Analysis of neighborhood constructs

I begin by separately assessing the fit of the CFA models of my four key latent neighborhood constructs: neighborhood satisfaction, social disorder, physical disorder, and common perception of crime. As the results in Table 2.4 highlight, these constructs generally do a reasonable job of capturing these neighborhood constructs. On the one hand, the fit of these models tends to be excellent. For all four measures, the chi-square is non-significant; thus I conclude that I fail to reject the null hypothesis that there is no difference between the sample covariance matrix and the model implied covariance matrix. On the other hand, while these R^2's are in line with findings from other neighborhood studies (Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997), they are nonetheless somewhat modest. For instance, the neighborhood social disorder latent construct explains about 17 percent of the variance in the individual assessments of social disorder. Even for crime, only about 30 percent of the variance in individual responses is explained by the neighborhood construct of common perception of crime. Thus, there is still considerable variability among residents of the same block in assessing these neighborhood constructs.

Structural equation model: disorder and crime as mediators of neighborhood satisfaction

I next turn to the results from the estimation of the full model shown in Figure 2.2, and begin by focusing on the results for the individual-level part of the model. Recall that this focuses on the degree of fit for the individual with the neighborhood, rather than the overall quality of the neighborhood. First, note that there is strong evidence here that those who perceive more social disorder, physical disorder, or crime in the neighborhood are also less satisfied. A one-unit increase in perceived social disorder results in reporting 1.42 points less neighborhood satisfaction, while perceiving one more unit of physical disorder reduces satisfaction 0.95 points, as shown in Table 2.5. A one-unit increase in logged perceived crime reduces satisfaction .9 points, where neighborhood satisfaction ranges from 0 to 10. Thus, we see evidence that, for instance, individuals who perceive more crime than their neighbors are also less satisfied than those neighbors.

Regarding whether the selection model or the social injustice model better explains the neighborhood satisfaction of minority respondents and those with lower SES, we see strong support for the social injustice model's prediction that such residents will have less neighborhood satisfaction than their neighbors due to greater expectations of their neighborhood. While income has little effect here, we see that those with higher levels of education are in fact *less* satisfied with their neighborhood than are their neighbors. There is an additional indirect reduction for these respondents since they also perceive more crime and disorder in the neighborhood (and greater perceived crime/disorder then reduces satisfaction). The last three columns of Table 2.5 show the indirect effect of each construct on neighborhood satisfaction, the total effect (which is simply the sum of the indirect and the direct effect) and the percent of the total effect that is indirect. This latter value can be viewed as an estimate of the percentage of this measure's impact on neighborhood satisfaction that is mediated by crime and disorder. Thus, whereas an additional year of education directly reduces reported neighborhood satisfaction .026 points, it also reduces reported satisfaction another .014 points through increased perceived crime and disorder. This suggests that crime and disorder mediates about 1/3 of the effect of an individual's education on their reported neighborhood satisfaction. To give an idea of this metric, whereas neighborhood satisfaction ranges from 0 to 10 with a standard deviation of 2.16, a college graduate will be about .16 points less satisfied (-.04*4=-.16) than a high school graduate. This is consistent with the social injustice model that such individuals will be less satisfied with their neighborhood than their less educated neighbors. Likewise, we see that Latinos and African-Americans report more direct satisfaction with the neighborhood than whites, and also perceive less crime and disorder than whites, which subsequently increases reported satisfaction. Again, about 1/3 of the greater satisfaction of nonwhites can be explained by their reduced perception of crime and disorder compared to whites. This is consistent with the supposition that such individuals have lower expectations for the quality of the neighborhood.

There are mixed results for the community of limited liability's argument that social and economic investment increases satisfaction. While the economic investment of homeownership leads to less perceived crime, owners perceive *more* physical disorder. And the social investment of marriage and children shows mixed effects. There is no support for the hypothesized effect that the presence of children heightens social investment and hence increases reported satisfaction. There are only some modest effects for marital status: those who are married perceive somewhat more social and physical disorder than singles/widows, whereas those who are divorced report more crime and less satisfaction.

There is no support for the systemic model's hypothesis that households with greater length of residence in the neighborhood will be more satisfied: increasing length of residence actually has a *negative* direct effect on satisfaction and a negative indirect effect through increased perceived crime and disorder. This perceived crime and disorder is particularly important, as it accounts for almost 60% of the diminished satisfaction of longer-term residents. There is also evidence that those new to the neighborhood in the last year perceive less crime than others. This is consistent with the notion that households will not knowingly move into an area with crime if they can avoid it: the fact that such new residents are no less likely to perceive the existence of more tangible characteristics such as physical disorder suggests that crime is less readily observable, and only becomes apparent after longer residence.

There is evidence that females perceive more crime and disorder in the neighborhood. While the finding for crime is consistent with past research (Austin, Furr, and Spine 2002; Ross and Jang 2000), past studies have generally found no such effect by gender for disorder (Austin, Furr, and Spine 2002; Geis and Ross 1998; Ross and Mirowsky 2001; Sampson and Raudenbush 2004). But while females perceive more crime and disorder (which indirectly reduces their neighborhood satisfaction), they report more direct satisfaction with the neighborhood than do males. Finally, those who are older report more satisfaction with the neighborhood, and about 1/3 of this effect is mediated by their reduced perception of crime and disorder.[25]

[25] While there may be concern that the effect of age is "soaking up" the effect of length of residence, subsequent probing of the model suggests this is not the case. I ran two additional models: one excluding individual length

Neighborhood-level results of physical characteristics

While the results presented up to this point have focused on the individual level, I next turn to viewing neighborhood-level effects. We do see evidence that neighborhood-level perceived crime and disorder reduce overall satisfaction with the neighborhood. Thus, it is not just the case that those who perceive more crime and disorder report less satisfaction with the neighborhood, but also that neighborhoods with more reported crime/disorder result in less overall reported satisfaction.

How much of the relationship between crime/disorder and neighborhood satisfaction is simply an individual-level effect and how much is a neighborhood-level effect? Recall that in this model perceptions of crime/disorder are not simply an individual-level perception, but are in part driven by the latent variables of neighborhood common perception of crime, physical disorder, and social disorder. We can consider this question in a couple ways. First, we can calculate the total effects implied by this model. For illustration, Figure 2.4 shows a subset of the model for one particular construct's effect on neighborhood satisfaction. We can calculate the effect of a one-unit increase in an individual's perception of crime on their reported neighborhood satisfaction from the coefficient for path E1 in this diagram. Thus, the model in Table 2.5 showed that a one-unit increase in perceived crime resulted in a .9 reduction in reported neighborhood satisfaction. What about a one unit increase in the neighborhood's common perception of crime? This will affect an individual's reported neighborhood satisfaction in two ways: 1) it will work through the H*E1 path, as the one-unit increase in neighborhood common perception of crime increases the individual's

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of residence, and a second excluding individual age. In the model dropping the age measure, individual-level length of residence continues to have no significant effect on reported satisfaction and increases perceived crime and physical disorder. In the model dropping length of residence, individual age still reduces perceived crime and social disorder, while still having a direct positive effect on reported satisfaction. Thus, we can conclude that the results of this main model are not an artifact of the specification.

perceived crime (path H), and then this increase in perceived crime will affect their reported neighborhood satisfaction (path E1); 2) it will work through the D1*J path, as the one-unit increase in neighborhood common perception of crime increases the overall neighborhood satisfaction (path D1), and then this increased overall neighborhood satisfaction increases the individual's reported satisfaction (path J). Note that in instance 1, the H path is scaled to one, so this reduces to path E1 (the same as the individual effect above), and in instance 2, path J is scaled to one, so this reduces to path J. Thus, the total effect of a neighborhood's common perception of crime on neighborhood satisfaction reported by respondents is –1.444 (-.9-.554= - 1.444) (the -.554 comes from Table 2.5, which shows the neighborhood-level effects, estimated simultaneously with the individual-level effects). Note that the neighborhood effect will always be stronger this model if both paths D1 and E1 have the same sign. All of these tested effects are significant at $p < .05$.

While calculating the total effects implied by the model provides key information, some may feel a sense of dissatisfaction with this outcome since it appears that the deck is stacked in favor of neighborhood effects. So consider a second approach. Recall that in the CFA model nearly 30 percent of the variance in individual perceived crime is due to the latent construct of perceived neighborhood crime: so assume that 30 percent of the variance in an individual's reported perceived crime is due to these neighborhood effects.[26] What

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[26] Note that important assumptions are embedded in this approach. First, it assumes that there aren't important individual-level characteristics common to the individuals of the block that explain this commonality in assessment of neighborhood crime, rather than the actual level of perceived crime. While it is impossible to rule out this possibility, the fact that in separate analyses I estimated similar structural equation models using a large sample of metro areas and found that using a measure of the official violent crime in the census tract in general explained at least 50% of the variance in the perceived crime latent variable. This relatively high relationship between this perceived crime latent variable and official crime rates suggests that it is less likely that the common characteristics of the households are creating the relationship. Nonetheless, it cannot be ruled out that at least some of this commonality is indeed due to individual characteristics. And no such validity test is possible for a measure such as *social disorder* in these data. Second, as is the case in analyses using hierarchical linear modeling, there is an assumption in this approach that the individual- and neighborhood-level

about the other 70 percent of the variance? This could be due to any number of other neighborhood or individual effects, but assume that all 70 percent is due to individual "free will." Thus, this assumption to some extent might be "stacking the deck" in favor of individual effects. Recall in the previous paragraph we said a one-unit increase in a neighborhood's common perception of crime reduces individual neighborhood satisfaction –1.444. What about an individual's perceived effect? If 30 percent of the variance in individual perceived crime is explained by neighborhood perceived crime and we assume that the other 70 percent of the variance is due to individual characteristics independent of the neighborhood, this suggests the individual's perceived crime will change 2.33 units for every one unit change induced by the neighborhood (70 % / 30%). A 2.33 increase in perceived crime for the individual decreases their reported neighborhood satisfaction -2.097 (-.9 * 2.33 = -2.097). Thus, while individual perceptions are important, the effect of the neighborhood is quite strong, as it accounts for about 41 percent of the change in reported individual satisfaction due to perceived crime (-1.444 / (-1.444 + -2.097) = .408). The analogous neighborhood proportions for social and physical disorder are 26 and 53 percent respectively.[27]

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effects are independent. This is likely not realistic. Nonetheless, to the extent that such shared variance between individual- and neighborhood-level effects reduces the explained variance of each proportionally, the estimated proportions of variance explained at each level estimated here would remain unchanged. These caveats suggest that this is more of a heuristic exercise, given the theoretical interest in making the distinction between individual-level and neighborhood-level effects.

[27] For social disorder, a one-unit increase in neighborhood perceived social disorder reduces individual perceived neighborhood satisfaction –2.585 (-1.42 - 1.165). Since 83.5% of perceived social disorder is not due to the neighborhood effect, this suggests that an individual's perceived social disorder will have a –1.11 effect on neighborhood satisfaction (-1.42 * (.835 / .165)= -7.19). Thus, the neighborhood accounts for 26 percent of the effect of perceived social disorder on satisfaction (-2.585 / (-2.585 – 7.19) = .265). For physical disorder, a one-unit increase in neighborhood perceived physical disorder reduces individual perceived neighborhood satisfaction -3.765 (-.95 – 2.815). Since 78% of perceived physical disorder is not due to the neighborhood effect, this suggests that an individual's perceived physical disorder will have a -.355 effect on neighborhood satisfaction (-.95 * (.78/ .22) = -3.37). Thus, the neighborhood accounts for 53 percent of the effect of perceived physical disorder on satisfaction (-3.765 / (-3.765 – 3.37) = .528).

The measures of physical characteristics in the neighborhood generally work as expected.[28] I first estimated a model including the household-level characteristics and these physical characteristics and crime and disorder (but not including the aggregate demographic measures). In this model, the presence of higher quality schools (as measured by the completion rate of students in local schools) was positively related with neighborhood satisfaction. And the presence of restaurants and recreation sites increases neighborhood satisfaction. On the other hand, the presence of more bars and liquor stores indirectly reduces satisfaction since they are positively related to more crime in the neighborhood. And the presence of toxic waste sites was negatively associated with neighborhood satisfaction. The measures of percent vacant units and crowded units increase perceived crime and disorder, as expected. These results largely remained unchanged when including the aggregate demographic measures; the only change was that the measure of toxic waste sites became insignificant in this full model.

Neighborhood-level results of demographic characteristics

I next ask what effect the neighborhood demographic composition has on neighborhood satisfaction, and find evidence consistent with a selection effect in which those with the greatest economic resources are able to move into the most desirable neighborhoods. Recall that these neighborhood-level effects are estimated simultaneously with the household-level effects just discussed. Thus, neighborhoods with higher average levels of education and income report more overall satisfaction, and blocks with higher average levels of income also report less social and physical disorder. In fact, about half of the effect of

[28] This paragraph's results are not shown in the table- TCRDC output subject to review.

higher income on increased neighborhood satisfaction is explained by the lower overall crime and disorder in such neighborhoods. Recall that we saw no concomitant individual-level effect, as those with higher levels of education actually reported *less* individual satisfaction with the neighborhood than their block neighbors. We also see that blocks with higher percentages of African-American households report less overall satisfaction, and about 40 percent of this effect is due to the greater level of common perception of crime and social disorder in such neighborhoods. This is consistent with the hypothesis that such households have less ability to move into more desirable neighborhoods.

We again see mixed results for the community of limited liability. There is evidence that neighborhoods with more homeowners perceive less crime, which then increases satisfaction, and an additional direct positive effect on satisfaction. But there is no evidence that increasing the number of households with children on the block increases satisfaction: in fact, there is a negative relationship with neighborhood satisfaction. Instead, the story here is one of *single parent* families having particularly strong negative effects on neighborhood satisfaction. This can be seen in the twin results that a higher proportion of married households increases satisfaction and reduces crime and disorder, while a higher proportion of households with children reduces satisfaction and increases perceived disorder. For married couples with children, these effects largely cancel each other out, so that a greater number of such households has a similar effect on the neighborhood as do single individuals (whereas higher proportion of married couples without children result in more satisfaction). On the other hand, it can be seen that the sum of these negative effects occurs with a greater proportion of unmarried households with children. Such households are associated with more crime and disorder, consistent with a long line of literature in the social disorganization literature (Roncek and Maier 1991; Rountree and Warner 1999; Sampson and Groves 1989). Indeed, in this model we see that 33 percent of the effect of children and 50 percent of the effect of married households on neighborhood satisfaction is due to the increased crime and disorder. Nonetheless, this model suggests that greater numbers of single-parent families in a block also have a direct negative effect on neighborhood satisfaction beyond their effect on disorder and crime.

While I found no support for the systemic model hypothesis that an individual living a longer period of time on a block will express more neighborhood satisfaction, we do see an aggregate effect where residential stability on a block is associated with greater neighborhood satisfaction. This greater stability has an additional positive indirect effect on neighborhood satisfaction by reducing neighborhood perceived social disorder. Nonetheless, while consistent with the systemic model hypothesis, it is possible that the causal effect is reversed, and suggests an avenue for future research.

Measures of social distance

I next turn to the question of what effect social distance has on neighborhood satisfaction, both directly and indirectly through its effect on perceived crime and disorder. As an individual-level measure, there is evidence that greater social distance from one's neighbors will impact one's perceptions of them, at least as measured by the presence of "undesirable persons," and results in reporting more social disorder, as seen in Table 2.5. There is also evidence that social distance at the individual level increases perceived physical disorder and modestly increases perceived crime, and this increased disorder and crime then indirectly reduces neighborhood satisfaction. There is also modest evidence of a direct effect of social distance on an individual's neighborhood satisfaction, though almost half of this effect is mediated by the increased perceived disorder and crime. This contrasts with previous studies that have only measured social distance based on race/ethnicity and found no individual-level effect. To match these previous studies, I estimated a subsidiary model in which I also included a measure of the distance of the respondent from his/her neighbors based on race/ethnicity.[29] This measure of racial/ethnic distance had no effect on any of the constructs, whereas the effect of total social distance remained unchanged. This highlights the importance of measuring other determinants of social distance beyond race/ethnicity.

But while measuring social distance along a number of determinants shows a strong effect upon neighborhood satisfaction, the story is different for aggregate social distance in a block. When treating aggregate social distance linearly and including a measure of the average social distance in the block, it shows no effect on crime, disorder, or neighborhood satisfaction. Instead, at the aggregate level it is social distance along the single characteristic of race/ethnicity that is particularly important for affecting neighborhood satisfaction. Greater ethnic heterogeneity in the block has an indirect negative effect on neighborhood satisfaction by increasing the perceived crime and disorder in the block, as seen in Table 2.5. When I estimated a subsidiary model excluding block ethnic heterogeneity, I found that the average social distance in the block had a positive effect on crime and physical disorder, and a modestly negative direct effect on neighborhood satisfaction (results not shown here). Thus, it appears that when testing the linear effect of aggregate social distance on neighborhood disorder and crime, race/ethnicity is key. It is also important to highlight that this model also answers the question why ethnic heterogeneity is important for neighborhood

[29] This is calculated as the proportion of other block members not in the same racial/ethnic group as the respondent. Thus, this measure has a value of zero when all other block members are the same race/ethnicity, and a value of one when all are members of different racial/ethnic groups.

satisfaction: it increases neighborhood crime and disorder. In fact, crime and disorder entirely mediate the effect of ethnic heterogeneity on neighborhood satisfaction.

I next tested Bellair's (1997) thesis that the weak ties of a neighborhood are important for reducing the amount of crime by including a nonlinear component of total social distance in the equation predicting neighborhood perceived crime. The notion here is that while no social distance should foster strong ties and high social distance likely inhibits tie formation, a moderate amount of social distance may result in fewer strong ties but a greater number of weak ties, creating more bridging social capital that would reduce crime. We see support for this hypothesis in the model predicting neighborhood common perception of crime in Table 2.5, as social distance in the block has an inverted-U relationship with neighborhood perceived crime. This effect is depicted graphically in Figure 2.5, and illustrates that areas with a moderate amount of social distance have the least perceived neighborhood crime. This is consistent with the notion of the importance of weak ties for crime reduction, though speculative given the lack of network data in this sample.

Finally, I further explored whether the existence of subgroups on a block—based on social distance between residents—affect neighborhood satisfaction and failed to find any effects. I tested this in several manners. When estimating a model including both the average social distance in a block as well as the variance in block social distance (as this latter measure is designed to capture the degree of clustering in a block), I found minimal effects. This measure had no effect on neighborhood satisfaction and only a modest positive effect on perceived physical disorder. The weakness of this finding, along with the fact that the presence of groups is least theoretically likely to affect perceived disorder, diminishes the significance of these results. Additionally, models testing more directly for the presence of groups found no effects: a model including the size of the largest group in the neighborhood showed no significant effects for any of these outcome measures, suggesting that the presence of a large group of residents more similar to each other has no effect on these neighborhood constructs. Since simply measuring the size of the group does not take into account the closeness *within* the group, I also estimated a model including the average distance within each of the two groups, as well as the average social distance across the two groups. Thus this model not only takes into account the closeness within each of the two groups, but also takes into account how much difference there is between the two groups. Nonetheless, this model showed no significant effects for any of the neighborhood-level constructs.

Conclusion

While numerous studies have looked at the determinants of greater reported neighborhood satisfaction by residents, they generally adopt one of two strategies: 1) a national sample of households, or 2) a sample of households nested in neighborhoods from a single city. National studies of households are limited in that they implicitly assume that the respondent provides an error-free assessment of the neighborhood, and also in that they are unable to disentangle household-level effects from neighborhood-level effects. Samples of neighborhoods from a single city are limited in that they often lack statistical power due to having a small number of neighborhoods, and also in that results from such studies may not be generalizable to other cities if the city has unique characteristics affecting the nature of the analyzed relationship. This study using a national sample of households nested in blocks has overcome these limitations. This sample design also allowed me to address four other key limitations of prior work: 1) I have theoretically taken into account the household's degree of fit with the neighborhood and shown that past research failing to take this into account obtains confounded results. 2) I have shown that taking into account the household's degree of fit with the neighborhood suggests the possible importance of social distance—as measured along various social categories—for fostering satisfaction. While past studies have focused simply on racial/ethnic difference, I have shown that measuring distance along a number of categories simultaneously is important, and has different implications whether measured as an individual-level construct or as a neighborhood-level measure. 3) I have exploited this nested design to test whether crime and disorder show neighborhood-level effects on reported satisfaction; while past studies have found such an individual-level relationship, recent critiques have suggested that such findings may simply be capturing psychological effects (Taylor 2001). 4) I have exploited this nested design to test whether the crime and disorder of neighborhoods can help explain compositional effects of neighborhood demographics on reported satisfaction. I next elaborate on each of these issues.

My sample design allowed me to take into account an important, but often overlooked, characteristic of neighborhood satisfaction: the household's degree of fit with the neighborhood. While the residential mobility literature explicitly considers the household's degree of fit based on life course stage, the neighborhood satisfaction literature has paid less attention to this issue. Failing to take this complication into account poses problems for studies wishing to simply compare the quality of neighborhoods *across* neighborhoods based on survey responses of households. Thus, samples of households (as opposed to samples of neighborhoods) that ask the household to rate their neighborhood are obtaining a confounded response: both the degree to which the neighborhood is more desirable than others, but also the degree to which the particular household fits with the neighborhood. Relatedly, if certain types of households systematically report lower satisfaction with the neighborhood than their neighbors, this will confound attempts to compare neighborhoods across neighborhoods. One consequence of my approach parsing apart individual-level perceptions of neighborhood satisfaction and aggregate-level measures is that I have been able to detect the expected effect where those with greater SES are able to obtain access to more desirable neighborhoods. This highlights a weakness of past studies conceptualizing neighborhood satisfaction as an individual level construct: for instance, some studies have failed to find significant effects on neighborhood satisfaction for education (Adams 1992) and income (Bolan 1997; Jagun, Brown, Milburn, and Gary 1990; McHugh, Gober, and Reid 1990), or even counter-intuitive negative effects for education (Jagun, Brown, Milburn, and Gary 1990). A possible explanation for these previous surprising results comes from this study's findings that the effects of SES differ depending on whether they are measured at the individual level or aggregate level: at the individual level, those with higher levels of education are less satisfied than their neighbors, but at the aggregate level, neighborhoods with higher levels of average education are more satisfied. This individual-level finding for education, along with that for racial/ethnic groups, was consistent with the social injustice model's prediction that the higher expectations of those with higher SES or from dominant racial/ethnic groups will make them less satisfied with the neighborhood than their neighbors.

Overlooking the theoretical importance of the degree of fit of the household with the neighborhood has obscured a potentially fruitful avenue of research for neighborhood satisfaction scholars: the effects of social distance. My unique sample design of all eleven households on each of approximately 660 blocks across the U.S. has allowed me to measure social distance along a number of categories both at the level of the household as well as at the neighborhood level—as the average social distance (Blau 1977; Blau 1987; McPherson and Ranger-Moore 1991). While prior studies have occasionally viewed the effects of social distance on neighborhood satisfaction, they have almost always focused simply on racial/ethnic distance. My findings here suggest that while race/ethnicity is clearly important for fostering social distance, it should not blind us to other determinants of social distance that also have important implications for neighborhoods. For instance, whereas my findings mirror those of prior research in that an individual's distance from their neighbors based on race does not affect reported neighborhood satisfaction (Harris 2001; Stipak and Hensler 1983), I did find significant effects when measuring social distance along a number of categories simultaneously. In particular, individuals more socially distant from their neighbors—as measured simultaneously along the determinants of race/ethnicity, income, life course, and social background— tend to perceive more undesirable neighbors and physical disorder, which then reduces their reported satisfaction. This is consistent with the notion that such households perceive a less good 'fit' with the neighborhood than their neighbors.

On the other hand, it appears that compositional effects for social distance are more pronounced when measuring distance simply along race/ethnicity. Thus, neighborhoods with greater racial/ethnic heterogeneity reported less satisfaction. While this finding mirrors past research (Adams 1992; Connerly and Marans 1985; Harris 2001), I have extended this by testing *why* such a relationship occurs. The findings here suggest that racial/ethnic heterogeneity does not reduce satisfaction simply because it is inherently undesirable, but rather because it increases neighborhood crime and disorder. Indeed, the effect of ethnic heterogeneity on neighborhood satisfaction was entirely mediated by crime and physical and social disorder. My total social distance measure only affected the common perception of crime on the block, and did so in a nonlinear fashion. While blocks with no social distance or a high degree of social distance reported higher perception of crime, blocks with a modest amount of social distance reported the least amount of crime. If moderate amounts of social distance reduce the number of strong ties but increase the number of weak ties, this would produce this result consistent with the observation of scholars that bridging ties are most important for reducing neighborhood crime (Bellair 1997; Beyerlein and Hipp 2005; Putnam 2000). While speculative, given the lack of network data in these analyses, this poses a potential avenue for future research.

My nested data has allowed me to test whether the relationship between crime/disorder and neighborhood satisfaction is simply a psychological one (Taylor 2001), or whether neighborhood-level effects are indeed present. The findings here showed that there are indeed significant effects of neighborhood-level measures of crime, physical disorder, and social disorder upon neighborhood satisfaction. And while this sample showed that there are additional individual-level effects in which a resident who perceives more crime and disorder than their neighbors also is less satisfied than their neighbors, the neighborhood-level effects are non-trivial. My structural equations modeling strategy allowed me to compare the size of these various effects: as described above, a conservative estimate suggests that the neighborhood can explain 41 percent of the relationship between perceived crime and neighborhood satisfaction, and 26 and 53 percent of the relationship for social and physical disorder, respectively. The fact that the neighborhood effect is strongest for the assessment of physical disorder is unsurprising given that this construct is more tangible than are social disorder or crime (Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997).

While recent studies using data with households nested in neighborhoods finding relationships between aggregate demographic characteristics and neighborhood satisfaction are often left to speculate on the causes of these relationships, I have suggested that building on the insights of the social disorganization model is instructive for explaining some of these relationships. While past studies have considered the role of social disorganization in fostering neighborhood satisfaction, they have been limited in that they 1) generally have only used individual-level assessments of crime and disorder to test their effect on neighborhood satisfaction (Adams 1992; Davis and Fine-Davis 1981; Parkes, Kearns, and Atkinson 2002; Woldoff 2002); 2) they have failed to test whether this crime and disorder plays a role in mediating the relationship between neighborhood demographic composition and neighborhood satisfaction. My findings here suggest that crime and disorder play an important role: they entirely mediated the effect of ethnic heterogeneity on satisfaction, they explained 50 percent of the relationship for measures of crowding, average income, and percent married, and they explained about 1/3 of the effect for percent African-American and percent with children.

In addition, my strategy of disentangling household- and neighborhood-level effects also allowed testing the hypotheses of two key neighborhood theories: the systemic theory and the community of limited liability theory. Similar to Sampson's (1991) findings of a sample from England, I found no individual-level effect for length of residence upon satisfaction, but that neighborhoods with greater stability report more satisfaction and less social disorder. While consistent with the systemic model, a more thorough test would be necessary to determine if the causal direction does not run in the opposite direction: greater neighborhood satisfaction leads to more stability. I also found mixed results for the community of limited liability theory. The strongest evidence was found for the economic investment of homeownership, as owners report more satisfaction and perceive less crime in the neighborhood. There was also an aggregate effect, as blocks with a higher proportion of homeowners reported greater overall satisfaction and less perceived crime. However, there was little evidence that the social investment of children increases satisfaction, either for individual households, or as an aggregate effect for neighborhoods.

While this study has provided important new insights to the literature on neighborhood satisfaction, certain limitations need to be acknowledged. First, a key challenge to neighborhood studies is the possibility of selection effects: certain types of people may choose to move to more desirable neighborhoods. The cross-sectional analyses presented here cannot take this into account. While a fixed effects strategy is one possible way to address this issue, such a strategy throws away considerable amounts of information and thus has low statistical power, requiring rather large sample sizes to detect effects. Given that this study lacked the power necessary to detect effects using a fixed effects strategy, despite the very large sample size by neighborhood studies standards, suggests a large hurdle indeed for future work. Second, while I have suggested and shown that crime and disorder are important mechanisms that partially explain the relationship between certain aggregate demographic characteristics and overall desirability of the neighborhood, other mechanisms are certainly likely, and will require consideration in future work. For instance, the prevalence of theoretical models implicating the role of neighborhood networks as a possible mediator of various demographic characteristics suggests a fruitful direction for future work, though this is yet another approach that is data intensive if approached in a quantitative fashion. An alternative strategy would be for qualitative studies to explore possible network mechanisms, providing more guidance to the collection of network data for quantitative studies.

Nonetheless, this study provides guidance to the neighborhood satisfaction literature by disentangling individual- and neighborhood-level effects. Taking these different effects into account can guide future theoretical work attempting to understand the genesis of satisfaction with the neighborhood, and how that might change over time. This study has also highlighted the important role crime and disorder plays in this neighborhood satisfaction, and the need to take into explicit into the determinants of neighborhood crime and disorder when attempting to understand neighborhood desirability.

Tables and Figures

Table 2.3. Summary statistics for variables used in analyses. American Housing Survey national sample, special non-rural neighborhood sub-sample, 1985, 1989, 1993

	Mean	SD
Block-level measures		
Proportion African-American	0.139	0.273
Proportion Latino	0.083	0.174
Proportion other race	0.026	0.066
Ethnic heterogeneity	0.220	0.223
Average Education	12.830	1.857
Average Income	3.252	1.801
Average length of residence (logged)	1.880	0.625
Proportion married	0.507	0.242
Proportion with children	0.584	0.507
Proportion owners	0.573	0.357
Average persons per room (logged)	0.491	0.158
Proportion vacant units	0.073	0.144
Average distance in the neighborhood	0.465	0.079
Average variance of distance in the neighborhood	0.038	0.014
Average distance in biggest group	0.376	0.080
Average distance in smallest group	0.418	0.095
Average distance across groups	0.589	0.112
Household-level measures		
Neighborhood satisfaction	7.840	2.159
Perceived crime	0.323	0.488
Social disorder	0.166	0.345
Physical disorder	0.069	0.223
Female	0.561	0.474
Age	48.749	17.444
African-American	0.139	0.346
Latino	0.085	0.278
Average Education	12.838	3.103
Average Income	3.258	2.926
Average length of residence (logged)	1.879	1.169
First year in residence	0.155	0.362
Married	0.508	0.500
Divorced	0.187	0.390
Have Children	0.316	0.450
Home owner	0.574	0.482
Average persons per room (logged)	0.491	0.292
Total social distance	0.462	0.109
Social distance by race	0.231	0.300

N= 26,499 households in 2,409 block time points

Table 2.4. Assessing the reliability of neighborhood constructs of the American Housing Survey (AHS) non-rural neighborhood subsample of the national sample using confirmatory factor analysis models, 1985, 89, 93

CFA Models	**Chi Sq**	**df***	**p-value**	**CFI**	**TLI**	**RMSEA**	**Indicator R-squares**
Crime	62.1	57	0.300	0.999	0.999	0.006	0.295
Social disorder	81.2	63	0.061	0.972	0.972	0.011	0.165
Physical disorder	59.7	57	0.379	0.992	0.992	0.004	0.219
Neighborhood satisfaction	77.9	84	0.749	1	1.001	0	0.251

** Degrees of freedom are estimated when using weighted least squares with mean and variance adjusted estimation for crime, social disorder, and physical disorder models*
N= 26,499 households in 2,409 block time points

Table 2.5. Full structural equation model with neighborhood satisfaction as outcome. Using social disorder, physical disorder and crime at household and block level as mediators. Including household- and block-level demographic and social distance measures. American Housing Survey special non-rural neighborhood sub-sample, 1985, 1989, 1993

	Neighborhood satisfaction: direct effect		Perceived crime		Perceived social disorder		Perceived physical disorder		Neighborhood satisfaction: indirect and total effect		
Individual outcome and measures									Indirect	Total	% mediated
Female	0.168	**	0.018	**	0.016	**	0.019	**	-0.057	0.112	-50.9%
	(5.71)		(2.76)		(3.25)		(5.99)				
Age	0.008	**	-0.002	**	-0.001	**	0.000	**	0.004	0.013	33.1%
	(8.18)		-(8.84)		-(5.91)		-(3.25)				
African-American	0.294	**	-0.093	**	-0.049	**	-0.005		0.158	0.451	34.9%
	(4.05)		-(5.36)		-(4.36)		-(0.70)				
Latino	0.394	**	-0.098	**	-0.059	**	-0.013	†	0.185	0.579	31.9%
	(6.50)		-(6.93)		-(5.30)		-(1.76)				
Education	-0.026	**	0.008	**	0.003	**	0.003	**	-0.014	-0.040	35.0%
	-(4.79)		(5.10)		(3.48)		(4.14)				
Income	0.003		0.004	*	0.000		0.001		-0.004	-0.001	
	(0.52)		(2.33)		(0.01)		(1.37)				
Length of residence (logged)	-0.039	*	0.032	**	0.012	**	0.011	**	-0.055	-0.094	58.6%
	-(2.02)		(6.62)		(3.51)		(4.78)				
First year in residence	-0.060		-0.042	**	-0.015	†	0.000		0.060	0.000	
	-(1.40)		-(3.01)		-(1.80)		-(0.07)				
Married	0.022		0.014	†	0.014	*	0.013	**	-0.046	-0.024	100.0%
	(0.44)		(1.72)		(2.43)		(2.96)				
Divorced	-0.100	*	0.026	*	0.010		-0.001		-0.036	-0.136	26.4%
	-(2.10)		(2.41)		(1.54)		-(0.21)				
Persons per room (logged)	0.016		-0.008		-0.002		-0.025	**	0.035	0.051	68.0%
	(0.27)		-(0.50)		-(0.16)		-(3.25)				
Presence of children	0.000		0.016		0.007		-0.007		-0.018	-0.018	99.2%
	(0.00)		(1.57)		(0.99)		-(1.60)				
Home owner	0.059		-0.024	*	0.004		0.025	**	-0.008	0.051	
	(1.30)		-(2.05)		(0.53)		(4.77)				
Perceived crime	-0.899	**									
	-(31.02)										
Perceived social disorder	-1.418	**									
	-(38.95)										
Perceived physical disorder	-0.952	**									
	-(16.33)										
Social distance	-0.321	†	0.094	†	0.126	**	0.054	*	-0.316	-0.637	49.6%
	-(1.65)		(1.67)		(3.17)		(2.47)				

(continued)

Neighborhood outcome and measures	Neighborhood satisfaction: direct effect	Perceived crime	Perceived social disorder	Perceived physical disorder	Neighborhood satisfaction: indirect and total effect		
					Indirect	Total	% mediated
Perceived crime	-0.554 **						
	-(3.76)						
Perceived social disorder	-1.165 **						
	-(2.58)						
Perceived physical disorder	-2.815 **						
	-(3.59)						
Percent African-American	-0.369 **	0.273 **	0.030 †	0.009	-0.211	-0.580	36.4%
	-(3.35)	(8.96)	(1.70)	(0.79)			
Percent Latino	-0.512 **	0.188 **	-0.062 *	-0.003	-0.024	-0.536	4.5%
	-(3.45)	(4.52)	-(2.35)	-(0.16)			
Percent other race	-0.623	-0.075	-0.219 **	-0.056	0.454	-0.169	
	-(1.24)	-(0.68)	-(3.77)	-(1.26)			
Ethnic heterogeneity	0.090	0.113 **	0.083 **	0.036 *	-0.260	-0.170	100.0%
	(0.53)	(3.24)	(3.95)	(2.50)			
Average Education	0.077 **	0.004	-0.004	-0.001	0.006	0.083	7.3%
	(5.03)	(0.98)	-(1.56)	-(0.72)			
Average Income	0.041 *	-0.003	-0.011 **	-0.010 **	0.042	0.082	50.4%
	(2.27)	-(0.66)	-(3.60)	-(4.83)			
Average length of residence (logged)	0.123 **	-0.016	-0.019 *	-0.002	0.036	0.158	22.5%
	(2.80)	-(1.34)	-(2.45)	-(0.36)			
Percent married	0.270 *	-0.189 **	-0.070 **	-0.030 *	0.272	0.542	50.1%
	(2.19)	-(5.14)	-(3.00)	-(2.07)			
Percent with children	-0.197 **	0.023	0.035 **	0.015 **	-0.095	-0.292	32.6%
	-(3.94)	(1.58)	(4.40)	(2.65)			
Percent owners	0.206 *	-0.063 *	0.004	-0.003	0.038	0.244	15.7%
	(2.07)	-(2.09)	(0.22)	-(0.26)			
Average persons per room (logged)	-0.326 †	0.143 *	0.102 **	0.068 **	-0.390	-0.715	54.5%
	-(1.65)	(2.49)	(3.03)	(3.03)			
Percent vacant units	0.307 †	0.139 **	0.075 **	0.053 **	-0.313	-0.005	
	(1.74)	(3.32)	(2.93)	(2.77)			
Average social distance	-0.283	-2.116 **	0.030	0.042	1.019	0.736	
	-(0.82)	-(3.97)	(0.50)	(1.07)			
Average social distance squared		2.405 **			-1.332	-1.332	
		(4.15)					
Indicator for 1985	0.109 *	-0.026 *	-0.014 †	0.002			
	(2.42)	-(2.01)	-(1.96)	(0.30)			
Indicator for 1989	-0.011	-0.010	-0.016 *	0.003			
	-(0.23)	-(0.84)	-(2.21)	(0.58)			
R-square (individual construct)	0.378	0.222	0.092	0.079			
R-square (neighborhood construct)	0.703	0.416	0.364	0.344			

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). N = 26,499 households in 2,409 block time points. T-value in parenthesis*

Average model fit over five imputations: chi square = 9502.3 on 8333 df, RMSEA = .008, TLI = .989, IFI = .996, CFI = .996, using a maximum likelihood estimator

Figure 2.1 Theoretical determinants of social distance

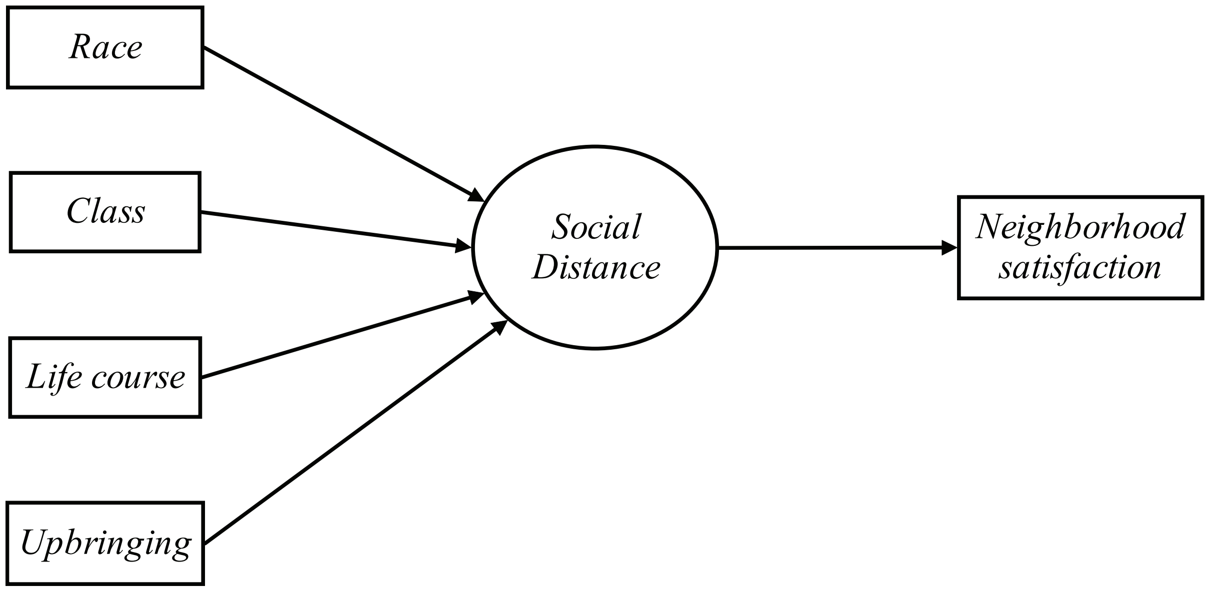
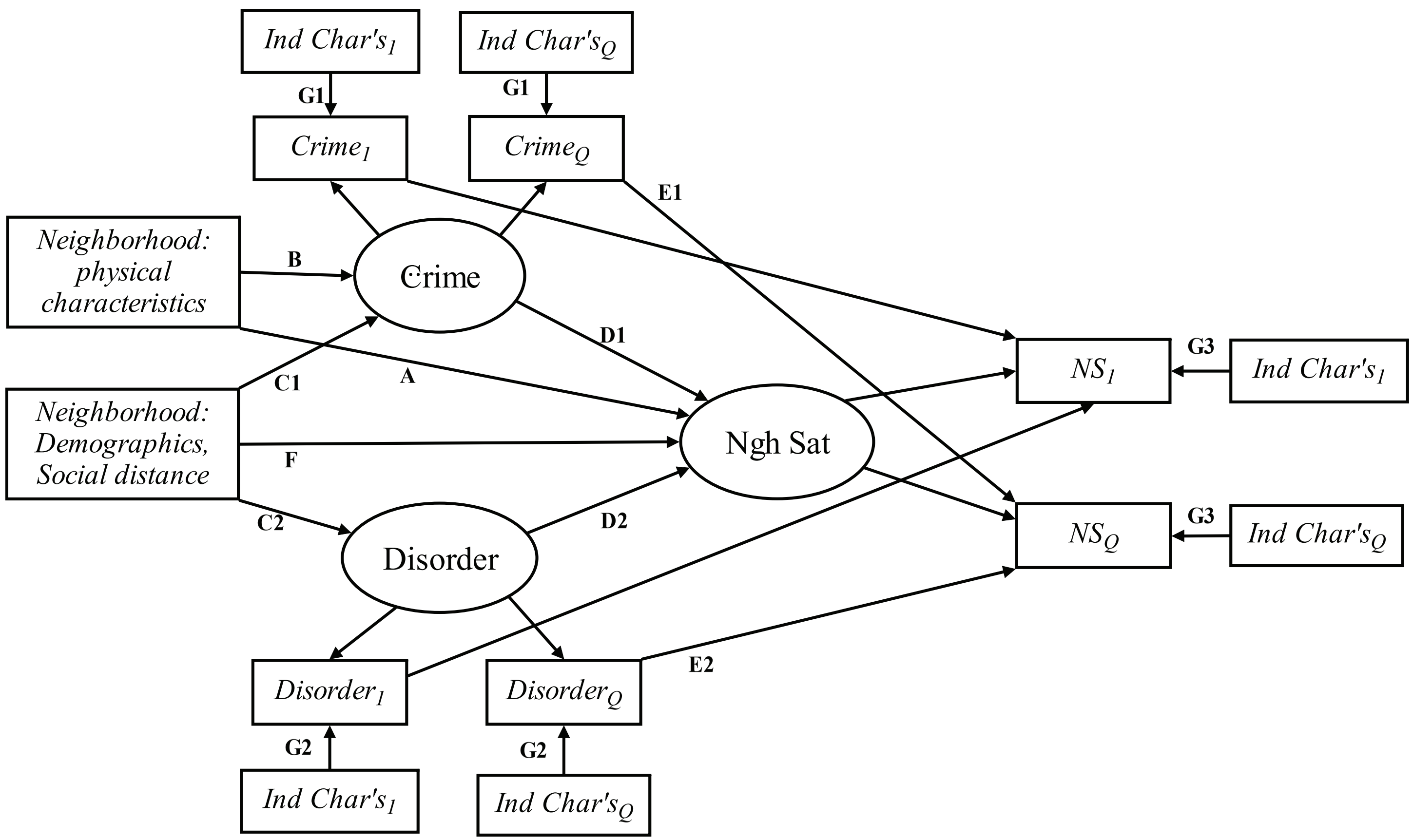


Figure 2.2. Conceptual model of how social disorder mediates the effect of social distance on neighborhood satisfaction



Model also allows covariances between all exogenous variables, covariances between disturbances of indicators of crime and disorders for the same household, and allows covariances between the disturbances of the intervening latent variables of crime and disorders,.

When extending the model longitudinally, covariances are estimated between the disturbances of the same construct over time (i.e., of $crime_t$ with $crime_{t+1}$) for both the intervening constructs and the neighborhood satisfaction construct, and between the indicators of the same construct for the same household over time (both the intervening variables of crime and disorder and the outcome of neighborhood satisfaction).

Figure 2.3a. Hypothetical neighborhood with equal social distance among residents

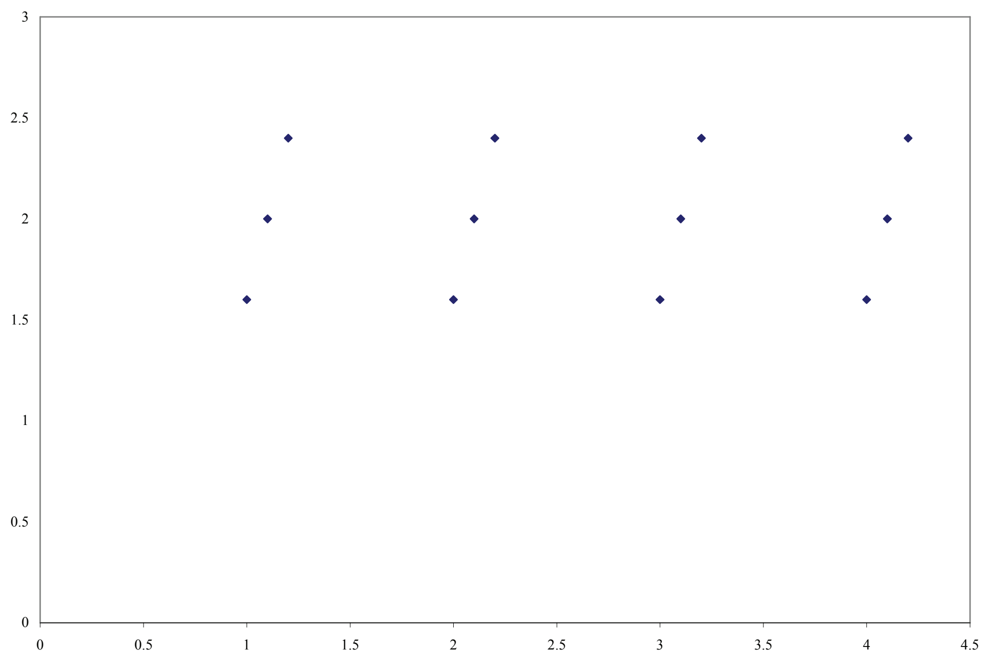


Figure 2.3b. Hypothetical neighborhood with variance in social distance among residents (cliques)

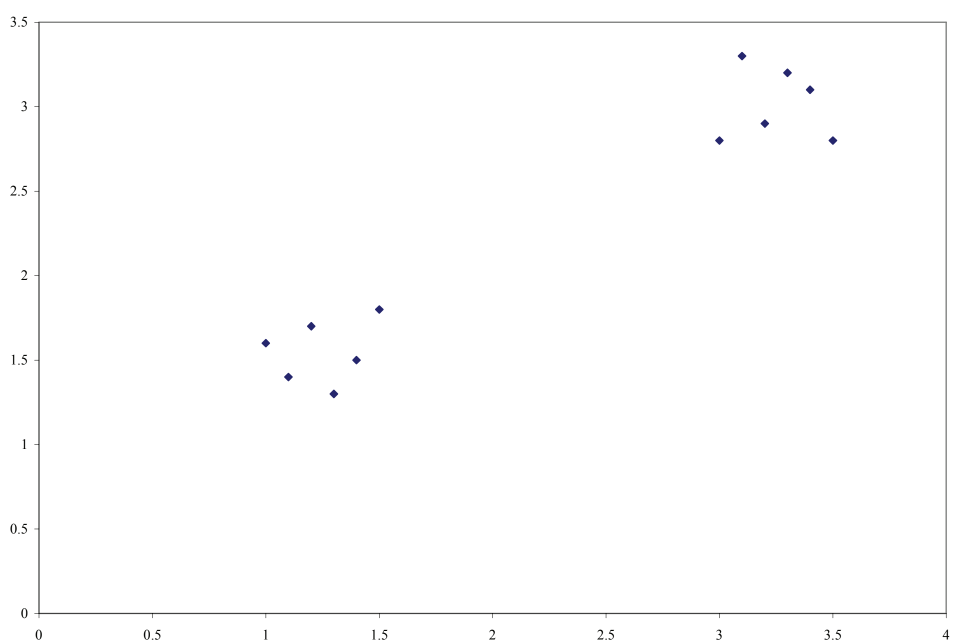


Figure 2.4. Interpreting household and neighborhood-level effects

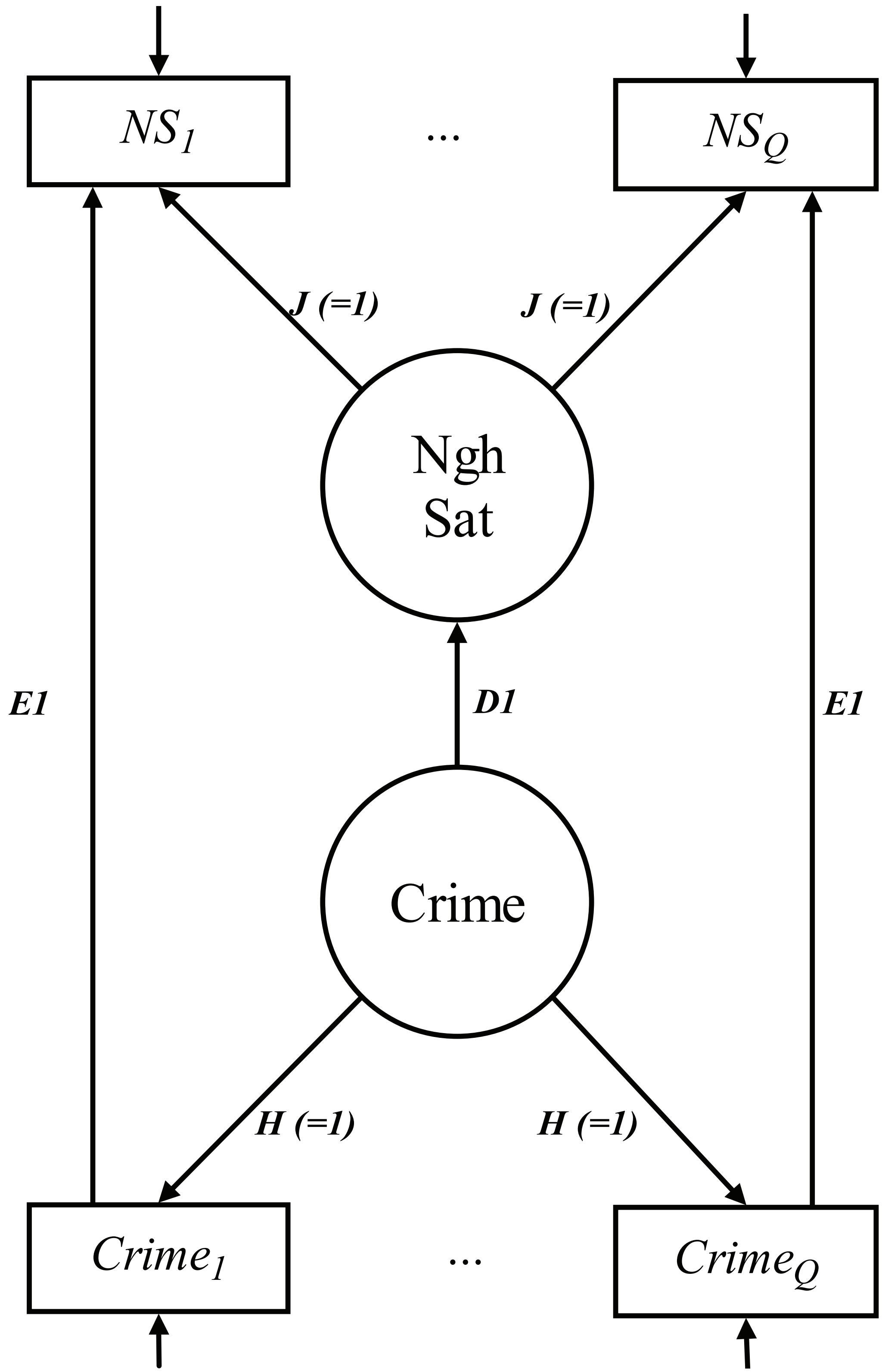
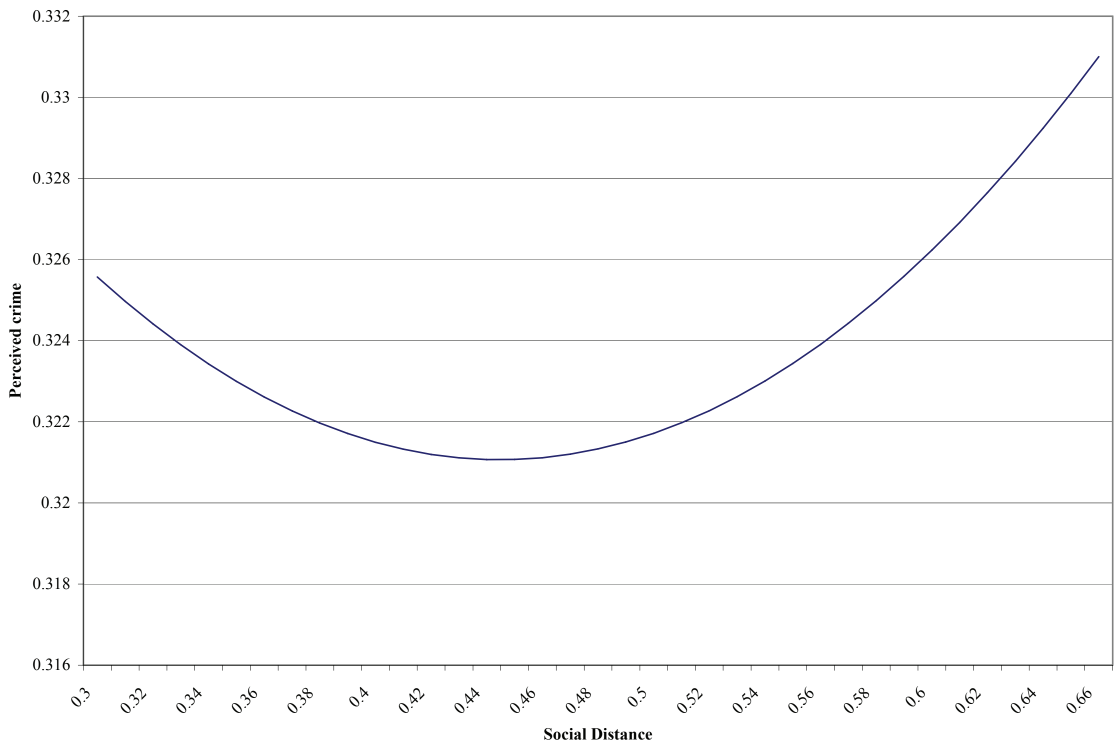


Figure 2.5. Effect of block social distance on block perceived crime from full structural equation model simultaneously estimating both household and block effects



III. Fight or Flight? Household Mobility Decisions, Neighborhood Transformation, and Crime

Urban neighborhoods and their transformation have been a bedrock concern of sociology extending back at least to Simmel (1971), Wirth (1956a; 1956b), and Park and Burgess (1921). Neighborhoods differ on characteristics that most would consider inherently desirable, such as the presence of certain amenities (such as quality schools), the amount of crime, or the existence of positive relations among the residents. Furthermore, the quality of such neighborhoods is important for the investment they represent to many homeowners for whom the value of their home represents much of their net worth. Because of this importance of neighborhoods, there naturally is interest in how neighborhoods change over time. Two broad perspectives focus on neighborhood change. One emphasizes the importance of residential mobility decisions for creating racial/ethnic and economic transformation of neighborhoods, while the other emphasizes the importance of resident decisions to affect the level of crime through such civic activism as providing informal social control.

The first perspective focusing on neighborhood transformation is the residential segregation literature, and gives primacy to the study of household residential mobility decisions (Frey and Farley 1996; Massey, Gross, and Shibuya 1994; South and Crowder 1997a; South and Crowder 1997b; Van Valey, Roof, and Wilcox 1977). In this view, whether or not households choose to leave a neighborhood is of importance. This residential segregation literature focuses on whether household residential mobility decisions lead to a residential transformation in such important neighborhood structural characteristics as racial/ethnic composition and economic resources (Jargowsky 1996; Massey and Denton 1987; Massey and Fong 1990). This transformation of individual neighborhoods then has implications for the larger question of the racial/ethnic residential segregation within larger communities and its relationship to "white flight" (Frey 1979; Krysan 2002; Marshall 1979; Massey, Gross, and Shibuya 1994). An important implication for such transformed neighborhoods that end up with the most "truly disadvantaged" based on race and income is that they likely will experience such negative consequences such as higher rates of crime (Peterson and Krivo 1993; Wilson 1987).

The second perspective focusing on neighborhood transformation is the social disorganization model of Park and Burgess (1921) in criminology, which largely disregards residential mobility decisions while focusing on whether or not residents will engage in civic activism to combat crime. The social disorganization model provides a causal mechanism for why three key structural characteristics—poverty, ethnic heterogeneity, and residential stability—should increase crime. In this model, these three characteristics increase the physical and social disorganization of neighborhoods, reducing the interaction among residents and hence reducing the willingness to engage in various guardianship activities that might reduce the rate of neighborhood crime (Park and Burgess 1921; Sampson and Groves 1989; Shaw and McKay 1942). As a result, this inhibits the ability of a community "to realize the common values of its residents and maintain effective social controls" (Sampson and Groves 1989). While key work in this field by Sampson and colleagues explicitly focused on measuring the mechanisms of social disorganization in neighborhoods in London (Sampson and Groves 1989) and Chicago (Sampson and Raudenbush 1999), these and most other studies in this perspective use cross-sectional data (Bellair 1997; Bellair 2000; Hirschfield and Bowers 1997; Sampson and Groves 1989; Sampson and Raudenbush 1999; Smith, Frazee, and Davison 2000; Veysey and Messner 1999; Warner 2003; Warner and Pierce 1993). One implication of the recent development of this theory generally employing cross-sectional studies is that less attention is paid to the possibility that higher rates of crime might increase *residential mobility*.

I suggest that these two perspectives on neighborhoods have complementary aspects that can be fruitfully combined. Whereas the residential mobility literature largely focuses on whether households move or stay in a neighborhood in response to structural conditions, it can be extended to take into account the possibility that households mobility decisions may also depend on the level of crime in the neighborhood (Liska and Bellair 1995; Liska, Logan, and Bellair 1998; Marshall 1979). This mobility option can then be linked to the social disorganization model's focus on whether or not households provide informal social control to reduce crime. This suggests a need for a multilevel theoretical model that explicitly takes into account the actions of households, consistent with the recent call to theoretically integrate the interrelationship between crime and residential mobility (Liska and Bellair 1995: 604; South and Messner 2000). I will develop such a model in which households can respond to various problems in the neighborhood, such as crime, either through residential mobility, providing informal social control to reduce crime, or neither.

One insight gained from employing this household level model is that to the extent that households adopt an exit strategy *in response to* the level of crime, this can help explain the existence of various structural characteristics of neighborhoods. If households choose to leave neighborhoods when the crime rate increases, the rate of residential instability will increase. Likewise, if households of different racial/ethnic backgrounds have differential abilities to leave high crime areas, this will change the racial/ethnic composition of the neighborhood.[30] And to the extent that households prefer areas with less crime, I show below how this can give rise to residential mobility decisions that result in high crime areas containing a high degree of households in poverty. In all three instances, it is the higher level of crime that *causes* these structural characteristics, rather than a causal relationship from these structural characteristics to crime as postulated by the social disorganization model.

Despite the theoretical plausibility of a reciprocal relationship between household residential mobility decisions and these key structural neighborhood characteristics, few studies have addressed these questions at any level of analysis, much less at the level of neighborhoods. For instance, while some recent studies have tested for a reciprocal relationship between crime and informal social control (a mechanism of social disorganization), such studies assume that individuals only respond to crime through the amount of informal social control they provide and not through residential mobility decisions (Bellair 2000; Markowitz, Bellair, Liska, and Liu 2001; Sampson and Raudenbush 1999). Thus, virtually no studies have tested for a possible reciprocal relationship between crime and residential instability. Likewise, few studies have tested whether crime also leads to a clustering of those living in poverty. While Park and Burgess (1921) implicitly suggested an economic model in which households choose neighborhoods at an appropriate income level, this does not explicitly suggest that the rate of crime in a neighborhood *causes* this clustering. Thus, while studies using the Panel Study of Income Dynamics (PSID) have shown that lower economic resources funnels residents into poor neighborhoods and limits their ability

[30] While there is little reason to expect that households of some races "prefer" crime, this can still occur if households of different races have different levels of resources. I incorporate this into the model explicitly down below.

to leave such areas (Quillian 1999; South and Crowder 1997a) these studies do not test whether crime is actually a key part of the causal process. Finally, while two recent studies used longitudinal data to find that higher levels of crime can result in a greater concentration of nonwhite population in cities (Liska and Bellair 1995; Liska, Logan, and Bellair 1998), they failed to test these processes at the level of local neighborhoods, a more appropriate geographic level as described in the initial Shaw and McKay model. One longitudinal study of neighborhoods in Chicago using a small number of control variables found that the delinquency rate in 1960 increased the number of non-whites in 1970, though this paper did not test a reciprocal model (Bursik 1986).

In what follows, I develop an explicit household level theoretical model of household response to neighborhood problems, and suggest that it can be seen as a bridge between the residential segregation literature focusing on mobility decisions and the social disorganization literature focusing on civic participation. This theoretical model helps to explain the *generation* of neighborhood social structural characteristics through these household level decisions. One implication of this model is that a reciprocal relationship between crime rates and the structural characteristics of neighborhoods should exist: while research has failed to explicitly test this using neighborhood-level data, I am able to do so here given my longitudinal sample of households nested in blocks in the United States. Finally, an additional advantage of my sample, given the controversy surrounding the proper definition of a neighborhood, is that I can test whether the ecological effects of the local block are most important for generating mobility decisions or crime prevention activities, or whether the surrounding census tract has a larger impact.

Household Choice Model

I employ a household level model developed by Lyons and Lowery (1986) building on the insights of Hirschman's (1970) notions of exit and voice, in which households can respond to neighborhood problems through four possible responses: 1) exit; 2) voice; 3) loyalty; 4) neglect (Lyons and Lowery 1986; Orbell and Uno 1972). Exit is choosing to moving out of a neighborhood experiencing problems. Voice entails various political responses, including individualistic ones such as writing to newspapers, contacting public officials, signing petitions or voting; it also includes collective responses, such as working through existing groups or forming new ones (Orbell and Uno 1972). Loyalty implies remaining committed to the neighborhood: such individuals might be less likely to notice issues that other residents classify as 'problems'. Finally, neglect would be a person noticing such problems but simply doing nothing about them. I extend this model by considering crime as a particularly salient neighborhood problem that will engender one of these four responses of exit, voice, loyalty, or neglect.

Early work in the social disorganization literature often implicitly assumed that households would respond to crime events with neglect. That is, households were viewed as passive actors at the whims of neighborhood events. Recent research has suggested that some households may respond to neighborhood problems with voice by joining neighborhood associations and other activity designed to combat crime (Gerson, Stueve, and Fischer 1977; Perkins et al. 1990; Skogan 1989; Taylor 1996). However, work has rarely considered the theoretical implications if households respond to crime by choosing exit. Nonetheless, it is relatively uncontroversial and theoretically plausible to suspect that households desire neighborhoods with less crime, and that higher rates of crime will give rise to greater levels of mobility.

Thus, I utilize a simple household-level model containing few assumptions. While additional preferences are clearly important for households, I suggest that adding these to this model would only provide nuance without changing the substantive conclusions. First, I assume that a major housing preference is to live in a neighborhood with little crime. Second, I assume that households are homogeneous in their characteristics with two exceptions: 1) there are differences in economic resources; 2) there are differences in homeowner status. The first assumption has face validity in that it is hard to conceive of any households desiring to have criminal events inflicted upon them.[31] Even those who engage in criminal acts themselves do not wish to have others physically attack them or take their possessions. In addition, empirical evidence supports the hypothesis that households respond to crime by leaving the area: for instance, Skogan (1990) found for 40 neighborhoods that crime rates cause dissatisfaction and a desire to move. Although South and Deane (1993) found no effect for *perceived* crime, two other studies found significant effects for *actual* crime events (Cullen and Levitt 1996; Dugan 1999). Given this initial framework, below I extend the model by 1) considering the possibility that a household's race/ethnicity may limit their access to more desirable neighborhoods; and 2) allowing households the ability to change the level of crime in the neighborhood—this is a key assumption of the social disorganization model, and can be conceived as a form of "voice" in my schema.

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[31] There are conflicting views on this. On the one hand, some research points out that areas with larger numbers of delinquents will provide larger markets encouraging the location of more criminally-minded individuals in such an area (Glaeser and Sacerdote 1999). However, to the extent that such an increase in the demand for illegal drugs or other illicit services simply increases the number of suppliers, this will not benefit any individual supplier. In addition, some research suggests that even those who are criminally minded wish to maintain the relative safety of their own neighborhoods, and thus conduct their illegal affairs in neighboring communities while engaging in efforts to reduce crime in their own neighborhoods (Pattillo 1998).

If attainment of crime-free neighborhoods is entirely governed by a price mechanism, households' level of economic resources will explain entry into low-crime neighborhoods, ceteris paribus. To begin, consider a simple model represented by a 3x3 table of households differing by income level and neighborhoods differing by level of crime, as shown in Table 3.1.

In this model, the most desirable (and hence expensive) neighborhoods will be those with low amounts of crime. Since all households prefer less crime, the areas with the least crime will be most desirable and hence have the highest rents and home values. At equilibrium, households with the most resources (high-income households) will reside in low crime neighborhoods (cell I); those with average levels of income will reside in neighborhoods with average levels of crime (cell E); and low income households will reside in high crime neighborhoods, represented by Cell A in the table. This implies clustering along the diagonal of this table.[32] This distribution of households suggests a Pareto efficient equilibrium as none will be interested and/or able to move to a different neighborhood: while a low income household would prefer to live in a neighborhood with less crime (cells D or G), this would require displacing a higher income household who would then end up in the high crime neighborhood (cell B or C).[33] The household with more resources is willing and able to pay more to live in the neighborhood with less crime, and would not be willing to move to a higher crime neighborhood without other compensating features. Given this equilibrium, how does neighborhood change occur?

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[32] This only occurs in a perfect market-clearing instance. There are many reasons to expect that housing markets do not clear readily, though the implications of this do not affect the substance of these arguments.

[33] Pareto efficiency occurs when it is not possible to reallocate resources such that one individual is made better off without making any other individual worse off.

In this simple model, households will leave the neighborhood under two circumstances: 1) if their own income status changes or 2) if the neighborhood crime rate changes.[34] First, consider an instance where the household's income changes. For a hypothetical household with average level income currently in an average level crime neighborhood (cell E), an increase in their income will move them to the off-diagonal cell F.[35] These greater resources will allow them to look for a unit in a low-crime neighborhood, abandoning this mid-level crime neighborhood and moving them into cell I.[36] On the other hand, if this household experiences a decrease in income they will become a low-income household living in this neighborhood with mid-level crime, or cell D. Their lower income level will place economic pressure on them to leave this neighborhood for one with a lower rent level (and higher crime), moving them into the equilibrium position of cell A.

There may also be instances in which the neighborhood itself changes. Consider the same hypothetical household residing in cell E: an increase in the crime rate transforms this into a high crime neighborhood, moving the household to cell B.[37] This higher crime rate

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[34] There are other reasons why households might leave a neighborhood, though they do not have important implications for the theory here. For instance, retirees might choose to leave the neighborhood for a retirement community, or households might need to move due to a job change. However, in such instances the household would be replaced by another of similar economic resources since there has been no fundamental change in the neighborhood. Therefore, since such mobility does not change the results here, I do not consider it further.

[35] These income levels and rent/home values are all *relative*. For instance, if the income level of all households increases equally, there will be no relative change, and thus no movement of households.

[36] Of course, this household may not be able to displace another household in existing stock, suggesting the stickiness of the housing market to clearing. One solution is the creation of new housing stock, which I discuss below.

[37] Note that the cause of this exogenous shock is of considerable interest in its own right. Building on the work of the social disorganization model and the routine activities theory, I would suggest a model along the lines of that developed by Wilcox, Land, and Hunt (2003). In this view, crime requires the convergence of motivated offenders, suitable targets, and ineffective guardianship. Thus, the change in any one of these three could lead to an increase in crime. For instance, if more motivated offenders moved into the neighborhood or a nearby one, this could lead to a spike in crime. Note that this wouldn't necessarily lead to a spike: if the neighborhood had potential effective guardianship that could be employed to counteract the increase in motivated offenders, the rate of crime would not increase. This suggests that a "reserve supply" of effective guardianship may be

makes the neighborhood less desirable, producing two simultaneous outcomes. First, the household will choose to leave the neighborhood and move to another cell E neighborhood. Second, since the initial neighborhood is now less desirable, the lower rent reflecting this will induce a low-income household to move into the vacated unit. This implies that an increase in the crime rate can induce a change in the economic resources of the neighborhood's households. Note that this implies a causal relationship from an increase in crime to a change in the economic structure of a neighborhood's households, precisely the opposite of theories such as social disorganization, which predict that decreasing household income in a neighborhood will *cause* an increase in crime. This all suggests a series of hypotheses:

Hypothesis A-1:[38] *If the crime rate rises in a neighborhood, rents and home values will decrease.*

Hypothesis HH-1: If the crime rate rises in a neighborhood, households (especially those with higher income) are more likely to move out of the neighborhood.

Hypothesis HH-2: If the crime rate rises in a neighborhood, most households moving into the neighborhood will have lower income.

Hypothesis A-2: Combining hypotheses 1 and 2, at the aggregate level neighborhoods with increasing rates of crime will experience decreasing average household income.

On the other hand, there might be instances where the crime rate in a neighborhood *decreases*. This would move this household with average income from cell E to cell F: they are now in a more desirable neighborhood than they originally could afford. In such an

important for a neighborhood: as long as they area did not have many motivated offenders, the guardianship would be unnecessary for minimizing crime. But its presence could help ameliorate possible spikes in crime of the sort I describe here. It is possible that the presence of homeowners and their unique investment in the neighborhood would be particularly likely to provide such guardianship---this speculation is consistent with the results I obtain. However, I do not have the data to test this question explicitly and thus leave it to future research.

[38] I use the prefix to distinguish between household level hypotheses (HH) and aggregate-level hypotheses (A).

instance, rents and home values will increase in the neighborhood. If this household is renting, the higher rent will induce them to move out of the neighborhood and into another cell E neighborhood. However, if they own their home, they will reap the benefits of this change by remaining in a more desirable neighborhood than they could otherwise afford.[39] Thus, we see evidence of heterogeneity in who chooses to move in response to an increase in crime. Note that this leads to an asymmetric hypothesis where it is only decreasing crime rates that will bring about a change in the tenure status of neighborhood residents.

Hypothesis HH-3: If the crime rate decreases in a neighborhood, renters will be more likely to move out of the neighborhood.

Race as a Substitute for Income

While the model thus far only considers a household's income level as a constraint on access to desirable neighborhoods, I next take into account the possibility that access to some neighborhoods is circumscribed for some racial/ethnic groups, as suggested by much prior literature (Cutler, Glaeser, and Vigdor 1999; Kain and Quigley 1975; Rosenbaum 1994; South and Crowder 1997a; South and Deane 1993).[40] For instance, a study using the Panel

[39] To the extent that property taxes are based on housing values, an increase in values in a neighborhood will increase a household's housing costs through this increase in taxes due to the higher value of the home. However, this likely would be a small amount relative to the actual home value increase, and therefore likely would have minimal effect on mobility decisions. A possible exception to this would be households on a fixed income. However, the push to change the structure of property taxes—such as the Prop 13 movement in California—can ameliorate this, as can recent developments in reverse mortgages which allow utilizing this increased equity to pay for the increased tax rates.

[40] An alternative possibility is that households simply prefer to live in areas that are ethnically homogeneous. However, such a simple selection model would imply no changes to the model proposed here: An area with an average amount of crime and households of an average income level of one racial/ethnic group would simply transform into a similar such neighborhood composed of households of another racial/ethnic group. There is no reason to then expect an increase in the level of crime in the neighborhood. Thus, while Schelling-type (1978) tipping models are useful for explaining the ethnic transformation of a neighborhood, they have no implications

Study of Income Dynamics (PSID) found that among those who moved out of a poor neighborhood, African-Americans were less likely to move into a nonpoor tract, even controlling for income (South and Crowder 1997a). African-Americans may have fewer neighborhoods to choose from when making a move for several reasons. This can occur simply due to preferences if most African-Americans are unwilling to move into a neighborhood dominated by all whites (Farley, Steeh, Krysan, Jackson, and Reeves 1994). On the other hand, gatekeepers can have strong effects. Considerable evidence suggests that real estate agents may steer potential tenants towards particular neighborhoods (La Gory and Pipkin 1981). Likewise, gatekeepers can reduce access: a phone study found that speaking in a black English vernacular reduced the chances of being directed to a rental unit (Fischer and Massey 2004). I now briefly work through the implications of this added complexity in the model.

If a racial/ethnic group is systematically denied entry to more desirable neighborhoods, they will be clustered in cells A, B, F, and possibly C. That is, low-income members of this group will be clustered in high crime areas in cell A, as expected. However, since average income members are systematically denied access to average crime neighborhoods, they will be clustered in the off-diagonal cell B with high crime. And high income members of this group will be denied access to the low-crime neighborhoods in cell I and instead have to locate in the average crime neighborhoods of cell F or even the high crime cell C. One implication of this is that this minority group will live in higher crime neighborhoods simply due to this forced location in less desirable neighborhoods. Thus, past research suggesting a positive causal relationship between some racial/ethnic groups and the

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for the model developed here. Instead, my model relies on systematic restriction of access to neighborhoods for a particular racial/ethnic group.

crime rate may have the causal direction reversed (Crutchfield 1989; Gyimah-Brempong 2001; Krivo and Peterson 1996; McNulty 2001; Ouimet 2000; Peterson, Krivo, and Harris 2000; Roncek 1981).

Hypothesis HH-5: Households of minority groups are more likely to reside in high crime neighborhoods.

A limitation of this hypothesis is that it is also consistent with a model where the presence of minority groups increases crime. Therefore, a dynamic hypothesis is needed. Indeed, there are dynamic implications of this model: consider a cell E neighborhood occupied entirely by white households. With a rise in the crime rate, the simpler form of this model predicts that lower-income whites would replace households that left the neighborhood, transforming this into a cell A neighborhood. However, this added axiom suggests that an alternative possibility is that middle-income minority households who lack access to other neighborhoods will replace these households, transforming this into a cell B neighborhood.

Hypothesis HH-6: Neighborhoods with increasing crime rates will have an influx of minority group households (controlling for an increase in low-income households).

Collective Action to Reduce Crime

Up to this point, I have treated the level of crime in a neighborhood as exogenous to the model: households simply take the level of crime as given and are unable to affect it. However, a key assumption of the social disorganization model is that the banding together of residents in a neighborhood through informal networks and voluntary organizations can reduce the amount of crime (Crenshaw and St. John 1989; Friedman 1998; Guest and

Oropesa 1984; Taub, Taylor, and Dunham 1984). These informal networks provide guardianship capabilities in which criminal offenders are dissuaded by the presence of these "watchful eyes," while voluntary organizations minimize crime by providing communication among residents, facilitating response when problems arise and by providing legitimate activities to otherwise potential offenders.

Since it is always in the interest of residents to reduce the amount of crime in their neighborhood, the question becomes why isn't this *always* done? This is the classic collective action problem: it is in the interest of all in the neighborhood to have their neighbors provide guardianship activities without themselves actually having to providing it (Olson 1971). Note that this implies that time and effort is required to provide this informal social control. This then raises the question: who will provide this guardianship?

One answer to who will provide this guardianship is that there must at least be a *possibility* of reaping the benefits of an improving neighborhood. This suggests that homeownership status may be particularly important: while renters are generally less invested in the neighborhood due to their more temporary status, the fact that they cannot reap the economic benefits of an improving neighborhood should make them particularly unwilling to engage in efforts to reduce the amount of crime. That is, any reduction in the neighborhood crime rate should simply translate into higher rents, inducing the household to leave the neighborhood for one with lower rents and the previous level of crime.[41] On the other hand, homeowners and landlords would reap the benefits of a lowered crime rate, as it

[41] While it is possible that increasing income levels of renters would allow them to remain in such transforming neighborhoods, they would still have little reason to engage in these crime deterrent behaviors. That is, a dominant strategy for renters would be to simply use their higher levels of income to move to a more desirable, low crime, neighborhood rather than spending time and effort to reduce the rate of crime in their current neighborhood. Thus, the ability to reap the benefits of such effort is key in the model.

increases their home value without increasing their housing costs.[42] These observations are consistent with past research showing the importance of homeownership as a determinant of involvement in the neighborhood through such activity as participation in neighborhood associations (Oliver 1984; Taub, Surgeon, Lindholm, Otti, and Bridges 1977) and knowing one's neighbors (Hunter 1975; Logan and Spitze 1994). Consistent with this, cross-sectional studies have found a negative relationship between the percentage of homeowners in a neighborhood and the rate of crime (Chilton 1964; Gyimah-Brempong 2001; Krivo and Peterson 1996; Smith, Frazee, and Davison 2000).

Hypothesis A-4: Increasing the percentage of homeowners in a higher crime neighborhood will decrease the crime rate.

A second answer to who will provide this guardianship is that joining these voluntary organizations implies a time commitment. Thus, when is it most cost-effective for households to engage in such behavior to reduce the amount of crime in the neighborhood? Given that associating with others is an important component of providing this public good of guardianship, reducing the cost of *association in general* enhances the ability to provide this public service. If households are willing to associate with other neighbors independent of any provision of public safety, they will perceive lower costs for forming such associations to provide public safety. To the extent that increasing length of residence increases the number of neighbors households know, this greater level of general association should ease the provision of informal social control. Indeed, there is considerable evidence that length of residence is positively related to the amount of neighboring or number of

[42] To the extent that property taxes are based on housing values, an increase in values in a neighborhood will increase a household's housing costs through this increase in taxes due to the higher value of the home. However, this likely would be a small amount relative to the actual home value increase, and therefore likely would have minimal deterrent effect on a household's decision to provide this public good of safety to the neighborhood.

neighbors known (Adams 1992; Bolan 1997; Campbell and Lee 1992; Connerly and Marans 1985; Logan and Spitze 1994; Sampson 1988; Sampson 1991). In addition, multilevel studies have found that overall residential stability in the neighborhood increases the number of neighbors known above and beyond this individual-level effect (Connerly and Marans 1985; Logan and Spitze 1994; Sampson 1988; Sampson 1991).[43]

Hypothesis A-5: Areas with greater length of residence will be more willing to engage in guardianship behavior and hence have a lower rate of crime.

In addition, past research has suggested that the amount of social distance between households reduces the possibility of association in general, and therefore should reduce the number of network ties and provision of social control. While social distance can be measured along a number of social dimensions, research in the twentieth century has often focused exclusively on the dimension of racial/ethnic differences; indeed, many "social distance" measures are synonymous with racial/ethnic difference (Aldrich et al. 1985; Bogardus 1947; Jargowsky 1996; Jones 1991; Payne, York, and Fagan 1974; Rosenbaum 1992). A long line of research showing a strong relationship between racial/ethnic differences and various outcomes supports this viewpoint. For instance, empirical evidence suggests that the social distance created by ethnic differences decreases the number of neighbors individuals know (Connerly and Marans 1985; Rountree and Warner 1999; Warner and Rountree 1997), neighborhood satisfaction (Adams 1992; Connerly and Marans 1985; Harris 2001), and community attachment (Connerly and Marans 1985; Sampson 1991). Researchers have also consistently found a positive association between ethnic heterogeneity and crime rates in neighborhoods (Bellair 1997; Roncek and Maier 1991;

[43] While one study found non-significant effects for neighborhood stability and ethnic heterogeneity on neighboring (Adams 1992), it is likely that such lack of findings is due to the crude construction of these measures (each were simple dichotomies).

Rountree and Warner 1999; Sampson and Groves 1989; Smith, Frazee, and Davison 2000; Warner and Pierce 1993; Warner and Rountree 1997).[44]

Hypothesis A-6: Areas with less social distance as measured by racial/ethnic heterogeneity will be more willing to engage in guardianship behavior and hence have a lower rate of crime.

Summary

In times of neighborhood stress, households can choose different possible responses based on the principles of exercising "voice" or "exit" (Hirschman 1970; Lyons and Lowery 1986). Thus, when a neighborhood begins experiencing more crime households confront the following choices: 1) move away; 2) turn to informal networks and voluntary organizations to address problems; 3) fail to recognize the problem; 4) simply retreat from social life and allow the crime rate to rise. The first choice is "exit," the second expresses "voice," the third is a form of "loyalty," while the fourth is "neglect" (Lyons and Lowery 1986). Note that the social disorganization model generally focuses on choices two and four. The model I develop here suggests also considering choice one. While some working with the social disorganization model have also suggested that households may choose to leave a community

[44] I focus on these household characteristics since their predicted effect on providing informal social control is straightforward. Other measures are less clear-cut. For instance, some might argue that those with children or greater income would have higher opportunity costs and thus provide less informal social control. However, a counter argument is that those with lower income also have fewer civic skills, and these limited skills actually raise their costs (Oliver 1984). Indeed, some empirical evidence suggests that those with higher income and education are more likely to participate in most civic activism (Miner and Tolnay 1998; Oliver 2000; Oliver 1984). And while the presence of children likely limits the biographical availability to volunteer time, children may also increase involvement by increasing parents' interest in neighborhood safety. Moving may be less desirable for such households given the evidence that mobility is related to poorer school performance of children. Additionally, evidence suggests that presence of children increases the number of neighbors known, which should also ease participation. These offsetting effects leave it an empirical question whether the presence of children increases involvement, and studies often find a null effect (Hipp 2003a; Taub et al. 1977; Woldoff 2002).

in trouble (Kasarda and Janowitz 1974), this then poses the question of what characteristics about a neighborhood enable it to discourage households from choosing option one. I explicitly focus on this question here.

Since the theory developed here suggests possible reciprocal relations between household decisions, neighborhood structure, and crime rates, longitudinal data is necessary for disentangling these processes illustrated in Figure 3.1. Employing a double lagged model, I can 1) test whether the level of these three structural factors (residential instability, ethnic heterogeneity, or poverty) at time one affect the level of crime at time two; and 2) simultaneously test whether the level of crime at time one disproportionately affects residential mobility decisions at time two that then change these three structural characteristics. This latter model is illustrated in Figure 3.2, and suggests that household mobility decisions aggregate up to the structural characteristics of neighborhoods. Note the multilevel nature of this conceptual model: while crime at one time point has an effect on crime at the next time point, residential stability at one time point does not directly affect residential stability at the next time point, but rather affects the household's decision to move at the next time point. These household decisions aggregate up to the neighborhood level of residential stability. This latter model tests 1) whether crime increases residential mobility in general, 2) whether minority members are less likely to move, and 3) whether higher income households tend to be replaced by lower income ones.

Data and Methods

I utilized multilevel data for the analyses as I combined household-level data from three waves of the special neighborhood subsample of the national American Housing

Survey (AHS) with census tract contextual data from several other sources. This survey has been used in other studies to view neighborhood satisfaction, residential mobility decisions or housing values (Kiel and Zabel 1997; Lu 1998; Lu 1999a; Lu 1999b; Marullo 1985). A particularly underutilized feature of this survey is the special neighborhood subsample that was conducted in 1985, 1989, and 1993, and has the appealing feature that the eleven closest households on a block were all interviewed. While some studies have used this special neighborhood sample to model household mobility decisions (Ioannides and Zabel 2002), virtually none have used it to create estimates of block-level crime rates. This data set allows me to construct a multilevel model in which households are at level one and the block aggregation of household characteristics is at level two. In addition, through special access to data at the Triangle Census Research Data Center I am able to place these blocks in their respective census tracts. Thus, I am able to include measures aggregated to the census tract, and can test whether the context of the block or the tract has greater effect in my models rather than simply assuming that a particular geographic unit of analysis constitutes the 'neighborhood'.[45]

Data: Dependent Variables

<u>Measuring Residential Mobility</u>

The AHS sampling strategy follows housing units over time, so measuring residential mobility is straightforward.[46] I am able to determine whether the people in the household

[45] There are too few tracts containing multiple blocks to treat the census tract as an additional level in a traditional multilevel framework.

[46] I am unable to determine if the unlikely event of all household members dying between waves. That is, I can determine if one household member died and the other remained; if one household member died and the other then moved then I consider this a migrating household. However, I am not able to determine if the household contained a single household member who died between waves, necessitating selling the property. However,

moved during the four years between the two waves of the sample.[47] I only classify a housing unit as undergoing mobility if all members of the household have left between the two waves.

Measuring Crime

Ideally, we would like to know the actual amount of crime in a neighborhood. However, no perfect measure of this construct exists. While one common research strategy employs official statistics of incidents reported to the police, it is often pointed out that not all incidents are reported to the police. To the extent that such reporting is related to constructs of interest in the model, we will not obtain unbiased estimates of the determinants of crime. A second approach uses victimization surveys. While appealing, this approach is limited in that such data also have recall response biases present (Gove, Hughes, and Geerken 1985), and the relative rarity of experiencing such events requires extensive samples to get reasonable estimates of crime rates in smaller units of analyses such as blocks or neighborhoods. A third approach is to use the assessments of the amount of crime in the neighborhood by residents on the block. While relying on the crime assessment of any single respondent would contain an undesirably large amount of measurement error, utilizing the reports of a number of residents on the block allows constructing a more accurate measure. Such an approach uses the subjective assessments of crime by several AHS respondents on a block to construct a latent variable of common perception of crime (for an example of this strategy in another context, see Mroz, Bollen, Speizer, and Mancini 1999). Sampson,

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these are likely rare events that will not affect the analyses. Given that such households tend to be characterized by older members, I am able to take this possibility into account by controlling for age of household members.

[47] Note that a limitation common to many residential mobility studies is that I do not know whether the household migrated away and then returned. Thus, this measure relatively underestimates overall residential mobility. However, my theoretical interest is only in households that choose to essentially “abandon” the neighborhood. Those who leave and come back within five years are not “abandoning” the neighborhood and are also not changing the social structure of the neighborhood, and hence are not of theoretical concern to me.

Raudenbush and Earls (1997) adopted a similar approach in their study of perceived crime in Chicago.

The AHS asks respondents a series of three questions about the neighborhood (as defined by the respondent): is crime a problem, is it so much of a problem that it's a bother, and is it such a bother that the respondent wishes to move. I combine these responses into a four point response where the respondent either replies "no" to all questions, replies "yes" to one, "yes" to two, or "yes" to all three. The equation with the latent common perception of crime as a predictor is:

$$y_{ik} = \Lambda_1 \eta_k + \varepsilon_{ik} \tag{1}$$

where y_{ik} is the combined four-point response in the AHS regarding the level of crime reported by the *i*-th respondent of *M* respondents in the *k*-th block, η_k is the latent variable of common perception of crime in the block, Λ_1 measures the impact of perceived crime on the respondent's report of crime (since the ordering of respondents in neighborhoods is random, these λ's are constrained equal), and ε_{ik} is a disturbance term (the variances of the ε's can also be constrained equal). To handle the ordinal nature of this measure, I created a polychoric correlation matrix and estimated the model using maximum likelihood in the structural equation modeling software Mplus 3.0. This assumes that these ordinal measures have unobserved continuous measures underlying them that are normally distributed. Such an approach is analogous to simultaneously estimating each individual y_{ik} as an ordered probit equation. I can assess the reliability of these individual reports by viewing the R^2's for each of these equations.

While my measure of subjective crime is conceptually distinct from measures of official crime rates, I did test its relationship with official crime reports on selected metropolitan samples of the AHS for which I had official crime data.[48] In these models in which I used the measure of official crime in a census tract to predict the amount of *perceived* crime in the census tract, I found that this perceived crime is most closely related to *violent* crime. That is, measures of aggravated assault or a sum of all violent crimes consistently explained about 50 percent of the variance in this neighborhood measure of perceived crime. It is notable that such property crimes as burglary and larceny showed very little relationship with this latent variable of common perception of crime, reinforcing that it is largely capturing the effect of *violent* crime.

Finally, I take into account the possibility of systematic bias in responses to the crime question. That is, certain types of people may answer this question differently. I account for this by allowing several demographic measures to have a direct effect on the amount of crime perceived by the respondent. The model then becomes:

$$y_{ik} = \lambda\eta_k + \Gamma X_{ik} + \varepsilon_{ik} \qquad (2)$$

where the previous model has been augmented by X, a matrix of exogenous predictors with values for each individual i_k of I_k individuals in block k, and Γ which shows the effect of these predictors on the subjective assessment. This model is also estimated using Mplus 3.0. The model is identified since the latent variable component has more than three indicators, while the component adding the demographic predictors is exactly identified if the parameters are allowed to vary over time points. I gain additional degrees of freedom by constraining these effects over time points since there is no reason to expect them to change, and because these additional restrictions showed to decrement in fit. I find that in my sample, net of the latent variable, "common perception of crime," homeowners, those who

[48] The results of this analysis are suppressed, awaiting Census Bureau permission to report results. The analysis was conducted on several metropolitan areas in the late 1980s and early to mid 1990s.

are older, and those who have moved into the unit in the last year all perceive less crime in the neighborhood. On the other hand, those with more education and those with greater length of residence perceive more crime in the block. Note that these residents are all assessing the level of crime while living on the exact same block, and yet perceiving differing levels of crime.[49] Taking these perceptual differences into account allows me to obtain a more accurate measure of the level of crime in the neighborhood: failing to do so, I might mistakenly attribute a lower level of crime to, for instance, a neighborhood with many older households and homeowners when in fact the differences were simply due to perceptual differences on the part of the respondents. These effects are incorporated into my full models below.

Data: Independent Variables

Crime Model

My key neighborhood variables are constructed in two manners. The block-level variables are constructed by summing the characteristics of interest of AHS respondents on the block, while the tract-level measures are taken from aggregate census data. I measured neighborhood residential instability as the logged average length of residence (reverse coded by subtracting from 4).[50] To capture the effect of homeownership, I include a measure of the proportion homeowners.

[49] Note that this could occur for many reasons: it is possible that some types of people just perceive more crime. It is also possible that some people take into account a larger geographic area when assessing this question, and therefore this colors their response. It is not my interest to adjudicate these reasons here, but rather I am simply interested in taking this bias into account in my analyses.

[50] I first tested measuring this construct as a latent variable with two indicators: 1) the proportion of residents who have moved into the neighborhood during the last four years (since that is the time period between survey waves), and 2) the logged average length of residence. In a model estimating this residential instability latent

Since the social disorganization model suggests that interaction will be reduced when individuals differ based on racial/ethnic differences, I used a single measure of ethnic heterogeneity to parsimoniously capture this effect. The ethnic heterogeneity (EH) in a neighborhood *k* is represented by an identity based on a Herfindahl index (Gibbs and Martin 1962: 670) of four racial/ethnic groupings[51], and takes the following form:

$$\text{EH}_k = 1 - \sum_{1}^{j=J} G_j^{\,2} \tag{3}$$

where G represents the proportion of the population of ethnic group *j* out of *J* ethnic groups. Subtracting from 1 makes this a measure of heterogeneity. Alternatively, I could include a measure of the percent of each racial/ethnic group and its squared term to capture these nonlinear effects: however, given that I have no theoretical reason to expect that the actual proportions of each group matter beyond their relative proportion as captured by the Herfindahl index, I adopt this more parsimonious measure. In this sample of four racial/ethnic groups, this variable can range from 0 to .75.

Finally, since the social disorganization model suggests that neighborhoods with a greater percentage of residents in poverty will have greater levels of crime due to their inability to obtain resources from the larger community, I included a measure of the percent of the block or tract with income at or below 125% of the federal poverty level. I calculated

variable at the two time points (and allowing the two time points to covary), I found that the R^2 for the logged average length of residence variable was essentially 1. This suggests this variable is a nearly perfect measure of this construct, which makes intuitive sense since one would expect residential stability to be some mathematical function of the average length of residence in the neighborhood (in this case, the mathematical function is a natural log transformation). Therefore I use it alone in the analysis since models including this latent variable had estimation difficulties.

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

this based on household income and the age and number of residents in the household, based on federal guidelines for each of the sample years.[52]

I included several additional measures to minimize the possibility of spurious results. To capture socio-economic status, I followed past convention in measuring education as the percentage in the block or tract with at least a bachelor's degree. Since youth are more likely to be involved in delinquent activity, I included a measure of the percentage of the population between 15 and 29 years of age. To capture the effect of broken families that might reduce oversight capability, I included a measure of the percentage of families that are single parent households.[53] To capture crowding, I included a measure of the percentage of households living in crowded conditions (defined as having more than one person per room). Finally, I included a measure of the proportion of housing units that are occupied.

Residential mobility Model

In the model predicting residential mobility of individual households, I included measures at both the household level and the neighborhood level. I included a number of household-level controls that past studies have shown are important for mobility decisions. These variables view three key perspectives in predicting mobility decisions. First is the notion that life course dictates decisions to move (McAuley and Nutty 1982; Rossi 1955). I accounted for this by including measures of the age of the household head, the presence of

[52] This information was obtained from the U.S. Census Bureau website. For instance, information on poverty thresholds for 1985 can be obtained at http://www.census.gov/hhes/poverty/threshld/thresh85.html.

[53] Similar to the footnote above for the residential instability measure, I tested a latent variable model for broken families in the neighborhood with two indicators at each of the two time points: 1) the percentage of families that are divorced, and 2) the percentage of families that are single parent households. While showing good fit, in these models the R^2 for the percent single parent families variable was essentially 1. This suggests this measure is accurately capturing this construct, which makes intuitive sense theorists have hypothesized that it is the lack of parent figures that is important for the construct of broken households (and thus the information provided by the percent divorced variable is not necessary). Therefore I use this observed measure of single parent families rather than the latent variable in these analyses.

children at various ages (0 to 5, 6 to 12, and 13 to 18), marital status, and persons per room in the household (presuming this increases the desire to move). Second, is the notion that sunk costs in a housing unit will affect decisions to move (Rossi 1955). I accounted for this by including measures of length of residence and whether or not the household owns the home. Third, while Speare (1974) suggested that dissatisfaction will lead to mobility decisions, more recent work argues that one must have the resources to act upon such desires (Landale and Guest 1985). To measure the existence of opportunities, I included measures of household income, education level of the head of household, an indicator of whether the household is in poverty, and the race of the household (white, African-American, Latino, and other).[54]

I also included several neighborhood-level predictors in the residential mobility model. Since the presence of nearby vacant units may make a neighborhood less desirable and thus increase mobility, I included the percentage of vacant units. Since the presence of over-crowding may also make a neighborhood less desirable, I included the percentage of households living in crowded conditions—following convention I measured this as households in which the ratio of persons to rooms was greater than one. The presence of homeowners may indicate a degree of stability in the area and hence be desirable, so I included the percentage homeowners. Likewise, the three key predictors of crime: poverty ethnic heterogeneity, and residential instability may affect mobility decisions, so I included the three measures of these constructs defined above. Finally, since these blocks are a random sample of urban areas in the United States, I take into account the different characteristics of the metro area in which the block is located with a measure of percent

[54] There are too few Asian-Americans in this AHS sample to perform meaningful analyses. Therefore, they are included in the 'other' category.

urban in the county.[55] I list the summary statistics of the variables used in the analyses in Table 3.2.[56]

Methodology

My key focus is on estimating the reciprocal relationship between the crime rate and residential mobility decisions. Given that the relationship between changing crime rates and mobility decisions are probably not instantaneous, a lag model is appropriate. Thus, the model specifies that the crime rate at time one causes mobility within the next four years, while residential instability, ethnic heterogeneity, and poverty at time one affect the crime rate four years later.

This implies a model with two equations. First, there are several determinants of the individual household's decision to leave a neighborhood:

$$y_{ik\,t+1} = B\eta_{k\,t} + \Gamma X_{ikt} + \Omega Z_{kt} + \varepsilon_{ikt} \quad (4)$$

where I am modeling the probability that the dichotomous measure $y_{ik\,t+1}$ equals 1 for a household choosing to move at the next time point versus not choosing to move, $\eta_{k\,t}$ is the crime rate at time *t* while the B matrix contains its effect on the residential mobility decision, X_{ikt} is a matrix of individual-level predictors for individual *i* at time point *t* whose effect on moving is contained in the vector of Γ parameters, and Z_{kt} is a matrix of measures for neighborhood *k* at time point *t* whose effect on moving is contained in the Ω vector. To

[55] The Census Bureau defines urban areas as a central city and its surrounding urban fringe that together have a population of at least 50,000 with a population density of at least 1,000 people per square mile (Hadden and Leger 1990).

[56] Research has also found that the recent occurrence of certain events has a strong impact on mobility decisions. In particular, a recent change in marital status or in employment status affects mobility decisions. However, since these events have a fairly quick effect on mobility decisions, I am unable to take these into account here due to the length of time between survey waves.

handle the dichotomous nature of y_{ik}, and the ordinal nature of the crime measure, I created a polychoric correlation matrix and simultaneously estimated the full model using maximum likelihood in the structural equation modeling software Mplus 3.0. To take into account the clustering of respondents on blocks, I used the Huber-White correction for the standard errors.[57] I also allowed for autocorrelation between the disturbances of this residential mobility equation over time periods.

For the second equation, the crime rate in a community is a function of residential stability, ethnic heterogeneity, and poverty as well as several other factors:

(5) $$\eta_{k\,t+1} = K_k + \beta_1 S_{kt} + \beta_2 EH_{kt} + \beta_3 P_{kt} + \Gamma X_{kt} + \zeta_{kt}$$

where $\eta_{k\,t+1}$ is the crime rate in neighborhood k at time point $t+1$,[58] K_k is an intercept term, β_1 is the effect of the residential stability at time t (S_{kt}) on the crime rate, β_2 is the effect of ethnic heterogeneity at time t (EH_{kt}) on the crime rate, β_3 is the effect of poverty (P_{kt}) at time t on the crime rate, Γ is a vector of parameters showing the effects of various measures in the X_{kt} matrix for neighborhood k at time point t, and ζ_k is a disturbance term for each neighborhood. In this model, β_1, β_2 and β_3 are the crucial tests of the social disorganization theory, which predicts that each will have a positive effect on the crime rate in the future. Note that this equation is at the level of neighborhoods. In the full model I allow for autocorrelation of these disturbances (ζ_{kt}) over time periods. I also freely estimate the correlation between the disturbances of the crime equation (ζ_{kt}) and the residential mobility

[57] Correcting the standard errors resulted in only minor differences since there is little evidence of clustering for this outcome. For instance, while the intra-class correlation for a model treating the outcome as continuous and not including any covariates is .12, this falls to .02 when including the full model specification.

[58] In my first sub-sample, this is measured as the crime rate in the tract reported by the local police department. In the second sub-sample, this is either the crime rate in the tract or else the crime rate for the entire city. In the third sub-sample, this is the latent variable of perceived crime constructed from AHS respondents.

equation (ε_{ikt}) at the same time point, in case omitted variables from each of these equations induce such a correlation.

Finally, to determine who is moving into a neighborhood I tested additional models on a subsample of the housing units that changed occupants between survey waves. Observe that neighborhood change can occur in two fashions: 1) the household itself can change, or 2) the household moves out and is replaced by one with different characteristics.[59] That is, even if a household moves little neighborhood change will occur if one similar on all characteristics replaces it. In such an instance, the only structural change in the neighborhood would be the increase in the residential instability measure due to this new household. While the previous residential mobility model explores the characteristics of households that choose to *leave* a neighborhood, these models then ask whether they are *replaced* by households that differ along three key dimensions: race, poverty status, and ownership status. Change in these characteristics in this second step of the process is necessary to effect change in the neighborhood's structural characteristics. Thus, in these models I am not interested in the effect crime has on households *currently* living in the neighborhood, but rather am interested in the characteristics of households that choose to *move into* the neighborhood. The outcome is an indicator of the new household's characteristics at the second time point: for instance, in the model testing for an influx of poverty households, the outcome measure is an indicator of whether or not the new residents are now in poverty. This equation is:

(6) $$y_{ik\,t+1} = \beta_y y_{ik\,t} + B\eta_{k\,t} + \beta_{y_\eta}\eta_{k\,t} y_{ik\,t} + \eta_{k\,t} + \Gamma X_{ikt} + \Omega Z_{kt} + \varepsilon_{ikt}$$

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[59] A separate question would focus on #1: whether the rate of crime affects the change in a household. In this instance, it is possible that higher rates of crime affect whether the household falls into poverty or becomes an owner while staying in the same residence. While interesting, this question is beyond the scope of this research project.

where all terms are as defined previously, $y_{ik\,t}$ is the characteristic of interest at the current time point that has a β_y effect on the construct at the next time point, and $\eta_{k\,t}y_{ik\,t}$ is the interaction of crime and *y* at the current time point which has a β_{y_η} effect on y at the next time point.[60] These models were also estimated in Mplus 3.0 using the polychoric correlation matrix, and I again accounted for clustering using robust standard errors.

Results of structural equation models

Neighborhood level model of crime

While the full model simultaneously takes into account the reciprocal effects of household migration decisions and crime rates, I begin by focusing on the equation with neighborhood perceived crime as an outcome. This equation mirrors past literature in focusing on the effects of neighborhood structural characteristics on crime rates. However, an important difference is the dynamic nature of this model: here I am looking at the relationship between neighborhood structural characteristics at one point in time and the level of perceived crime four years later, controlling for neighborhood perceived crime at the first time point. Thus, I am using a requirement of temporal precedence for determining causal relationships. Note also that in this model I am taking into account the possible bias of these household responses: though not a primary concern of the analyses, Table 3.3 presents the coefficients for the effects of the household's characteristics on their perception of crime. For instance, the positive coefficient for length of residence in this model shows that those

[60] Since crime is a latent variable, I accomplish this by adopting the Kenny and Judd (1984) approach of creating a new latent variable whose indicators are products of the race of the household and the reported level of crime. That is, for each of the eleven households on the block, I create a new measure that multiplies the dichotomous measure of the household's race by their report of the level of crime. Each of these eleven variables are used as indicators of the latent variable representing this interaction of crime and race. While this approach can create additional non-normality through the interaction of a continuous measure and a dichotomous one, I use robust standard errors in making inferences.

who have lived longer in their unit perceive more crime than their neighbors when viewing the same block.

In the equation in model 1 of Table 3.4, there is no evidence that residential stability has a positive effect on perceived crime. Thus, there is no evidence here for hypothesis A-5 that increased stability in a neighborhood will increase contact among neighbors and thus reduce crime. This is the case regardless of whether residential instability is measured at the level of the block or the census tract. In fact, residential instability when measured at the block level actually has a modest, though unexpected, negative relationship with perceived crime four years later. On the other hand, in support of hypothesis A-4, we see that the percentage of homeowners on the block has a strong negative effect on the amount of neighborhood perceived crime four years later. A one standard deviation increase in the percentage homeowners in a block results in an expected .145 standard deviation decrease in perceived neighborhood crime four years later.

It is informative to note the differing effects of these two measures, especially given that researchers commonly employ exploratory factor analysis and create a factor labeled "residential stability" that combines the percentage of new households reverse coded and the percentage of home owners (Morenoff, Sampson, and Raudenbush 2001; Peterson, Krivo, and Harris 2000; Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997). This sample makes clear that such an approach can obscure the unique effects these two measures may have on crime. While past research has shown that home owners and longer term residents are more likely to know their neighbors (see, for instance Adams 1992; Logan and Spitze 1994; Sampson 1988; Sampson 1991), and thus plausibly should reduce the rate of crime through various social control mechanisms, it appears that, consistent with the model I have proposed, the instrumental interests homeownership uniquely engenders may be particularly important for fostering an attachment to the local block that results in crime reducing activity.[61] It is interesting to note that this effect appears to be particularly localized, as a model using the percent homeowners in the *tract* did not show a significant effect. This suggests that this mechanism requires that these owners are geographically close enough to watch out for each other.

In this same model we also see strong evidence that the level of ethnic heterogeneity in a neighborhood leads to higher rates of crime four years later. This is consistent with hypothesis A-6 that increased social distance between residents will reduce interaction and hence reduce the ability and willingness to engage in crime deterrent behavior. In contrast with the effect of homeownership, which worked at the geographical micro scale of the *block*, ethnic heterogeneity has an even stronger effect on perceived neighborhood crime four years later when it is measured at the level of the census *tract*. That is, while ethnic heterogeneity on the local block apparently affects interaction, increased ethnic heterogeneity in the larger surrounding area has an even stronger effect, suggesting that the importance of such potential ties is not limited to the local block. This points out the limitation of research measuring ethnic heterogeneity as a linear effect of race (see, for instance Crutchfield 1989; Krivo and Peterson 1996; Peterson, Krivo, and Harris 2000; Roncek 1981). The same limitation occurs in research utilizing an exploratory factor strategy and including the

[61] On the other hand, it is interesting to note that most of these studies only include one of these measures in their models. And studies that do include both frequently find one or both are insignificant (see, for instance Campbell and Lee 1992; Hunter 1975; Woldoff 2002)

percentage nonwhite linearly in a factor solution labeled “disadvantage” (see, for instance Bellair 2000; Lipton and Gruenewald 2002).[62]

Rather than including a factor score of disadvantage, I have included the third major construct of the social disorganization model as a single measure of poverty, and I find that this parsimonious measure has a strong positive effect on neighborhood perceived crime four years later. Thus, while a long line of literature has shown a positive contemporaneous relationship between poverty and crime, we see evidence of temporal precedence in which higher levels of poverty lead to higher block-level perceived crime four years later. This is consistent with the social disorganization perspective that such neighborhoods lack the resources and the ability to obtain resources from the larger community to combat crime. It is also notable that while the percentage of broken families is often included in factor scores of disadvantage, the measure of percent single parent familes is not significant in these longitudinal models.[63] Additionally, in subsidiary analyses I estimated models in which I included a factor score combining measures commonly used in measures of disadvantage: the percent in poverty, median income, percent with a bachelor’s degree, percent divorced families, and percent single parent families. The results with this measure were essentially identical to those for poverty in Table 3.4, suggesting that the key construct being tapped in this factor is poverty whereas the other measures appear to add little important information for predicting crime rates.

[62] While including the percent non-white nonlinearly is a reasonable approximation, it is still preferable to use the ethnic heterogeneity measure that I use here since there is reason to suspect that heterogeneity among non-white groups will have a similar inhibiting effect on interaction and hence crime.

[63] This result also highlights the importance of performing longitudinal tests. In subsidiary analyses I estimated the crime equation as a cross-sectional model and found that both poverty and percent divorced were positively associated with contemporaneous crime. The longitudinal analyses highlights that poverty is more important for generating long-term effects on crime.

Household level model of residential mobility

Given the evidence that certain structural characteristics appear to lead to higher perceived crime four years later, I next turn to my household level model of residential mobility which attempts to explain the generation of these structural characteristics. I begin by asking whether there is evidence in this sample that households indeed prefer to avoid neighborhoods with more crime. The full simultaneous model shows evidence consistent with this intuitive notion: in model 2 of Table 3.4 we see that higher rates of crime increase the probability of moving. For instance, while the overall probability of moving in this sample is .388, a one-unit increase in the common perception of crime increases this probability to .425, a 9.5 percent increase.

Note that this effect of crime on mobility is net of several other measures commonly associated with mobility decisions. Consistent with past studies, we see that the household measures of homeownership and greater length of residence are associated with reduced likelihood of residential mobility, while those in more crowded conditions or with children less than school age are more likely to move. There are also ecological effects present in this model: blocks with a greater number of vacant units or with greater residential mobility in the previous time period increase the likelihood of the household moving by the next period. Thus, instability has a reinforcing effect upon itself.

Recall that an implication of this desire to avoid neighborhoods with crime is that an increase in the rate of crime should result in a decrease in home values and rents. I test this in subsidiary analysis with a fixed effects model in which I cluster at the block level and view the relationship between the change in perceived crime and logged average rent or logged average home values over a four-year period. This model thus takes into account unchanging unobserved characteristics of the blocks, and the logged measures allow interpreting the results as elasticities. In simple models without any additional controls, in support of hypothesis A-1 I find that a one unit increase in the common perception of crime results in a $12,500 decrease in the value of homes and a $52 decrease in the level of rents. These changes are about 13 percent of the mean values of these two outcome measures, and are consistent with the intuitive notion that households prefer neighborhoods with less crime, and thus the reduced demand for housing units in such neighborhoods will lower the rent asked.

Who moves out?

Given this evidence that households prefer to avoid neighborhoods with higher rates of crime, I next ask whether certain characteristics of households explains who will move out. I first test whether those with fewer economic resources are less likely to migrate from a high crime neighborhood by modifying the main model to include an interaction between the crime rate and household level of poverty. Recall that hypothesis HH-1 proposes that those with less income or in poverty will be least likely to move out of a high crime neighborhood. There was no support for this hypothesis, as the nonsignificant interaction term in model 1 in Table 3.5 illustrates that crime has an equally positive effect on mobility decisions for households in this sample regardless of their economic resources.

My household level model also suggests that owners and renters will respond differently to crime. While hypothesis HH-3 suggests that renters are more likely to leave the neighborhood if crime decreases, this was not supported in the data. Including an interaction between ownership status and the amount of neighborhood perceived crime in model 2 in Table 3.5 showed no significant effects: ownership status does not differentiate households in their desire to leave neighborhoods with higher rates of crime. To test the asymmetry of this hypothesis, I also estimated models in which I included either 1) an indicator of whether or not crime had decreased in the previous period of time, or 2) an interaction between this indicator of a decrease in crime and the actual change in crime. Neither of these models found any support for this hypothesis (results not shown).

I next tested whether nonwhite households have constraints on their mobility decisions that inhibit their ability to leave high crime neighborhoods. It is clear in simple cross-sectional t-tests that non-whites live in neighborhoods with greater levels of perceived crime: in support of hypothesis HH-5, in the first two waves of this sample the average level of crime reported by whites based on this four-point scale is .46, while Latino and other race households report .71 and African-American households report .84.[64] But why is this the case? If it is indeed through mobility decisions, there are two possible ways this could occur: 1) non-whites could be less sensitive than whites in choosing to *leave* neighborhoods with higher rates of crime, or 2) non-whites could be less sensitive than whites in choosing to *move into* neighborhoods with higher rates of crime. I tested the first possibility by including an interaction term between the race of the household and the perceived level of crime in the neighborhood. As seen in models 3 and 4 in Table 3.5, I find no evidence that whites or African-Americans respond to crime any differently than others when it comes to mobility decisions. The insignificant interaction effects in these models suggest that all households prefer to leave neighborhoods with higher rates of crime. This suggests that potential discrimination is not limiting the ability of minority households to *leave* high crime neighborhoods.

[64] The differences between whites and all other groups are all significant at $p < .01$.

Who moves in?

Although I found no evidence that the racial/ethnic composition or the level of economic resources of the household affect who is most likely to *leave* the neighborhood, I next asked about the characteristics of those who are *moving into* the neighborhood. I tested this by estimating a model on the subsample of households that experienced a change in residents between the two waves. As can be seen in model 1 in Table 3.6, while hypothesis HH-2 suggested a transition in housing occupants from non-poverty to poverty status would be more likely in high crime neighborhoods, the effect in this model is indeed positive, but not significant, when controlling for the other effects in this model. We do see a strong stasis effect in which blocks with lower average income and higher levels of poverty increase the likelihood that the new household will be in poverty. Model 2 performs a similar estimation, but tests whether the new household will be a homeowner. This model also shows a strong stasis effect where the ownership status of a housing unit tends to remain unchanged when a change in residents occurs, and that blocks with a higher proportion of homeowners greatly increase the likelihood that the new occupants will be owners. But whereas crime indeed has a negative effect on the likelihood that the new occupants will be owners, the effect is not significant in this model.

On the other hand, we do see evidence that the level of crime plays an important role in the racial/ethnic transition of neighborhoods. Model 3 in Table 3.6 shows that, among the subsample of housing units in which a change in residents occurred, the presence of crime has a negative effect on the probability of the household being white at the second time point. Note that this effect occurs even controlling for the strong stasis effect of white households being more likely to move into housing units occupied by a white household and into blocks with a higher proportion of white residents. We see that the likelihood the new household will be white drops considerably as the proportion of various other races in the block increases. For instance, in a unit in which the household was white at the previous time point and all the other variables were at their mean values, a ten percentage point increase in African-Americans in the block (with a similar reduction in whites) reduces the predicted probability that the new household will be white from .78 to .73. A similar effect is seen as the proportion Latino or other races increases. The effect of the race of the previous residents in the *unit* is even stronger: if the previous residents were African-American instead of white, the predicted probability of the new household being white drops from .78 to .25. Despite these strong same-race preferences, this model shows that the presence of crime has an independent effect: a one-unit increase in the common perception of crime reduces the predicted probability that the new household will be white, on average, from .78 to .71. This reflects the desire, and perhaps ability, of whites to avoid high crime neighborhoods.

But shouldn't other racial/ethnic groups also prefer to avoid high crime neighborhoods? In an analogous model in which the outcome is an indicator of whether the household at time two was African-American I find very different effects, as seen in model 4 in Table 3.6. We again see strong racial/ethnic stasis effects in this model: in a unit in which the household was African-American at the previous time point and all the other variables were at their mean values, a ten percentage point increase in whites in the block (with a similar reduction in African-Americans) reduces the predicted probability that the new household will be African-American from .33 to .25. And if the previous household was white instead of African-American the predicted probability that the new household will be African-American becomes very slight (.04). Nonetheless, we again see that crime influences decisions on where to move. A one-unit increase in neighborhood common perception of crime increases the predicted probability that the new household will be African-American from .33 to .42 (a 27 percent increase).

The story is the same for Latinos, the other minority group tested. While Latinos are most likely to move into units and blocks populated by other Latinos, they are also more likely to move into neighborhoods with a higher common perception of crime, as seen in model 5 of Table 3.6. The predicted probability that the new household will be Latino if the previous household was Latino and all other variables are at their mean value, is .087, but this increases to .119 for a one-unit increase in the common perception of crime (a 37 percent increase). Thus, we see striking evidence here that rather than shunning high crime areas as whites do, Latinos and African-Americans are being funneled into neighborhoods that have higher rates of perceived crime. This is consistent with hypothesis HH-6 that neighborhoods with greater levels of crime will see an influx of minority group households, even controlling for income level.

Conclusion

I have emphasized here the need to conceive of crime and mobility decisions in a dynamic fashion. My findings suggest that past studies failing to take into account the possibility that households can respond to crime in various fashions are failing to capture this dynamic process. Specifically, I proposed a household-level model to explain the mobility decisions of households and showed how it is related to the structural characteristics of neighborhoods that are hypothesized to cause crime. I have suggested that utilizing the accounting framework of Lyons and Lowry (1986) provides insight into the four choices households face in a neighborhood when confronted by a neighborhood problem such as crime. Households can either exit, or else express voice, loyalty, or neglect (EVLN). Understanding when households will respond to crime with each of these expressions is a useful avenue for future research.

The data I have employed here were particularly suited to the tests I wished to perform. By using a longitudinal dataset of blocks nested in tracts, I have been able to avoid the problems of cross-sectional studies by imposing a criterion of temporal precedence on factors of crime. This more stringent test is more appropriate, especially given some of the reciprocal relationships I have proposed. In addition, I have been able to relax the assumption of a single geographic measure of neighborhoods, and tested the effects of my structural characteristics when measured at both the block level and the census tract level.

While past research in the social disorganization model has suggested that residential stability has a causal effect on crime, my theoretical model and my empirical results show that this is a more nuanced relationship than previously conceptualized. Specifically, I showed that households are more likely to choose to move out of a neighborhood if it is characterized by higher rates of crime. This has important implications for past studies testing a cross-sectional relationship between residential stability and crime: the results here suggest that at least some of this relationship travels from crime to residential stability. This suggests that past studies using cross-sectional neighborhood data finding the expected positive relationship between crime and residential instability may have mistakenly attributed all of the causal direction from instability to crime (Heitgerd and Robert J. Bursik 1987; McNulty and Holloway 2000; Warner and Pierce 1993; Warner and Rountree 1997). In addition, my more stringent test of the residential stability hypothesis employing longitudinal data found no relationship between it and perceived crime four years later.

These results also highlight that residential stability and homeownership are distinct constructs. While studies frequently combine these two constructs into a single factor (Morenoff, Sampson, and Raudenbush 2001; Peterson, Krivo, and Harris 2000; Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997), my findings suggest the importance of distinguishing between them. The sunk costs and instrumental interests engendered by homeownership likely reduce the willingness to move at the first sign of trouble in the neighborhood. Indeed, my findings echoed those of past research that homeowners are less willing to move in general. In addition, given that the EVLN model predicts that homeowners are more likely to respond to neighborhood problems with voice—indeed, other evidence suggests that homeowners are more willing to join neighborhood associations when a neighborhood experiences problems such as crime (Gerson, Stueve, and Fischer 1977; Perkins et al. 1990; Skogan 1989; Taylor 1996)—it is not surprising that I found no evidence that homeowners are any more likely than renters to leave a neighborhood with higher rates of crime. This suggests that the instrumental interests of owners may make them more willing to engage in crime reducing behavior when confronted with problems rather than moving at the first sign of difficulty. Consistent with this, I found that the presence of homeowners on a block has a particularly strong inhibiting effect on perceived crime four years later.

It is interesting to note that the relationship I found between the presence of homeowners at one point in time and perceived crime four years later was a particularly localized one as it worked most strongly at the level of the block. This is consistent with the notion that these households are willing to provide watchful eyes on the street for their fellow neighbors. It is also interesting to speculate to what degree this ties in with the larger social movement literature: Chwe (1999) built a model in which collective action behavior was most likely to occur when individuals knew the attitudes of their neighbors and hence how they would behave. That is, one is most likely to provide the public good when one knows that one's neighbor also plans to participate. To the extent that homeowners are acutely aware of the feelings and attitudes of their closest neighbors, this suggests that such a process may also be at work here. This is clearly speculative, but suggests a possible avenue for future research.

I also found that the relationship between race and crime is more nuanced than commonly hypothesized. First, I found evidence that crime can change the racial/ethnic composition of a neighborhood. This does not occur in my sample because whites are any more likely to leave a high crime neighborhood than members of other racial/ethnic group, but rather because whites are less likely *to move into* neighborhoods with higher rates of crime. Thus, just as the transition in businesses in racially changing neighborhoods occurs not because white owners leave faster but because white owners stop coming in (Aldrich 1975), it appears that white homeowners don't leave high crime areas any faster but that white homeowners stop entering the neighborhood. Analogously, I found that Latinos and African-Americans are more likely to move into neighborhoods with higher rates of crime. These findings are consistent with the notion that these minority groups face more constraints in the housing market: indeed, consistent with this hypothesis I found that whites are more likely to move in general than nonwhites, mirroring the findings in older waves of this same dataset (South and Deane 1993). Again, this has important implications for studies viewing the cross-sectional relationship between racial/ethnic composition and crime rates: if crime can cause a change in the racial/ethnic composition, then clearly at least some of this relationship runs in a causal direction contra to past theoretical models. Additionally, I showed that past studies testing a linear relationship between racial/ethnic composition and crime may have been mis-specified: I found in this sample that it is more accurate to characterize this relationship as one between *ethnic heterogeneity* at one point in time and perceived crime four years later. These results are consistent with the theoretical model I have developed here in which the social distance between racial/ethnic groups limits interaction in general, and thus raises the cost of informal and formal organization of crime prevention activities. This effect was particularly robust, regardless of whether I measured ethnic heterogeneity at the local block level or at the level of the census tract. Given the nonlinear relationship of race and crime in this study, this also calls into question the strategy of including a linear measure of race in a factor labeled disadvantage (see, for instance Kubrin and Herting 2003; Morenoff, Sampson, and Raudenbush 2001; Nielsen and Martinez 2003; Sampson and Raudenbush 1999).

This paper has illustrated the advantage of theoretically integrating the criminology literature, the civic activism literature, and the residential segregation literature on residential mobility. Understanding when households will respond to neighborhood problems either through residential mobility decisions or through civic activism aimed at improving the neighborhood is crucial. I have highlighted that the outcome of these decisions are the neighborhood structural characteristics criminologists focus on when explaining the existence of crime in neighborhoods. This approach requires an explicitly multilevel and dynamic model, and highlights that viewing household decisions divorced from the geographic context in which those decisions are made will provide a limited perspective. Perhaps even more importantly, failing to take into account these household decisions in response to such ecological conditions blunts our awareness of neighborhood transformation and the genesis of the neighborhood structural characteristics that many theoretical models take as given.

Tables and Figures

Table 3.1. Theoretical model of households differing by three income levels and neighborhoods differing by three levels of crime

	Low income	Average income	High income
High crime	A	B	C
Average crime	D	E	F
Low crime	G	H	I

Table 3.2. Summary statistics, American Housing Survey (AHS) national non-rural neighbors sub-sample, 1985, 1989, 1993

Block level measures	**Mean**	**SD**	**Min**	**Max**
Proportion Aged 15-29	0.237	0.153	0	1
Proportion with children 0-12 years old	0.533	0.470	0	1
Proportion new households in last four years	0.483	0.249	0	1
Average length of residence, logged	1.786	0.622	0	3.77
Ethnic heterogeneity	0.167	0.200	0	0.74
Proportion in crowded conditions	0.196	0.207	0	1
Proportion divorced	0.142	0.131	0	0.9
Proportion single parent households	0.059	0.104	0	0.82
Average education level (years)	12.703	2.008	3.89	17.64
Proportion home owners	0.535	0.358	0	1
Proportion below 125% of poverty rate	0.203	0.224	0	1
Proportion vacant units in block	0.074	0.147	0	1
Percent white	0.777	0.332	0	1
Percent African-American	0.130	0.282	0	1
Percent Latino	0.081	0.183	0	1
Percent other race	0.006	0.032	0	0.80
Household-level measures				
Moved between waves	0.394	0.489	0	1
Age	48.173	17.204	16	102.6
White	0.659	0.474	0	1
African-American	0.104	0.306	0	1
Latino	0.065	0.246	0	1
Other race	0.004	0.061	0	1
Married	0.448	0.495	0	1
Divorced	0.138	0.345	0	1
Single	0.131	0.337	0	1
Widowed	0.113	0.316	0	1
Children less than 5 years old	0.143	0.351	0	1
Children 6-12 years old	0.156	0.363	0	1
Children 13-18 years old	0.145	0.352	0	1
Education	12.703	3.381	0	18
Income at or below 125% of poverty	0.203	0.402	0	1
Income (in 10,000's of dollars)	3.045	2.726	-1	40
Owner	0.531	0.496	0	1
Persons per room	0.485	0.289	0.07	5
Length of residence (logged)	1.820	1.163	0	4.52
First year in residence	0.169	0.375	0	1
Female	0.293	0.452	0	1
Perceived crime	0.546	0.915	0	3
Perceived crime, logged	0.305	0.474	0	1.39

N = 7,174 households in 649 blocks

Table 3.3. Household-level perception of crime from full structural equation model estimating longitudinal cross-lag models of neighborhood crime and household mobility using the AHS national non-rural neighbors sample, 1985, 1989, 1993

Age	-0.003	**
	-(10.850)	
African-American	-0.063	**
	-(3.630)	
Education	0.010	**
	(8.310)	
Owner	-0.025	**
	-(2.630)	
Length of residence	0.034	**
	(7.750)	
First year in residence	-0.037	**
	-(3.160)	
Female	0.018	**
	(2.750)	
R^2	0.25	

** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). N = 7,144 households in 646 blocks. T-value in parenthesis

Table 3.4. Longitudinal structural equation cross-lag models with dual outcomes of neighborhood crime and household mobility, using the AHS national non-rural neighbors sub-sample, 1985, 1989, 1993

	Common perception of crime		Moved out of unit	
Crime at previous time point	0.7652	**	0.0954	*
	(0.0514)		(0.0393)	
Residential instability	-0.0840	†	0.1760	**
	(0.0429)		(0.0656)	
Ethnic heterogeneity	0.2328	*	-0.0036	
	(0.1022)		(0.1264)	
Proportion below 125% of poverty rate	0.3820	**	-0.2132	
	(0.1361)		(0.1304)	
Proportion home owners	-0.2206	†	0.0538	
	(0.1156)		(0.1929)	
Proportion in crowded conditions	0.2812		-0.2902	
	(0.2555)		(0.3173)	
Proportion vacant units in block	-0.3408	†	0.3712	*
	(0.1837)		(0.1713)	
Proportion Aged 15-29	0.0796			
	(0.1353)			
Proportion with children 0-12 years old	-0.0012		0.1092	
	(0.1014)		(0.1130)	
Single parent female HH's	0.1820			
	(0.1735)			
Proportion with high education	0.0048			
	(0.0192)			

(continued)

	Common perception of crime	Moved out of unit	
Household-level measures			
Age		0.0006	
		(0.0012)	
African-American		-0.2224	*
		(0.1019)	
Latino		-0.1762	*
		(0.0791)	
Other race		-0.7836	**
		(0.2254)	
Divorced		0.2484	**
		(0.0620)	
Single		0.1638	**
		(0.0593)	
Widowed		0.3154	**
		(0.0683)	
Children less than 5 years old		0.1306	**
		(0.0362)	
Children 6-12 years old		0.0306	
		(0.0365)	
Children 13-18 years old		0.0110	
		(0.0375)	
Education		0.0046	
		(0.0088)	
Household income		0.0016	
		(0.0132)	
Owner		-0.5086	**
		(0.0582)	
Persons per room (logged)		0.2936	**
		(0.0870)	
Length of residence (logged)		-0.2076	**
		(0.0243)	
1985 R^2	0.53	0.23	
1989 R^2	0.57	0.23	

Average model fit over five imputations: chi square = 800.4 on 328 df, RMSEA = .014, CFI = .991, TLI = .991, using a weighted least squares with mean and variance adjusted estimator

** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). N = 7,144 households in 646 blocks. Standard errors in parenthesis

Table 3.5. Structural equation models of the effect of block perceived crime on residential mobility out of the housing unit by households of various characteristics, AHS national non-rural neighbors sub-sample, 1985, 1989, 1993

	Outcome: move out of unit, poverty household		Outcome: move out of unit, owner household		Outcome: move out of unit, white household		Outcome: move out of unit, black household	
Block level measures								
Crime at previous time point	0.276	**	0.297	*	0.281		0.228	*
	(2.76)		(2.11)		(1.45)		(2.15)	
Poverty household x crime	-0.023							
	-(0.20)							
Owner household x crime			0.087					
			(0.48)					
White household x crime					0.055			
					(0.26)			
African-American household x crime							0.222	
							(1.01)	

** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). N = 7,637 households in 721 blocks. T-value in parenthesis. Maximum likelihood estimation used.
Models include all covariates included in mobility model in Table 3.

Table 3.6. Structural equation models predicting the characteristics of the new household in the housing unit, using the sub-sample of households that underwent residential mobility, AHS national non-rural neighbors sub-sample, 1985, 1989, 1993

Block level measures	Poverty household in next wave	Owner household in next wave	White household in next wave	Black household in next wave	Latino household in next wave
Crime at previous time point	0.0726	-0.0788	-0.2160 **	0.2330 **	0.1796 *
	(0.0682)	(0.0703)	(0.0636)	(0.0770)	(0.0798)
Proportion new households	-0.0754	0.0204	-0.1042	0.2222	-0.0716
	(0.1458)	(0.1794)	(0.1355)	(0.2064)	(0.2220)
Average household income	-0.1714 **				
	(0.0326)				
Proportion below 125% of poverty rate	0.9920 **	-0.2386	-0.0740	0.2360	-0.2658
	(0.1876)	(0.1949)	(0.1874)	(0.1989)	(0.2041)
Proportion vacant units	-0.3154	0.3712	0.0894	0.0206	-0.8980 **
	(0.2423)	(0.2961)	(0.2163)	(0.2285)	(0.3400)
Proportion African-American	0.1670	0.0172	-1.6750 **		-2.7872 **
	(0.1311)	(0.2142)	(0.1807)		(0.3605)
Proportion white				-2.3008 **	-1.7926 **
				(0.1531)	(0.2463)
Proportion Latino	0.2228	0.1962	-1.8768 **	-2.6334 **	
	(0.1737)	(0.2269)	(0.2440)	(0.2923)	
Proportion other race	0.0944	0.9062 †	-3.2340 **	-5.4858 **	-5.4436 **
	(0.4397)	(0.5249)	(0.6276)	(0.5804)	(0.8766)
Ethnic heterogeneity	0.0094	-0.4368 †	-0.1748	0.3660	1.5304 **
	(0.1509)	(0.2299)	(0.1801)	(0.2237)	(0.2631)
Proportion home owners	0.0738	1.4746 **	0.0376	-0.0702	-0.2466
	(0.1261)	(0.1507)	(0.1285)	(0.1984)	(0.1623)
Proportion in crowded conditions	-0.2136	-0.0410	-0.8028 †	-0.5722	-0.1418
	(0.5311)	(0.4318)	(0.4100)	(0.5306)	(0.4883)
Proportion with children	0.1858 **	-0.0602	0.0394	-0.0626	-0.0086
	(0.0571)	(0.0626)	(0.0563)	(0.0838)	(0.0835)

(continued)

Household level measures	Poverty household in next wave		Owner household in next wave		White household in next wave		Black household in next wave		Latino household in next wave	
Age	0.0004		0.0042	*	0.0048	†	-0.0042		-0.0060	†
	(0.0021)		(0.0021)		(0.0025)		(0.0033)		(0.0031)	
African-American	0.0512		-0.2596	†	-1.4380	**			-0.4914	**
	(0.0855)		(0.1510)		(0.0907)				(0.1543)	
White							-1.3250	**	-0.4006	**
							(0.0851)		(0.0861)	
Latino	0.0140		-0.0120		-1.0980	**	-1.3496	**		
	(0.1075)		(0.1153)		(0.0842)		(0.1619)			
Other race	0.0472		-0.1872		-0.2408		-0.8180	*	-0.0380	
	(0.2768)		(0.2318)		(0.2605)		(0.3882)		(0.3822)	
Divorced	0.0350		-0.0456		0.0192		0.0382		-0.1392	
	(0.0674)		(0.0770)		(0.0661)		(0.0819)		(0.0952)	
Single	-0.0332		-0.1472	†	0.0196		0.0164		-0.1280	
	(0.0729)		(0.0777)		(0.0640)		(0.0831)		(0.0895)	
Widowed	-0.0872		-0.0932		-0.0380		0.0028		0.0830	
	(0.0986)		(0.0923)		(0.0938)		(0.1296)		(0.1498)	
Presence of children 0-5 years old	0.0382		0.0732		0.0314		0.0704		0.0732	
	(0.0400)		(0.0525)		(0.0472)		(0.0630)		(0.0635)	
Presence of children 6-12 years old	0.1062	**	0.0768	†	0.0220		0.0780		0.0484	
	(0.0370)		(0.0455)		(0.0443)		(0.0602)		(0.0524)	
Presence of children 13-18 years old	0.0844	†	0.1136	*	0.0586		0.0164		0.0704	
	(0.0493)		(0.0549)		(0.0570)		(0.0689)		(0.0571)	
Education	-0.0278	**	0.0092		0.0138		-0.0080		-0.0232	*
	(0.0083)		(0.0124)		(0.0107)		(0.0151)		(0.0115)	
Household income	-0.0566	**	0.0248	*	0.0002		-0.0070		-0.0156	
	(0.0179)		(0.0111)		(0.0115)		(0.0208)		(0.0187)	
Income at or below 125% of poverty	-0.0858									
	(0.0542)									
Home owner	-0.4090	**	1.7238	**	0.0640		-0.0806		0.0522	
	(0.0769)		(0.0797)		(0.0823)		(0.1103)		(0.0996)	
Persons per room (logged)	-0.0418		-0.1734		-0.3102	**	-0.2214		-0.0464	
	(0.0958)		(0.1253)		(0.1109)		(0.1669)		(0.1500)	
Length of residence (logged)	-0.0298		-0.0510		-0.0886	**	0.1042	**	0.0026	
	(0.0269)		(0.0380)		(0.0255)		(0.0349)		(0.0379)	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. N = 6,073 households, 743 blocks. Maximum likelihood estimation used.*

Figure 3.1. Three time points- crime and mobility cross-lagged model

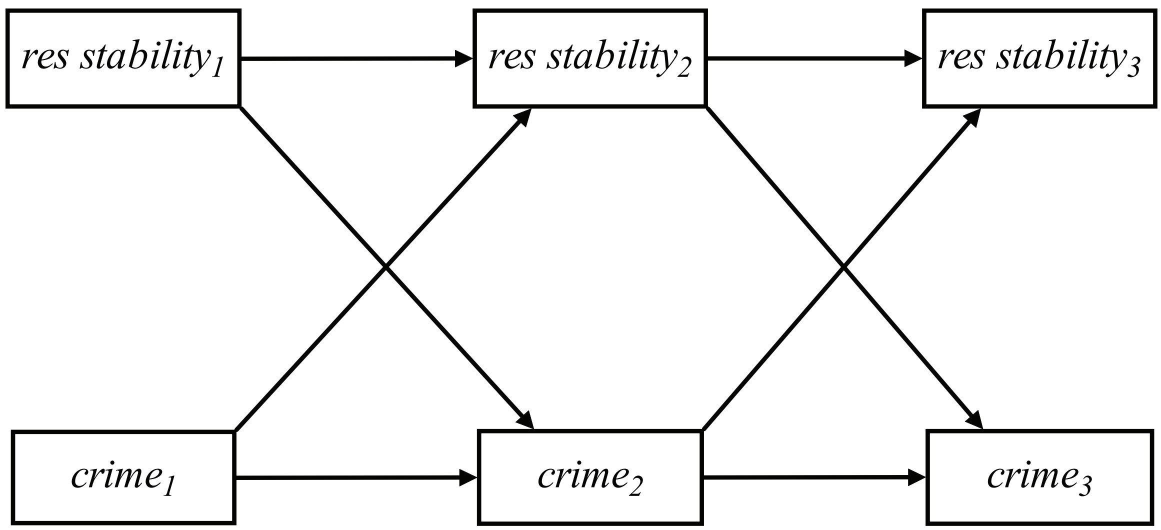
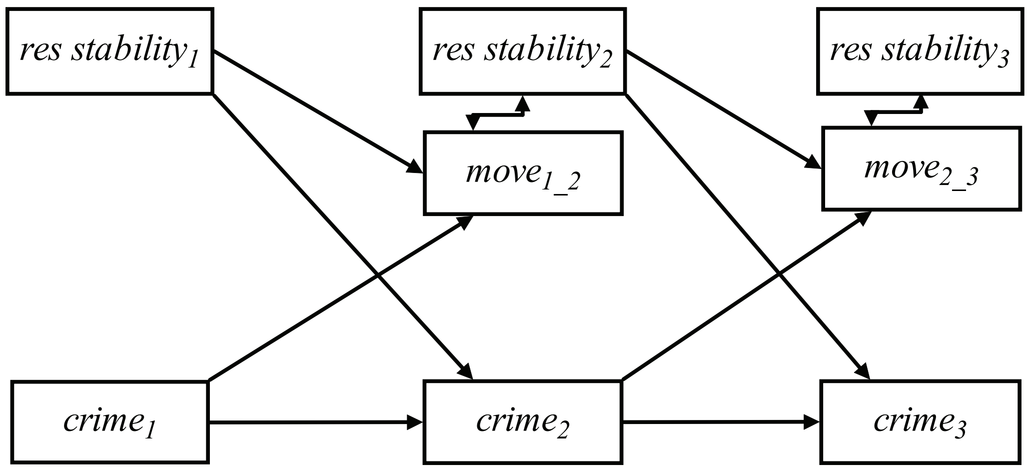


Figure 3.2. Three time points- crime and mobility two-level cross-lagged model



Notes:
Level 1: household; level 2: neighborhood (i.e., tract, block, etc.)
move: (level 1) whether the respondent moved in the two time points (1/0)
crime: (level 2) measured per capita
res stability: (level 2) residential stability in the neighborhood. Past research measures either as:
1) average length of residence
2) % who have lived longer than 5 years in the neighborhood

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

Scholars and the general public both have an acute interest in understanding why some neighborhoods have more crime and disorder than others. A common theme emerging from research studying this question is that the composition of households in a neighborhood plays an important role. In particular, theories suggest that two bedrock concepts of sociology—race and class—play a particularly important role, both in how they are distributed *across* neighborhoods as well as *within* neighborhoods. Most research has focused on testing whether the distribution of race and class *across* neighborhoods affects crime rates. Specifically, studies have tested how the distribution of economic resources across neighborhoods, as measured by income or poverty, or the distribution of racial/ethnic minority members across neighborhoods, as measured by the percent nonwhite, etc., affects neighborhood crime rates. Research has paid less attention to whether the distribution of racial/ethnic groups within neighborhoods affects crime, and almost completely neglected the question of whether the distribution of economic resources in neighborhoods affects crime.

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

As a result, the wave of research testing the importance of inequality and its interaction with racial/ethnic composition in the 1980's and early 1990's used data aggregated to units much larger than neighborhoods: generally, SMSA's, counties, or large cities (often greater than 100,000 population). While some found the expected positive relationship between inequality and crime (Balkwell 1990; Harer and Steffensmeier 1992; Kovandzic, Vieratis, and Yeisley 1998; Ousey 1999), others only found it for certain crime types or units of analysis (Blau and Blau 1982; Land, McCall, and Cohen 1990; Simpson 1985), while yet others found no significant relationship (Chamlin and Cochran 1997; Kposowa, Breault, and Harrison 1995). Likewise, studies testing for possible interaction effects between ethnic heterogeneity and inequality using large units of analysis have had mixed results, with some suggesting that inequality *between* races increases crime rates (Blau and Blau 1982; Blau and Golden 1986; Golden and Messner 1987), others did not find any effects Simpson, 1985 #5029. An alternative strategy proposed for the problem was to focus on race-disaggregated crime types—though still using large units of analysis—and studies adopting this approach found that inequality *within* race was a stronger predictor of crime types (Harer and Steffensmeier 1992; Shihadeh and Ousey 1996). However, given that the mechanisms explaining the relationship between race and class distributions and crime rates require interaction among residents, measuring the distribution of race and class for such a large unit of analysis does not capture the construct of interest. For instance, two *cities* with equal amounts of ethnic heterogeneity can have *neighborhoods* that look considerably different depending on the distribution of the population in the community: the community with a high degree of ethnic segregation will have neighborhoods that are very homogeneous with one racial/ethnic group dominating (and thus the ethnic heterogeneity occurs *across* neighborhoods), while the community with minimal segregation will have a high degree of ethnic heterogeneity *within* the neighborhoods (and little difference in ethnic heterogeneity *across* neighborhoods).[65] I therefore suggest that a more appropriate solution to the problem is to use smaller units of analysis more closely approximating neighborhoods to test these theories.

While the lack of empirical tests of these theories using neighborhood-level data is in part due to the difficulty of collecting neighborhood-level crime data, testing these theories present additional challenges: 1) some of these theories make similar predictions about expected empirical relationships (e.g., both social distance and relative deprivation theory expect to see a positive relationship between general inequality and crime rates), and 2) some also make predictions regarding interactions of ethnic heterogeneity and inequality (e.g., consolidated inequality predicts that inequality *across* racial/ethnic groups will increase crime, while relative deprivation predicts that inequality *within* racial/ethnic groups will increase crime). Regarding the first challenge, a study testing one of these theories and finding the expected relationship would not be able to discern whether the theory of choice

[65] An additional issue for studies measuring these structural characteristics at the level of larger communities is the high degree of collinearity between many of measures induced by such aggregation, making estimation of their separately effects difficult (Land, McCall, and Cohen 1990). Despite the conceptual need to tease apart the effects of these different constructs, it is simply not statistically feasible at such high levels of aggregation (Land, McCall, and Cohen 1990). For instance, it is difficult to parse out the affects of black inequality and poverty rates due to their high correlation rate in samples of highly aggregated units: a study of SMSA's in 1980 found a .80 correlation (Harer and Steffensmeier 1992).

truly explained the relationship, or whether another was responsible. This points out a need to either explicitly test the mechanisms, or to simultaneously consider various theories.

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

In the next section I first briefly introduce the competing theories being considered here. I then consider for each of the inequality and ethnic heterogeneity constructs how the mechanisms proposed by each of these theoretical models sometimes give rise to different predictions when using data measured at the neighborhood level. I follow that by describing the data I will use in the tests. I then present results: first for cross-sectional models, to compare the results to those using a strategy commonly employed when studying neighborhood-level crime, then using fixed effects models that take into account the change in neighborhoods. I conclude by summarizing the results and pointing out implications.

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

I begin by considering the posited mechanisms of inequality and ethnic heterogeneity for six key theoretical models. Table 4.1 lists the theories, showing which constructs they are hypothesized to affect, and the geographic level at which they should work. The relative deprivation model, sometimes referred to as reference group theory (Jasso 1980; Merton 1968), posits that perceived social inequality gives rise to deviant behavior on the part of individuals. That is, individuals compare themselves to others in their "reference group" and respond with deviant behavior if they feel they have an inequitable economic share. The social disorganization model refers to the ability of a neighborhood to have common values that enable maintaining effective social control (Janowitz 1975; Reiss 1951: 196; Sampson and Groves 1989: 777). In this model, social networks, voluntary organizations, and institutions within a community help maintain the social order (Sampson and Groves 1989; Shaw and McKay 1942). Third, the social distance model (Blau 1977; Blau 1987; McPherson and Ranger-Moore 1991; McPherson and Smith-Lovin 1987; Simmel 1955) focuses on explaining social interactions among individuals. In this model, the social statuses individuals have create social distance between individuals that then affects interactions. Thus, it focuses on explaining *who* interacts, whereas the social disorganization model focuses on the *consequences* of those interactions for neighborhood crime rates.

Table 4.1.

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

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

The fourth model I consider is the consolidated inequality model (Blau and Blau 1982), which is a variant of the relative deprivation model in which the combination of economic inequality and the ascribed status of race gives rise to particularly strong feelings of injustice and hence a violent deviant response. Thus, it focuses on inequality *across* races. The group threat model also focuses on inequality across races; however, it posits that when the economic differences between two groups *narrow* members of the *dominant* group will respond through violent behavior (Blumer 1958; Bobo and Hutchings 1996). Finally, the routine activities theory posits that a combination of potential targets, motivated offenders and the absence of guardians combine to increase the amount of crime in a neighborhood (Cohen and Felson 1979). Thus, inequality will increase potential targets and motivated offenders, leading to higher rates of crime. In summary, we see the considerable overlap in the predictions of these theories provide a challenge for disentangling these processes. I next explore in detail the posited mechanisms for each of the measures of inequality or heterogeneity.

Relative Inequality

Several of the theoretical models considered here posit that income inequality in the larger community will increase the rate of crime. However, they differ in how this inequality might affect crime when viewing smaller neighborhoods *within* the larger community. For instance, the social distance model (Blau 1977; Blau 1987) suggests that inequality reduces the amount of contact among neighbors, which should lead to more crime if this inhibits the ability of the neighborhood to respond in a collective fashion to crime and disorder. This suggests that the mechanism of inequality works at the geographic level of neighborhoods.

While the social disorganization model posits that anything reducing relations between neighbors will increase the crime rate, studies have rarely considered the effect of relative inequality. While the model suggests three key structural characteristics of neighborhoods lead to more crime—ethnic heterogeneity, residential instability, and poverty—only the first two are posited to affect crime by reducing interaction. The social disorganization model argues that areas with high rates of poverty will have higher crime rates due to their inability to obtain resources from the city to combat crime (Shaw and

McKay 1942; Taylor 1996). However, high poverty in a neighborhood implies *less* social distance (in the extreme case, everyone has equally few economic resources). Nonetheless, if the social distance model is correct in assuming that inequality will reduce interaction, the social disorganization model would conclude this should increase crime. The fact that the social disorganization model implies that both poverty and inequality will increase crime rates may explain why the few studies in the social disorganization literature that measure inequality generally collapse it into an index of "general economic distress" along with other measures including poverty. Nonetheless, since these two measures posit different mechanisms for increasing crime, an appropriate approach would test whether they indeed both increase crime rates. Thus, although the social disorganization model is ambivalent on the possible effects of inequality, if they do exist they will work at the geographic level of the neighborhood.

The relative deprivation model (or reference group model) (Jasso 1980; Merton 1968) posits that individuals compare their economic position with others, and those feeling deprived will respond by committing crimes. While the notion of distributive justice dates back at least to Aristotle (1946), Hyman (1942) first coined 'reference group' theory (Merton 1968: 329-30). In the relative deprivation model, individuals compare themselves with others similar to themselves socially when making these comparisons (Davis 1963).[66] Note that a challenge to the relative deprivation literature in general is determining what constitutes an appropriate reference group. In the context of this study, the appropriate reference group may be co-residents of one's neighborhood given that some work suggests that reference groups are limited to those one comes into contact with (Alwin 1987;

[66] A variant of this model is a dynamic one proposed by Kovandzic, et al (1998) in which inequality has a stronger effect at times when it spikes upward, as the differences become more salient. I do not test this more elaborate theory here given the limited time frame of my data.

Crutchfield 1989; Homans 1974). This implies crime rates will be higher in neighborhoods with more inequality (similar to the social distance and social disorganization models). On the other hand, it is possible that members of the larger community serve as the reference group: if the media is important for creating a reference group for viewing inequality, then relative inequality at the *community* level will be most appropriate.[67] This implies that *communities* with greater amounts of inequality will have higher crime rates in *neighborhoods containing larger numbers of low-income households*.[68] This criminal response might either be through property crimes aimed at "equalizing" the perceived injustice, or through violent crimes enacted through frustration.

Finally, the routine activities theory (Cohen and Felson 1979) suggests that high rates of inequality will increase crime rates by providing a large supply of potential offenders (the poor) and suitable targets (the wealthy). The geographical location of inequality in this model is intermediate: while it need not be limited to the local neighborhood, it should be within the distance offenders are willing to travel and thus relatively contiguous neighborhoods. Studies have suggested a distance decay function explains how far perpetrators will travel (Rengert, Piquero, and Jones 1999), and one study found an average distance between 1 and 2.5 miles, depending on the crime type (Pyle 1974). In summary, all four of these theories posit a positive relationship between neighborhood-level inequality and neighborhood-level crime rates, suggesting that neighborhood level data is the proper unit of analysis.

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[67] If the media is truly national, then it would be inequality at the nation level that would be most appropriate. While this may have an effect on national crime rates, given that it is a constant value for all cities in a nation, it cannot help explain variations in crime rates among cities, much less neighborhoods within those cities.

[68] Thus hypothesis would require multilevel data of neighborhoods in a large number of cities. The limited number of cities in my sample precludes such a test.

Ethnic Heterogeneity

Analogous to the mechanisms proposed for inequality, the social distance model posits that higher levels of ethnic heterogeneity limit the amount of interaction between residents, and the social disorganization model posits that the resulting lack of ties will lead to higher crime rates (Bellair 1997; Sampson and Groves 1989; Shaw and McKay 1942; Veysey and Messner 1999; Warner and Pierce 1993; Warner and Rountree 1997). These ties also should increase community attachment (Adams 1992; Connerly and Marans 1985; Sampson 1988; Sampson 1991), which then increases social control ability (Freudenburg 1986). Indeed, numerous cross-sectional studies have found that areas with higher levels of ethnic heterogeneity have higher crime rates (Bellair 1997; Dahlback 1998; Krivo and Peterson 1996; Miethe, Hughes, and McDowall 1991; Rountree and Warner 1999; Sampson 1985; Sampson and Groves 1989; Sampson and Wilson; Skogan 1990; Smith and Jarjoura 1988; Veysey and Messner 1999; Warner and Rountree 1997). Thus, the social distance and social disorganization models require measuring ethnic heterogeneity at the neighborhood level.

Inequality between racial/ethnic groups

A further distinguishing characteristic of the theories considered here is that some suggest that measuring inequality and ethnic heterogeneity separately is not enough, and that the *intersection* of these two constructs should be considered. For instance, inequality *between* racial/ethnic groups may affect crime rates. In the social distance model, the "intersecting parameters" of these two social dimensions will increase the social distance between members of these groups (Blau 1977; Blau 1987). Combined with the social disorganization's view that social interaction helps reduce crime rates, this suggests that it is inequality between groups *within the neighborhood* that will reduce interaction and lead to higher rates of crime. Note that the social disorganization model does not explicitly propose such a hypothesis—and studies have thus not tested it—though it naturally follows if this social distance affects interaction in the neighborhood.

Blau and Blau (1982) extended this notion of consolidated inequality in positing that an increasing amount of between-group inequality causes minority group members to feel disadvantaged.[69] This is clearly an extension of the relative deprivation model, as members of the minority group view this disadvantage as illegitimate and respond with diffuse forms of aggression such as criminal violence given their limited ability for political action (Golden and Messner 1987). Note that this model does not require that the inequality across racial/ethnic groups be spatially located in the neighborhood; however, for the response to be toward members of the dominant group it does require that such members at least be located in spatially contiguous neighborhoods. An important point to highlight is that the posited mechanism will lead to a *violent* response. Blau and Blau (1982) suggested not all inequality will be perceived as unjust: only when the individual perceives that their lower relative standing is due to their ascribed characteristics will they perceive it as unjust and respond violently towards those with more. This leads to an important distinction: whereas the social distance model predicts that inequality across racial/ethnic groups should increase both violent and property crime, the consolidated inequality theory predicts only a relationship with violent crime. Studies have failed to test this possible relationship with both violent and property crime.

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[69] Note that this perspective is also frequently used to explain social movement outcomes and the fostering of group cohesion within a minority group.

On the other hand, the group threat literature (Blumer 1958; Bobo and Hutchings 1996; Quillian 1995) posits that it is only as inequality across ethnic groups *diminishes* that the crime rate increases. The dominant group perceives the narrowing of the economic gap between the two groups as threatening, provoking a violent response. Note that this dynamic model also only pertains to violent crime. As well, this suggests a longitudinal model where it is the *change* in income level of the disadvantaged group that will be perceived as threatening. This requires longitudinal data to test properly. While this model does not necessarily imply that these economically improving minority members live in the same neighborhood as members of the dominant ethnic group, they clearly need to have at least a degree of spatial contiguity to allow for this hypothesized violent response. That is, members of a dominant group may not be aware or concerned about minority group members in distant neighborhoods with similar levels of income; however, an increasing number of minority members nearby at a similar level of income will be perceived as threatening.

Despite the necessity of groups' geographical contiguity for spawning criminal responses to inequality across racial/ethnic groups, the numerous studies testing this relationship in the 1980's used large units of analysis. The classic study was the Blau and Blau (1982) study of the 125 largest SMSAs in 1970 with over 125,000 population, finding that SES inequality across race significantly increased the murder, robbery, and assault rates, while income inequality increased the murder and assault rates. A later study showed that this relationship did not exist when measuring *income* racial inequality, and the effect for *SES* racial inequality disappeared when including a measure of the poverty rate (Golden and Messner 1987). Balkwell's (1990) solution was to construct a racial inequality measure that took into account the relative size of the groups by utilizing an inequality measure of Jasso

(1980). While his study of 150 SMSA's in 1980 found a strong effect with this measure (Balkwell 1990), it is notable that he failed to include a measure of ethnic heterogeneity. Given that his measure is implicitly an interaction between ethnic heterogeneity and inequality, this raises the possibility that his findings simply captured an ethnic heterogeneity effect.

Inequality within Racial/ethnic groups

While the relative deprivation theory posits a positive relationship between general inequality and crime rates, it is distinguished from the other theories here in that it also posits that inequality *within* a racial/ethnic group should increase rates of crime. That is, a key perspective of the reference group literature is that individuals will only compare themselves with others to whom they feel similar (Merton 1968: 296). Defining the appropriate reference group is a thorny issue for this literature. While residents may compare themselves with all other members of their neighborhood, it is certainly plausible that individuals are more likely to compare themselves with others of *their own* racial/ethnic group when determining the appropriateness of their economic rewards. This implies that large income disparities *within* a racial/ethnic group will increase the crime rate. Note also that this does not imply any particular spatial location to this inequality within the ethnic group: in one possible conceptualization, individuals will use other members of their group anywhere throughout the larger community as evidence of their own deprivation, leading to a criminal response. In this instance, *communities* with greater amounts of inequality within race will have higher crime rates in *neighborhoods containing larger numbers of members of that* *group at the low end of the economic scale.*[70] In another possible conceptualization, if individuals are more likely to compare themselves to others who are similar to themselves and with whom they come into frequent contact (Lau 1989), inequality within an ethnicity *within the neighborhood* will increase the crime rate.

Studies have failed to test this proposition using neighborhood level data, instead using larger units of analysis. A study using national level data in the United States from 1957-1990 found that while *between-race* inequality had no relationship with crime rates, *within-race* inequality was associated with increasing crime rates (LaFree and Drass 1996). A study using SMSA data for 1980 found that inequality within race affects white rates of violence, but generally has no effect for African-American crime rates (Harer and Steffensmeier 1992). Finally, a study of 136 cities in 1980 only found that within race inequality increased black larceny and black motor vehicle theft for African-Americans, but had no effect for other crime types (Shihadeh and Ousey 1996). Nonetheless, these studies failed to test whether it is the neighborhoods with larger numbers of low income members of the racial/ethnic group that are disproportionately driving the overall community crime rate, nor whether it is inequality within a race in the neighborhood that affects the crime rates.

Summary

To test the proposed mechanisms of the theories outlined here requires data for the neighborhoods within communities. While past neighborhood studies often use data only for a single city for such tests, I address this by using data from eleven cities. Second, I employ longitudinal data in a stringent test to determine whether *the change* in these various measures of inequality and ethnic heterogeneity over the decade affect *the change* in crime

[70] Again, this hypothesis requires multilevel data of crime rates in neighborhoods in a large number of cities, thus precluding my testing it here.

rates in neighborhoods. Using fixed effects models allows me to control for unobserved, unchanging characteristics of the nearly 3,000 tracts in over 4,500 tract decades of my data. Finally, studies rarely test these various mechanisms simultaneously; again, I address this limitation here. I am thus able to directly test the effects of the various forms of inequality and heterogeneity within neighborhoods on local crime rates.

Data and Methods

Data for analyses

This study utilizes crime data for census tracts in eleven cities over a period of time. Table 4.2 presents a list of cities and the years of crime data. An advantage of using census tracts is that past studies have frequently used them to proxy for neighborhoods, they contain a mean of about 4,300 residents in 2000 (with 95% of the tracts containing between about 1,400 and 8,000 persons), and they were initially constructed by the Census Bureau to be relatively homogeneous neighborhoods (Green and Truesdell 1937; Lander 1954). However, not all of my data is available for tracts. For instance, some of the crime data is only available for police beats, which on occasion may partially overlap more than one census tract. My measures of retail activity are aggregated to zip codes: zip codes tend to be larger in size than census tracts (containing approximately 8,700 residents in 2000, with 95% of the zip codes containing between 115 and 36,700 persons), and therefore multiple census tracts can be contained within a single zip code. Additionally, there are instances where census tracts lie in more than one zip code. I describe in the appendix to this chapter how I combined these data into common census tract units over time.

Dependent Variables

The dependent variables in the analysis measure the amount of crime in the tracts of the study. I combined various types of crime into measures of *violent crime* (a sum of robbery, aggravated assault, murder) and *property crime* (a sum of burglary, motor vehicle theft, and larceny). I also estimated models using four key types of crime separately: aggravated assault, murder, robbery, and burglary. These four vary along the dimensions of property/violent crime and personal/public (being defined on whether the crime generally occurs between people who know each other or generally between strangers). Aggravated assault is a violent crime that generally occurs between strangers; murder is a violent crime that often occurs between people who know each other; robbery is a combination of both violent and property crime (since it involves the threat of force, and the goal of obtaining something of value) that occurs between strangers (Cohen, Felson, and Land 1980); while burglary is a property crime that occurs between strangers. Testing these crime types separately provides insight into whether these inequality and ethnic heterogeneity measures behave differently for these different forms of crime. For each of these crime measures I calculated the number of crime events that occurred per 100,000 population and natural log transformed these variables to reduce the kurtosis and minimize the possibility of outliers.

Independent Variables: inequality and heterogeneity

My key predictor variables are the various measures of inequality and heterogeneity discussed above. These data are available from the census for decennial years: 1970, 1980, 1990, or 2000. I constructed a measure of the ethnic heterogeneity in the tract by using a

Herfindahl index (Gibbs and Martin 1962: 670) of five racial/ethnic groupings,[71] which takes the following form:

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

where G represents the proportion of the population of ethnic group *j* out of *J* ethnic groups. Subtracting from 1 makes this a measure of heterogeneity. Thus, in the most heterogeneous neighborhood composed equally of five different groups this measure will have a value of .80 ($1-(.2^2+.2^2+.2^2+.2^2+.2^2)=.80$), whereas it will take a value of zero in a completely homogeneous community ($1-(1^2+0^2+0^2+0^2+0^2)=0$).

I constructed three types of inequality measures: within-group inequality, between-group inequality, and overall inequality. Note that the first two approximately sum to the third measure, precluding simultaneously estimating these three effects.[72] There are three general measures of inequality that have scale invariance and obey the principle of transfers (where transferring money from a poorer to a wealthier person always increases inequality): the Gini coefficient, the coefficient of variation, and the Theil measure (Allison 1978; Bourguignon 1979; Braun 1988). Allison (1978) notes that these measures display different properties: for instance, the coefficient of variation is best for a flat distribution since changes at any point in the distribution have a similar effect on the measure. Nonetheless, research suggests that these measures tend to be highly correlated, and one study found that, with the exception of the coefficient of variation, these various measures tended to be equally

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[71] For most years, these groups are white, African-American, Latino, Asian, and other races. Since the 1970 data does not have information on Asians I use just the four groups for that year.

[72] These first two measures (inequality within and across groups) will exactly sum to total inequality if one uses inequality measures that are completely decomposable. There is a considerable literature exploring such decomposable indices (see, for instance Bourguignon 1979; Ebert 1999; Lambert and Aronson 1993; Mills and Zandvakili 1997; Shorrocks 1984).

correlated with other socio-economic variables (Braun 1988). I utilized the Gini coefficient here, given the arguments of Yitzhaki (1979) and Pedersen (2004) that the Gini coefficient contains the desirable property of capturing relative deprivation when measured on a population in which such relative comparison is appropriate.

I calculated a measure of overall inequality in the census tract based on the Gini coefficient, defined as:

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

where x_i is the household's value of income, μ is the mean income value, the households are arranged in ascending values indexed by *i*, up to *n* households in the sample. Since the data is binned (as income is coded into various ranges of values), I take this into account by utilizing the Pareto-linear procedure (Aigner and Goldberger 1970; Kakwani and Podder 1976), which Nielsen and Alderson (1997) adapted from the U.S. Census Bureau strategy (for further details of this algorithm, see Nielsen and Alderson 1997).[73]

Second, I included a measure of the inequality *between* racial/ethnic groups. While there are various ways to construct such a measure, they generally entail either calculating the difference between, or the ratio of, the income levels of the two groups (Golden and Messner 1987). I first calculated the average family income of each racial/ethnic group, logged these values, and then calculated the ratio of: 1) white to African-American logged income, and 2) white to Latino logged income.[74] Log transforming the average income

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

[74] I use average income rather than median income because of the need to collapse census tracts into common units over time. Whereas it is feasible to proportion the number of members of a racial/ethnic group into two tracts and to proportion the total income they earned into two tracts (thus allowing calculating the average

before calculating this proportion reduces the possibility of outliers. Thus, higher values indicate tracts in which white income is much higher than that of minority members, thus likely increasing perceived injustice. While Balkwell (1990) argued that a limitation of such measures is their inability to take into account the relative sizes of the two racial/ethnic groups and created a measure multiplicatively combining the racial composition and relative income, I prefer a strategy that includes measures of both ethnic heterogeneity and inequality between racial/ethnic groups, as well as a term measuring their interaction.

Third, I included a measure of within-group inequality. I constructed this as the average inequality measure of the racial/ethnic groups (weighted by the population size of each group). That is, I: 1) calculated the Gini coefficient for family income for each group, 2) multiplied each of these values by the proportion of the tract comprised by the group, 3) summed these values. Note that while this measure is likely positively correlated with overall inequality, they differ in that overall inequality is the composed of both within-group and between-group inequality. Thus, in a tract containing high within-group inequality but little between-group inequality, this summed measure will have a higher value than the overall Gini coefficient. In contrast, in a tract with little or no within-group inequality but a relatively large amount of between-group inequality the overall Gini will have a higher value than will the within-group inequality measure.

Independent variables: Spatial Clustering of Race and Class

I also included measures of the composition of race and class in these tracts. Since the social disorganization theory posits that neighborhoods with high levels of poverty will

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income from these figures), simply using a weighted average of the median income values of the tracts collapsing into this new tract to get a new median value is not appropriate (Pastor and Scoggins 2003).

lack the resources to combat crime when it appears in the neighborhood (Shaw and McKay 1942), and numerous neighborhood studies have tested this effect with cross-sectional data (Crutchfield, Glusker, and Bridges 1999; Krivo and Peterson 1996; McClain 1989; Warner and Pierce 1993; Warner and Rountree 1997), I measured the economic resources of a neighborhood by including: 1) the average family income in the tract, and 2) the percent of the population at or below 125% of the poverty rate. Studies using data for neighborhoods have consistently found that the percent African-American in a neighborhood is associated with higher rates of violent crime but less so for property crime (Krivo and Peterson 1996; McNulty and Holloway 2000; Ouimet 2000), giving rise to a theory of a culture of violence positing that African-Americans are more prone to violence. To capture effects of racial composition (beyond the effect of ethnic heterogeneity), I included the percent African-American, percent Latino, percent Asian, and percent other races (with percent white as the reference category).

Independent variables: additional controls

Finally, I included several additional measures to minimize the possibility of spurious results. Since homeowners have a greater investment in the neighborhood and hence likely engage in more crime-reducing behavior (see the extended argument in Chapter 2), I calculated the percentage of tract households who own their residence. To test the social disorganization theory that residential stability increases social interaction and thus reduces crime, I included the average length of residence in the tract. Since broken families are posited to reduce crime-inhibiting activities I calculated the proportion of divorced families in the tract. Cross-sectional studies have found evidence supporting the hypothesis that abandoned buildings provide opportunities in the residential environment for criminal behavior and hence increase crime (Krivo and Peterson 1996; Roncek 1981; Roncek and Maier 1991). I thus included the percentage of residential units that are occupied. While there are conflicting views whether higher unemployment increases crime by providing more potential offenders or decreases it by providing more guardians (since these individuals are at home), I test this effect here by including the percent unemployed in the tract.

Finally since certain types of retail outlets may affect crime rates, I included two measures to capture this. Numerous recent cross-sectional studies have found a positive relationship between the crime rate in a neighborhood and the presence of bars and liquor stores nearby (Alaniz, Cartmill, and Parker 1998; Gorman, Speer, Gruenewald, and Labouvie 2001; Gyimah-Brempong 2001; Lipton and Gruenewald 2002; Nielsen and Martinez 2003; Ouimet 2000; Peterson, Krivo, and Harris 2000; Roncek and Maier 1991; Smith, Frazee, and Davison 2000). I thus included a measure of the number of employees of bars and liquor stores per 10,000 population in the tract.[75] I also included a measure of the number of retail employees per 10,000 population in the tract, though there are conflicting predictions for the effect of this measure. On the one hand, the presence of retail establishments being patronized should increase criminal opportunities; indeed, cross-sectional studies have found such an effect (Ouimet 2000; Smith, Frazee, and Davison 2000). On the other hand, Klinenberg (2002) argued that the presence of a vibrant retail community may be a proxy for the social capital in a neighborhood, and hence we might expect it to reduce the rate of crime.

[75] I used the number of employees rather than the number of establishments, since this measure likely provides a more accurate depiction of the impact such businesses have on the neighborhood. That is, it is not the simple presence of these establishments that is posited to increase crime, but rather the number of people they attract (both patrons, and possible perpetrators). Since establishments with more business will have a greater number of employees, the number of employees thus better captures this effect than a simple count of the number of establishments.

I am able to test these competing hypotheses here.[76] The summary statistics for the variables used in the analyses are presented in Table 4.3. The final column of Table 4.3 shows the correlation of the particular measure over the two time points—this shows how much these measures change over the decade. Note that for certain measures—such as the racial/ethnic composition of the neighborhood and the percent homeowners—there is very little change over time as these correlations are over .95 between time points. Since the fixed effects models only look at change within neighborhoods (rather than across neighborhoods), it is difficult to detect effects for measures that show so little change over time.

Methodology

While I will begin by presenting cross-sectional models for the final year of data—2000—to compare the results with those from the extant literature, my main analyses utilized fixed effects models to estimate how the *change* in inequality and heterogeneity in a neighborhood affects the *change* in the neighborhood's crime rate over time. The ten-year period between censuses is an appropriate time period to test these effects. A fixed effects strategy allows me to take into account unchanging omitted variables with constant effects on the crime rate in a neighborhood (Greene 2000; Halaby 2004). I used a structural equations approach utilizing a technique outlined by Allison and Bollen (1997). In this approach, the omitted variables are captured in a latent variable Z. Thus, in a model with two time points, the equations can be written thusly:

(3) $$y_{k\,t+1} = \beta_1 IE_{kt+1} + \beta_2 EH_{kt+1} + \Gamma X_{kt+1} + Z + \zeta_{kt+1}$$

$$y_{k\,t} = \beta_1 IE_{kt} + \beta_2 EH_{kt} + \Gamma X_{kt} + Z + \zeta_{kt}$$

[76] Since both of these measures are taken from the U.S. economic census, which reports data based on zip codes, I needed to collapse this zip code information into census tracts. The process used is described in the appendix.

where y_k and $y_{k\,t+1}$ measure the crime rate in neighborhood k at time points t and $t+1$ respectively, β_1 is the effect of inequality (IE_k) at each time point on the crime rate, β_2 is the effect of ethnic heterogeneity (EH_k) at each time point on the crime rate, Γ is a vector of parameters showing the effects of various measures in the X_{kt} matrix for neighborhood k at each time point, the effect of the latent variable Z is constrained to unity at each time point, and the ζ_k's are disturbance terms for each tract at each time point. To account for the possibility that this model operates differently over these cities and time points, I estimated a multiple-groups model in which the model is estimated separately for each city decade and tested the appropriateness of constraining the coefficients equal over cities and decades. I describe the results of this test down below.

Spatial effects

While studies using neighborhood data generally need to be concerned with spatial effects (that is, a systematic relationship between neighborhoods located more closely to each other), a fortunate byproduct of using a fixed effects model is that the spatial effects present when viewing these neighborhoods in a cross-sectional analysis largely disappear when "differencing out" the neighborhoods over time. Consider a modified version of the fixed effects model presented above now altered to consider possible spatial effects. We can conceptualize four types of variables in this model:

(4)
$$y_{k\,t+1} = \Gamma_1 Z_{kt+1} + \Gamma_2 X_{kt+1} + \Gamma_3 W(ZQ_{kt+1}) + \Gamma_4 W(Q_{kt+1}) + \zeta_{kt+1}$$

$$y_{k\,t} = \Gamma_1 Z_{kt} + \Gamma_2 X_{kt} + \Gamma_3 W(ZQ_{kt}) + \Gamma_4 W(Q_{kt}) + \zeta_{kt}$$

where Z are unchanging variables within the neighborhood of interest, X are the time-varying variables of interest within the neighborhood, ZQ are unchanging *spatial* variables that affect the neighborhood of interest from nearby neighborhoods (as determined by the weight matrix W), and Q are changing *spatial* variables that affect the focal neighborhood. As is well-known, assuming that Γ_1 is equal at both time points results in the unchanging Z variables dropping out of the equation when subtracting the time *t* equation from the time *t*+1 equation. However, an additional benefit of this model is that if Γ_3 are equal over both time points, the unchanging spatial effects (ZQ) will also drop out of the equation. Thus, the only spatial effects of concern are *changing* ones (Q). While some changing spatial effects may have an effect on the focal neighborhood (e.g., rising crime rates in an adjacent neighborhood may cause a rise in crime rates in the focal neighborhood), the limited number of such possible effects likely explains why I found few spatial effects in my fixed effects model (see the technical appendix for a complete description of the tests performed and the results). Thus, while the cross-sectional models I estimated showed considerable spatial effects—and I thus estimated the models taking this spatial lag effect into account using a two-stage least squares estimator—the fixed effects models showed no such problem, and I therefore estimated them with a maximum likelihood approach assuming independence of the errors for neighborhoods within a particular city.

Assessing the Fit of the Model

Since these models are estimated within the Structural Equation Modeling (SEM) framework, I am able to assess the quality of their overall fit. I accomplish this by comparing the initial covariance matrix with the model implied covariance matrix and assessing the degree of difference. Thus, the hypothesis is that H_0:   =   (θ), where   refers to the population covariance matrix and   (θ) represents the covariance matrix as a function of the parameters in θ (for a more complete discussion, see Bollen 1989). Since I have a sample rather than the actual population, I use S and $\Sigma(\hat{\theta})$ to test these hypotheses, where S is the sample covariance matrix and $\Sigma(\hat{\theta})$ represents the sample covariance matrix as a function of the parameters in θ. While the test of the equality of the two covariance matrices (= (θ)) can be performed for each model, a large sample size makes it likely that there will be considerable power to detect even trivial differences in the model implied and sample covariance matrices (Bollen 1989: 268). Therefore, in addition to the chi square test, it is useful to employ several other omnibus fit indices that measure the *closeness* of these two covariance matrices (Bollen and Long 1993).

Results of cross-sectional and longitudinal models

Cross-sectional models

I first present results from cross-sectional models: I estimated these models on the cities with crime data in 2000.[77] While these results do not exploit the longitudinal nature of my data, I present them to provide a comparison with the common approach of using tracts from a single city at a single point in time—my sample of several cities provides a more powerful test than such single-city studies. I begin by viewing the results of the baseline models (not including the measures of inequality) for property crime and violent crime. Table 4.4 presents the results for these models estimated both as OLS models ignoring the spatial effects, and then with two-stage least squares estimation taking these spatial effects into account. The results for the economic and racial/ethnic composition of the neighborhood are generally consistent with past studies viewing cross-sectional effects of

[77] I also estimated cross-sectional models using the data for the other years (1970, 1980, 1990) and found the results to be substantively similar. Since the cross-sectional models are not the main focus of my analysis, I do not present the results of these additional models here.

neighborhoods. Tracts with a higher proportion of residents in poverty have higher rates of both violent and property crime. But while neighborhoods with higher levels of income are associated with higher levels of property crime in the OLS models, this effect disappears in the 2sls models correcting for spatial effects; indeed, income is negatively associated with violent crime in the 2sls models. The results for the racial/ethnic composition and distribution are generally as expected: consistent with past research, neighborhoods with a higher percent African-Americans have higher rates of violent crime (controlling for the other factors in the model). Likewise, neighborhoods with a higher percentage of Latinos have higher rates of violent and property crime. While there is a modest positive relationship between neighborhoods with more Asians and violent crime in the OLS model, this effect loses significance in the model taking into account spatial effects, and will change even more in the fixed effects results presented shortly. Finally, consistent with the social distance model, we see that neighborhoods with higher levels of ethnic heterogeneity have higher levels of both violent and property crime, even controlling for the racial composition of the neighborhood and these other predictors of neighborhood crime.

The control variables generally work as expected. Neighborhoods with a higher proportion of occupied units or a higher proportion of homeowners have lower rates of violent and property crime. Consistent with past research, neighborhoods with more bars and liquor stores have higher rates of violent and property crime. There is also evidence consistent with the hypothesis that retail shops will increase the rate of crime in neighborhoods by increasing criminal opportunities. However, a surprising finding is that neighborhoods with higher residential stability actually have *higher* rates of crime, inconsistent with the social disorganization view that such neighborhoods will have less crime. While there is a bivariate negative relationship between residential stability and crime rates, this disappears when including any of these other covariates. This suggests a spurious relationship where the correlation between residential stability and both the outcome and some of these other measures induces this bivariate relationship. Finally, we see minimal effects for neighborhoods with more broken families, suggesting that this characteristic does not add explanatory power beyond that of the other characteristics of the neighborhood included in the model.

I next explored the question of whether neighborhoods characterized by higher rates of inequality—either total, within racial/ethnic groups, or between racial/ethnic groups—have higher rates of violent or property crime. The key finding from these cross-sectional models is that inequality within racial/ethnic groups is important for explaining the existence of higher rates of violent or property crime, even controlling for these other important predictors of neighborhood crime rates. It is instructive to view model 1 of Table 4.5, which has added overall inequality in the neighborhood to the previous baseline models presented in Table 4.4. Based on this model, one would conclude that overall inequality helps explain which neighborhoods will have higher rates of violent crime, even controlling for the economic resources of neighborhoods and their racial/ethnic composition and distribution. However, model 2 substitutes the measure of inequality *within* racial/ethnic groups for this overall measure of inequality and comes to a similar conclusion: neighborhoods with higher rates of inequality within racial/ethnic groups have higher rates of violent crime. To clarify these conflicting findings, in model 5 I included both of these measures simultaneously, and the conclusion for this sample is clear: while inequality within racial/ethnic is associated with greater violent crime in tracts, overall inequality shows no effect in this model (and actually is slightly negative).[78]

These cross-sectional models show little effect for inequality *across* racial/ethnic groups. The only effect is a negative interaction between black/white inequality and ethnic heterogeneity. This finding is inconsistent with the suggestion of Balkwell (1990) that inequality across racial/ethnic groups will be particularly salient when a considerable number of these individuals are in close proximity to one another. It is worth noting how modest these findings are for inequality across racial/ethnic groups, in that a different story will emerge when we turn to the longitudinal analyses. Note also that the effects of racial composition and distribution remain relatively constant in these models including various types of inequality. Thus, the social distance created by ethnic heterogeneity is consistently related to neighborhoods with higher rates of violent crime.

The cross-sectional models for property crime tell a similar story as those for violent crime, as seen in Table 4.6. Once again, while overall inequality plays a deceptive role in explaining which neighborhoods will have higher rates of property crime—as seen in model 1—we again see that it is inequality within racial/ethnic groups that is important for explaining which neighborhoods will have higher rates of crime. When both of these measures are included in model 5 overall inequality has no effect, becoming somewhat negative. And while higher ethnic heterogeneity again is consistently associated with higher crime rates, these models show no effect for inequality across racial/ethnic groups.

[78] Note that the degree of correlation between these two measures is reflected in the fact that the standard errors for these two measures when including them simultaneously in model 5 are more than doubled in size from models 1 and 2 when they are included separately.

Longitudinal models: tests

While these cross-sectional models adopted an estimation strategy common to studies of neighborhood crime, my large longitudinal sample provides the advantage of estimating longitudinal models. Given that I am using data over two time periods, I first needed to assess whether a random effects model would be appropriate, or whether a fixed effects model is necessary. To test this, I estimated models in which the latent variable Z (from equation 3) is constrained to have zero covariance with the predictors in the model: this is identical to a random effects model, and the SEM approach adopted here allows me to use a chi-square test of the appropriateness of these constraints (Allison and Bollen 1997).[79] I then estimated a classic fixed effects model, which is accomplished here by freely covarying the latent variable Z with the predictors.[80] I found that the fixed effects models showed a much better fit than the random effects models. As can be seen in Table 4.7, while these fixed effects models all had significant chi squares—indicating a lack of perfect fit—they all showed a very good approximate fit. For instance, while values of .90 are often given as a criterion for satisfactory fit, the Tucker-Lewis index (TLI) ranges from .94 to .97 while both the comparative fit index (CFI) and the incremental fit index (IFI) are nearly always one. In contrast, the values of the TLI for the random effects models were just .83. And while root mean squared error of approximation (RMSEA) values below .05 have been suggested as a measure of close fit (Browne and Cudeck 1993), the random effects models are both above .08 whereas the fixed effects models all fall below the .05 threshold with the exception of the

[79] It is interesting to note that these random effects models yield identical results to seemingly unrelated regression models in this setup.

[80] As Allison and Bollen (1997) point out, using this SEM technique allows relaxing the assumption that the effects of the observed variables are equal at both time points by estimating separate coefficients at each time point. This latter model is exactly identified, and thus is the implicit comparison when assessing the fit of this fixed effects model.

aggravated assault model. These results suggest that the fixed effects model does a satisfactory job of capturing this process.

I next needed to assess whether it is appropriate to estimate a single set of coefficients for all of the cities in this sample, or whether this model operates differently over these cities and time points. I accomplished this by estimating a multiple-groups model in which the model is estimated separately for each city decade. Doing so allows me to test whether the coefficients are the same over the separate cities by first estimating a model in which the coefficients are allowed to vary over cities, and then estimating a model constraining them to be equal. Constraining the coefficients to be equal over cities did not result in a reduction in fit as assessed by the approximate fit indices. For instance, when estimating the initial fixed effects model for each of the six crime type outcomes, I found that the RMSEA and the TLI were always just as good in the model constraining the coefficients equal over cities and decades compared to the models freely estimating these coefficients, and sometimes were slightly improved. While there was some variability in the parameter coefficients over cities, the model fit results suggest that the parsimony gained by estimating these fewer coefficients outweighs the moderate degree of variability in the estimated coefficients over cities and decades.

Fixed effects models

I now turn to the fixed effects models. The results for the initial models not including the inequality measures differ from those for the previously presented cross-sectional models. Whereas the cross-sectional models showed a positive relationship between poverty and crime rates, in Table 4.8 we see few effects. Increasing poverty is not associated with any change in property or violent crime, controlling for these other measures and the fixed effects in the model, and is only positively associated with the specific crime of robbery.[81]

There are also some differences for the racial/ethnic composition and distribution measures. On the one hand, we continue to see strong effects in which areas experiencing an increase in African-Americans see an increase in all crime types except for overall property crime. Likewise, areas experiencing an increase in Latinos see an increase in all crime types except for aggravated assault. And areas experiencing an increase in ethnic heterogeneity are generally experiencing an increase in all types of crime (significantly so for four of the six measures of crime), even controlling for these other important predictors of neighborhood crime. On the other hand, the modest positive effects discovered for Asians in the OLS models do not exist here: areas with an increasing percentage of Asians, if anything, are experiencing a *decrease* in crime. These effects are strongest for the violent public offenses of aggravated assault and robbery, as well as for burglary.

The effects for the control variables are generally modest, but a couple of findings are worth noting. First, we see that increasing residential stability is significantly associated with increases in violent crime and the individual types of violent crime: robbery, aggravated assault, and murder. This is particularly strong evidence that residential stability does not have the hypothesized reducing effect on crime rates.[82] Second, it is notable that whereas the cross-sectional models showed that areas with more retail shops or bars and liquor stores had

[81] The high R-squares in these models are notable. In part, these are due to the fixed effects included in the model. These also explain why few spatial effects were found in these models: there is simply little additional variance to be explained, once taking into account these observed predictors as well as the unobserved fixed effects for the neighborhoods.

[82] To assess whether this may be simply capturing an effect of the "newness" of the neighborhood, I also tested a model in which I included the average age of the buildings in the tract. In models both with and without the residential instability measure, the measure of the average age of the buildings actually had a *negative* effect on crime. Importantly, the effect of the residential instability measure remained unchanged in these subsidiary analyses.

higher rates of all crime types, these effects largely disappear when controlling for the unobserved unchanging characteristics of these neighborhoods. Thus, we only see evidence that an increase in retail shops will lead to an increase in overall property crime and burglary, and that an increase in bars/liquor stores will lead to an increase in robberies, murder and burglary. These findings make intuitive sense from a routine activities perspective, as retail shops likely provide more opportunities for larcenies—a component of the overall property crime measure—and bars/liquor stores provide additional opportunities for robberies and murders.

I next turn to the theoretically important question of the role of increasing inequality and heterogeneity for increasing crime rates. In these fixed effects models for violent crime in Table 4.9, the story now is one where inequality *across* racial/ethnic groups is most important for fostering violent crime. Whereas there is only modest evidence that increasing overall inequality is associated with increasing violent crime (as seen in model 1), tracts experiencing an increase in inequality *between* African-Americans and whites experience an increase in violent crime, controlling for these important predictors of neighborhood crime. This is consistent both with the consolidated inequality model that inequality across racial/ethnic groups will lead to a violent response, and with the social distance model that social distance will increase crime through reduced social interaction and hence reduced social control. The effect for Latino/white inequality is also positive, though not significant here. Indeed, this effect for inequality across racial/ethnic groups is a powerful one that remains in models 6 and 7 when including the other measures of inequality. Thus, model 6 shows that areas with increasing overall inequality, and increasing black/white inequality have increasing levels of violent crime, controlling for these other important predictors of crime.

In these violent crime models we also see that inequality between racial/ethnic groups considerably diminishes the main effect of racial/ethnic heterogeneity. Thus, it is not simply difference in racial/ethnic groups that leads to more violent crime, but an accompanying income difference between them. Nonetheless, model 4 highlights an unexpected negative interaction effect between ethnic heterogeneity and black/white inequality. Probing this interaction in Figure 4.1 illustrates that neighborhoods increasing in ethnic heterogeneity (one standard deviation above the mean in this Figure) are experiencing increasing violent crime rate regardless of how black/white inequality is changing, as seen on the right hand side of Figure 4.1. On the other hand, neighborhoods experiencing increasing ethnic homogeneity (the left-hand side of this figure) will experience a particularly low increase in violent crime (or even decrease) if it is accompanied by a reduction in black/white inequality. But if this increasing homogeneity is accompanied by increasing black/white inequality, the negative impact on violent crime is essentially eliminated.

The story for property crime is generally similar. The models in Table 4.10 highlight that increasing overall inequality and inequality within racial/ethnic groups is not related to increasing levels of property crime. On the other hand, similar to the model for violent crime, model 3 shows that increasing inequality between minority groups and whites leads to increasing levels of property crime (significantly so for black/white inequality). This effect remains even when including the other two measures of inequality in models 6 and 7. It is important to highlight that whereas the social distance model predicts such a relationship with property crime, the consolidated inequality theory predicts that this relationship will only be observed for violent crime.

We again see that the main effect of ethnic heterogeneity is largely eliminated when taking into account the inequality between racial/ethnic groups. We also again see a negative interaction between ethnic heterogeneity and black/white inequality. Probing this interaction in Figure 4.2 shows a somewhat similar story to that for violent crime: in tracts with increasing racial/ethnic homogeneity, property crime does not decrease if this is accompanied by increasing black/white inequality, as seen in the left-hand side of this Figure. But in areas with increasing racial/ethnic heterogeneity, an accompanying decrease in black/white inequality in fact leads to a greater increase in property crime, as seen in the right-hand side of Figure 4.2. This counterintuitive finding is not predicted by any of the theories considered here.

Finally, I estimated similar models for the four individual crime types: aggravated assault, robbery, murder, and burglary. The pattern of results is similar, as seen in Table 4.11. For these four crime types, the story is the importance of the social distance created by ethnic heterogeneity and the inequality between racial/ethnic groups, particularly black/white inequality. While the effects for Latino/white inequality are generally weaker, and only statistically significant for robbery, the results are very robust for increasing black/white inequality leading to increasing crime for three of these four crime types. We also see a negative interaction between black/white inequality and ethnic heterogeneity for three of these crime types: while the effect of this interaction for aggravated assault and robbery is similar to that of property crime plotted in Figure 4.2, the effect for burglary is slightly different. As can be seen in Figure 4.3, while increasing ethnic heterogeneity has no effect on burglary rates in tracts with simultaneous large increases in black/white inequality, increasing ethnic heterogeneity is positively associated with burglary rates in tracts with less change in black/white inequality and in tracts with decreasing black/white inequality.

Conclusion

Race and class are bedrock concepts in sociology, and theories suggest that their composition and distribution in neighborhoods will affect crime rates. Although numerous studies have used cross-sectional data to look at the relationship between race and class compositions and neighborhood crime rates, almost no studies have tested whether the distribution of economic resources *within* neighborhoods affects the crime rate. Studies have been limited to large units of analysis—such as SMSA's or large cities—to test the relationship between various types of inequality and crime rates. But given that most theoretical mechanisms posit that this inequality should work due to the social interaction among residents, this suggests that testing it at the neighborhood-level is most appropriate. Thus, this study fills an important lacuna.

The few studies that have tested the relationship between the distribution of race or class in a neighborhood and crime rates are limited to neighborhoods within a single city at a single time point. Such studies have limited generalizability since they focus on neighborhoods in a single city. Additionally, the small sample size of such studies (often less than 100) reduces their statistical power: it is unclear whether a null finding in such a study indeed represents the absence of a relationship, or simply a lack of statistical power to detect the relationship. The longitudinal sample I utilized allowed me to view the change in neighborhoods over time, and the large sample size allowed me to take into account unobserved, unchanging characteristics of neighborhoods that might otherwise confound my results (Halaby 2004).

Given that at least six different theories propose that income inequality, ethnic heterogeneity, or some combination of these, will increase neighborhood crime rates it is incumbent upon researchers to simultaneously consider these inter-related constructs in tests. Finding a relationship for one type of inequality without testing for another form does not provide a strict test of such theories. For instance, I found here in cross-sectional models that overall inequality was positively associated with crime rates when not including other measures of inequality in the model. However, introducing inequality *within* racial/ethnic groups eliminated this positive effect, illustrating the need to simultaneously consider these theories.

So what have we discovered regarding the six theories tested here? First, we saw modest support for the relative deprivation theory. As is well-known, a key task when operationalizing this theory is accurately defining the reference group used by the individual in such injustice determinations. One approach would define the reference group as all other members of the neighborhood: the results here showed modest support for such a specification in the fixed effects models. A second approach would define the reference group as consisting of members of the neighborhood of *the same racial/ethnic group* as the individual. The cross-sectional findings here were consistent with this specification, as inequality *within* the racial/ethnic group was associated with higher rates of violent and property crime. However, these effects were generally not significant in the fixed effects models, suggesting caution when interpreting the results from the cross-sectional models.

There was also some support for the consolidated inequality theory suggesting that increasing inequality across racial/ethnic groups is important for increasing crime rates. The fixed effects models showed that the effect for black/white inequality was particularly robust for nearly all types of crime. However, the effect of Latino/white inequality only showed a statistically significant positive effect for robbery. The consolidated inequality theory specifies that this inequality between the dominant group and the minority racial group provokes strong feelings of injustice, resulting in a criminal response. However, an important caveat should be noted: in the original formulation of the consolidated inequality model Blau and Blau (1982) suggested that this perceived injustice will lead to a violent response and hence an increase in *violent* crime rates. Indeed, in their study they tested and found such a relationship when using SMSA's as the unit of analysis. The findings here were similar for the fixed effects models using census tracts as the unit of analysis. However, contrary to the predictions of the consolidated inequality model, we also saw that increasing black/white inequality led to increasing *property* crime. This highlights the need to simultaneously test these theoretical models, since observing some relationships (e.g., a positive relationship between black/white inequality and violent crime rates) does not distinguish between competing explanations for the mechanisms underlying this relationship.

In particular, the social distance model also predicts that inequality across racial/ethnic groups will lead to more violent crime. However, the scope of the theory is broader than the consolidated inequality theory as it makes additional predictions. First, the social distance model predicts that inequality across racial ethnic groups will affect crime not because of a perceived injustice, but because it will reduce social interaction that would otherwise allow the neighborhood to engage in crime prevention activities. As a result, the theory predicts that such neighborhoods will also have higher rates of *property* crime, precisely what was observed in this study. The theory also predicts that the social distance created by ethnic heterogeneity will reduce interaction and lead to higher levels of crime. Indeed, ethnic heterogeneity generally showed a positive relationship with the various types of crime—though in some instances it worked in concert with inequality across racial/ethnic groups. The one prediction that did not fare as well for the social distance model was that higher rates of general inequality would increase crime rates. There was only modest support for this hypothesis in the fixed effects models as it was modestly positively associated with robbery and violent crime. Instead, it appeared that racial/ethnic differences are most important, and that economic differences across these racial/ethnic differences particularly fostered increasing rates of crime.

While the social disorganization theory is an important mechanism for explaining how the social distance model works—as it suggests that these social interactions among residents can help foster a watchful environment that will reduce crime—it is important to point out that other predictions of the social disorganization model did not fare particularly well. For instance, there was virtually no evidence in this sample that higher residential stability leads to lower crime rates, a key prediction of the social disorganization theory. Instead, the cross-sectional models showed that when controlling for virtually any other predictors, residential stability was associated with *higher* rates of violent and property crime in neighborhoods. And the fixed effects models also showed this to be a particularly robust finding: neighborhoods that were experiencing increasing levels of instability were experiencing essentially no change in property crime and *falling* levels of the various types of violent crime, controlling for these other important predictors of crime. This is a particularly important failing of a component of the theory that researchers have generally tested with cross-sectional data. Second, while the social disorganization theory predicts that neighborhoods with higher levels of poverty will have more crime since the residents will be unable to lobby for various forms of support from the city government, the evidence for this was not particularly strong. On the one hand, the cross-sectional models showed that neighborhoods higher in poverty were associated with higher levels of violent and property crime, given the controls of the model. On the other hand, the fixed effects models were not nearly as consistent: the only statistically significant effect was that neighborhoods experiencing increasing poverty experienced increasing levels of robbery. However, even this effect lost significance when including the measures of inequality between racial/ethnic groups. Thus, the causal mechanism may be different than that specified by the social disorganization model.

There was little support for the other two theories predicting a relationship between inequality types and crime rates. The group threat literature predicted a *negative* association between inequality across races and crime. That is, the dominant group would perceive a diminishing level of inequality across racial/ethnic groups as threatening and respond violently. Instead, it appears that the economic threat to the dominant group is not an important dimension to measure, at least when considering the types of general crimes considered here. This finding is consistent with a study viewing the causes of racially motivated crime, which also found little effect for economic inequality between races as hate crimes were instead related to the influx of other racial groups into the neighborhood—explained as a defense of territory strategy (Green, Strolovitch, and Wong 1998). Thus, increasing ethnic heterogeneity led to more hate crimes. This highlights the possibility of different mechanisms explaining the same observed relationship: while the social distance model argues that ethnic heterogeneity will increase crime through reduced interaction, such racial/ethnic differences may provoke crime through the violent response of the dominant group. This points out the need for future research to directly test these posited mechanisms. Nonetheless, it is important to highlight that the positive relationship found here between increasing ethnic heterogeneity and increasing burglary and property crime rates are consistent with the social distance model's prediction of reduced social interaction, and inconsistent with a group threat model: the group threat literature does not hypothesize that the dominant group would respond to an influx of minority members by committing burglaries and other property crimes.

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

While this study has shown the importance of measuring inequality and ethnic heterogeneity within neighborhoods for explaining crime rates, certain limitations should be acknowledged. First, this study has not been able to measure the mechanisms posited by the various theories. In part, I attempted to address this by carefully considering the predictions of the various theories and simultaneously measuring them. Nonetheless, as I have highlighted above, there is a clear need for future research to explicitly explore certain of these mechanisms. For instance, the relationship between inequality across racial/ethnic groups and crime rates needs to be explored more carefully: the relationship between violent crime and inequality across racial/ethnic groups may be due to either the consolidated inequality model causing more perceived injustice, or the social distance model causing less social interaction. On the other hand, the fact that only the social distance model predicted the relationship between property crime and inequality across racial/ethnic groups suggests that the mechanism suggested by this model is likely at least partially at work in these findings. Second, while using eleven cities in a single study is a large advance over past research, it is still the case that the generalizability of the findings requires the assumption that these cities are at least fairly representative. Clearly, studies using additional cities will be necessary to assess this. Third, while there is a need to explore some of these theoretical mechanisms using multilevel data, my limited sample of cities precluded this. For instance, as pointed out above, it is possible that the relative deprivation models works such that either general inequality or inequality within racial/ethnic groups should be measured at the level of the city and that it is only in neighborhoods with high concentrations of such group members *with low income* that we would see elevated rates of crime. Testing such a hypothesis requires multilevel data.

Nonetheless, this study has provided an important test of the predictions of these six theories regarding possible relationships between inequality, ethnic heterogeneity, and neighborhood crime rates. By using a longitudinal sample, I have been able to move beyond simple cross-sectional analyses. Indeed, I showed how some of the relationships discovered in this data set differed whether one adopted the more common cross-sectional approach, or the more rigorous fixed effects approach. By taking into account unobserved, unchanging characteristics of neighborhoods, I have provided a more stringent test of what effect changing inequality and heterogeneity means for changing neighborhood crime rates. Regardless of the theoretical mechanisms present, two robust effects were found: increasing ethnic heterogeneity and increasing inequality *between* racial/ethnic groups led to increased crime. Ethnic heterogeneity showed a strong positive relationship with all crime types in the cross-sectional models, and generally showed a positive effect on crime rates in the fixed effects models that was independent of the effect of black/white inequality, or else was observed in the absence of black/white inequality. Thus, this study has shown that not only is the composition of race and class in neighborhoods important for explaining crime rates, but that the distribution of race and class *within* neighborhoods also has important effects.

Tables and Figures

Table 4.2. Cities, years, and crime types in analyses

City	Years	Tracts	Crime types*
Baltimore	1970-1980	202	All
Baltimore	1980-1990	202	All
Baltimore	1990-2000	202	Just violent and property crime
Chicago	1970-1980	858	Just murder
Chicago	1980-1990	858	Just murder
Cleveland	1980-1990	225	Just burglary, murder, and robbery
Cleveland	1990-2000	225	All
Denver	1990-2000	187	Just burglary, violent and property crime
Indianapolis	1990-2000	146	All
Los Angeles	1990-2000	569	All
Milwaukee	1990-2000	235	All
Sacramento	1990-2000	145	All
Seattle	1970-1980	126	Not property crime
St. Louis	1970-1980	113	Not aggravated assault
Washington, D.C.	1980-1990	192	Not property crime
Washington, D.C.	1990-2000	192	Just violent and property crime
Total tract years		4677	
Total unique tracts		2998	

* Unless otherwise noted, crime types are: violent crime, property crime, aggravated assault, robbery, murder, and burglary

Table 4.3. Summary statistics of variables used in analyses

	Mean	SD	Min	Max	Correlation over waves
Violent crime rate per 10,000 persons	7.0134	1.7341	0.000	12.228	0.80
Property crime rate per 10,000 persons	8.2522	1.4295	0.000	13.448	0.90
Aggravated assault rate per 10,000 persons	6.0917	1.5535	0.000	9.792	0.88
Robbery rate per 10,000 persons	5.9350	1.6058	0.000	13.442	0.59
Murder rate per 10,000 persons	1.7724	1.5788	0.000	7.160	0.58
Burglary rate per 10,000 persons	7.0743	1.4005	0.000	13.795	0.85
Ethnic heterogeneity	0.0358	0.2158	-0.300	0.478	0.84
Inequality	0.0231	0.0789	-0.420	0.580	0.65
Inequality within race	0.0276	0.1031	-0.400	0.356	0.61
Inequality between blacks/whites	0.0372	0.0779	-0.545	0.726	0.23
Inequality between Latinos/whites	0.0563	0.0739	-0.509	0.585	0.18
Owners	0.4689	0.2313	0.000	1.000	0.96
Occupied units	0.9160	0.0817	0.000	1.000	0.42
Divorced	0.4030	0.1941	0.000	1.000	0.84
At/below 125% of poverty	0.2642	0.1661	0.000	1.000	0.88
Average household income (in $10,000's)	5.0056	3.8377	0.201	36.790	0.92
Unemployment rate	0.1016	0.0778	0.000	0.967	0.60
White	-0.1785	0.3494	-0.600	0.400	0.95
African-American	0.1041	0.3838	-0.270	0.730	0.96
Asian	0.0115	0.0699	-0.030	0.632	0.88
Latino	0.0418	0.2198	-0.100	0.892	0.96
Other race	0.0210	0.0227	-0.003	0.457	0.08
Average length of residence	0.1082	0.0350	0.010	0.236	0.83
Bars and liquor store employees per capita	0.0468	0.0223	0.000	0.199	0.82
Retail employees per capita	0.0604	0.0087	0.004	0.139	0.89

Sample sizes of outcomes: violent crime = 2,880; property crime = 2,370; aggravated assault = 2,186; robbery = 2,524; murder = 4,240; burglary = 2,711

Table 4.4. Cross-sectional models predicting violent and property crime in 2000, using tracts in several cities (Baltimore, Cleveland, Denver, Indianapolis, Los Angeles, Milwaukee, Sacramento, Washington, D.C.)

	OLS regression				Two-stage least squares regressions, taking into account spatial lag			
	Violent crime		Property crime		Violent crime		Property crime	
Economic resources								
At/below 125% of poverty	1.863	**	1.707	**	1.528	**	1.194	**
	(0.356)		(0.390)		(0.357)		(0.338)	
Average household income	0.009		0.021	*	-0.024	*	-0.013	
	(0.010)		(0.010)		(0.010)		(0.010)	
Racial/ethnic composition and distribution								
Ethnic heterogeneity	1.281	**	1.161	**	0.549	**	0.367	†
	(0.182)		(0.214)		(0.183)		(0.208)	
African-American	1.183	**	0.360	†	0.850	**	0.274	
	(0.171)		(0.213)		(0.151)		(0.193)	
Latino	1.435	**	0.231		1.468	**	0.409	*
	(0.186)		(0.217)		(0.178)		(0.186)	
Asian	0.669	†	0.432		-0.196		-0.172	
	(0.366)		(0.476)		(0.344)		(0.459)	
Other race	0.792		-1.327		-0.213		-0.274	
	(1.383)		(1.655)		(1.249)		(1.405)	
Control variables								
Owners	-1.229	**	-1.487	**	-0.664	**	-0.739	**
	(0.241)		(0.246)		(0.232)		(0.219)	
Occupied units	-3.021	**	-2.670	**	-2.032	**	-2.025	**
	(0.509)		(0.454)		(0.485)		(0.410)	
Divorced	0.677	†	-0.324		0.091		-0.534	
	(0.350)		(0.436)		(0.320)		(0.415)	
Unemployment rate	-0.924	†	-1.945	**	-0.768	†	-1.549	**
	(0.499)		(0.548)		(0.453)		(0.455)	
Average length of residence	7.509	**	8.695	**	4.178	**	4.249	**
	(1.409)		(1.536)		(1.305)		(1.347)	
Bars/liquor stores per capita	0.135	**	0.118	**	0.098	**	0.059	*
	(0.021)		(0.026)		(0.019)		(0.026)	
Retail establishments per capita	0.092	*	0.167	**	0.070	†	0.150	**
	(0.042)		(0.047)		(0.037)		(0.042)	
Rho (spatial lag)					0.562	**	0.611	**
					(0.061)		(0.086)	
R-square	0.57		0.40		0.66		0.57	
N	5,290		4,654		5,290		4,654	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses*

Table 4.5. Cross-sectional models, using two-stage least squares (2sls) estimation to handle spatial lag, predicting violent crime in 2000, using tracts in several cities (Baltimore, Cleveland, Denver, Indianapolis, Los Angeles, Milwaukee, Sacramento, Washington, D.C.)

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Economic resources and distribution														
Inequality	1.2578	*							-2.778	*	1.291	*		
	(0.518)								(1.347)		(0.516)			
Inequality within race			1.7831	**					3.772	**			1.8057	**
			(0.406)						(1.076)				(0.407)	
Inequality between blacks/whites					0.0198		-0.081				0.0007		-0.05	
					(0.231)		(0.222)				(0.233)		(0.235)	
Inequality between Latinos/whites					-0.23		-0.279				-0.345		-0.323	
					(0.494)		(0.484)				(0.474)		(0.471)	
Inequality between blacks/whites X ethnic heterogeneity							-1.82	**						
							(0.490)							
Inequality between Latinos/whites X ethnic heterogeneity							-3.264							
							(2.115)							
At/below 125% of poverty	1.2631	**	1.1942	**	1.5297	**	1.4187	**	1.4072	**	1.2573	**	1.1889	**
	(0.370)		(0.346)		(0.359)		(0.353)		(0.384)		(0.373)		(0.349)	
Average household income	-0.03	**	-0.03	**	-0.024	*	-0.025	**	-0.025	*	-0.029	**	-0.029	**
	(0.010)		(0.009)		(0.010)		(0.010)		(0.010)		(0.010)		(0.009)	
Racial/ethnic composition and distribution														
Ethnic heterogeneity	0.5414	**	0.6095	**	0.5497	**	0.6723	**	0.6971	**	0.5412	**	0.6068	**
	(0.181)		(0.183)		(0.183)		(0.184)		(0.181)		(0.181)		(0.182)	
African-American	0.8124	**	0.7743	**	0.8703	**	0.8552	**	0.7731	**	0.8213	**	0.7438	**
	(0.148)		(0.143)		(0.227)		(0.218)		(0.142)		(0.228)		(0.223)	
Latino	1.5064	**	1.5171	**	1.4699	**	1.4613	**	1.4881	**	1.5066	**	1.5116	**
	(0.176)		(0.175)		(0.178)		(0.179)		(0.176)		(0.176)		(0.176)	
Asian	-0.199		-0.21		-0.197		0.048		-0.216		-0.202		-0.219	
	(0.343)		(0.343)		(0.346)		(0.345)		(0.345)		(0.344)		(0.344)	
Other race	-0.219		-0.475		-0.225		0.3368		-0.752		-0.23		-0.492	
	(1.247)		(1.248)		(1.249)		(1.247)		(1.228)		(1.246)		(1.247)	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. All models control for percent owners, percent occupied units, percent divorced, unemployment rate, average length of residence, bars/liquor stores per capita, retail establishments per capita, and indicator variables for each city year. N=5,290*

Table 4.6. Cross-sectional models, using two-stage least squares (2sls) estimation to handle spatial lag, predicting property crime in 2000, using tracts in several cities (Baltimore, Cleveland, Denver, Indianapolis, Los Angeles, Milwaukee, Sacramento, Washington, D.C.)

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Economic resources and distribution														
Inequality	1.858	**							-2.426	*	1.882	**		
	(0.492)								(1.078)		(0.485)			
Inequality within race			2.183	**					4.009	**			2.192	**
			(0.461)						(1.017)				(0.453)	
Inequality between blacks/whites					0.217		0.162				0.185		0.155	
					(0.228)		(0.230)				(0.232)		(0.231)	
Inequality between Latinos/whites					-0.225		-0.246				-0.418		-0.413	
					(0.501)		(0.495)				(0.503)		(0.500)	
Inequality between blacks/whites X ethnic heterogeneity							-1.035	*						
							(0.465)							
Inequality between Latinos/whites X ethnic heterogeneity							-1.265							
							(2.249)							
At/below 125% of poverty	0.784	*	0.760	*	1.202	**	1.143	**	0.934	**	0.788	*	0.766	*
	(0.354)		(0.347)		(0.339)		(0.342)		(0.356)		(0.355)		(0.348)	
Average household income	-0.022	*	-0.022	*	-0.014		-0.015		-0.017	†	-0.023	*	-0.022	*
	(0.010)		(0.010)		(0.010)		(0.010)		(0.010)		(0.010)		(0.010)	
Racial/ethnic composition and distribution														
Ethnic heterogeneity	0.343	†	0.413	*	0.375	†	0.430	*	0.485	*	0.349	†	0.418	*
	(0.204)		(0.206)		(0.208)		(0.213)		(0.208)		(0.205)		(0.206)	
African-American	0.211		0.180		0.447		0.446		0.185		0.365		0.312	
	(0.190)		(0.184)		(0.298)		(0.297)		(0.183)		(0.297)		(0.291)	
Latino	0.471	*	0.482	**	0.432	*	0.430	*	0.462	*	0.491	**	0.499	**
	(0.183)		(0.183)		(0.191)		(0.189)		(0.182)		(0.189)		(0.188)	
Asian	-0.189		-0.209		-0.140		0.003		-0.216		-0.160		-0.184	
	(0.458)		(0.452)		(0.472)		(0.469)		(0.448)		(0.470)		(0.465)	
Other race	-0.279		-0.484		-0.268		0.134		-0.655		-0.261		-0.466	
	(1.401)		(1.399)		(1.394)		(1.407)		(1.396)		(1.386)		(1.385)	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. All models control for percent owners, percent occupied units, percent divorced, unemployment rate, average length of residence, bars/liquor stores per capita, retail establishments per capita, and indicator variables for each city year. N=4,654*

Table 4.7. Assessing the model fit for structural equation models estimated as random effects and fixed effects models of various types of crime over decades for several cities

	Chi-square	df	TLI	IFI	CFI	RMSEA	RNI
Random effects models							
Violent crime model	1133.71	54	0.827	0.990	0.990	0.083	0.990
Property crime model	1035.47	51	0.829	0.988	0.988	0.090	0.988
Fixed effects models							
Violent crime model	105.30	14	0.944	0.999	0.999	0.048	0.999
Property crime model	65.23	14	0.968	0.999	0.999	0.039	0.999
Assault model	106.07	14	0.944	0.999	0.999	0.055	0.999
Robbery model	63.52	14	0.971	0.999	0.999	0.037	0.999
Murder model	91.57	14	0.965	0.999	0.999	0.036	0.999
Burglary model	74.09	14	0.964	0.999	0.999	0.040	0.999

Note: df: degrees of freedom; TLI: Tucker-Lewis Index; IFI: Incremental Fit Index; CFI: Comparative Fit Index; RMSEA: root mean squared error of approximation; RNI: relative noncentrality index

Sample sizes of outcomes: violent crime = 2,880; property crime = 2,370; aggravated assault = 2,186; robbery = 2,524; murder = 4,240; burglary = 2,711

Table 4.8. Fixed effects models predicting the change in various types of crime for several cities over various decades spanning the 1970-2000 period

	Aggregated crime				Individual types of crime							
	Violent crime		Property crime		Aggravated assault		Robbery		Murder		Burglary	
Economic resources												
At/below 125% of poverty	-0.256		0.190		0.239		0.562	*	0.354		0.144	
	(0.244)		(0.157)		(0.238)		(0.225)		(0.254)		(0.163)	
Average household income	-0.028	**	-0.015	*	-0.012		-0.040	**	0.006		-0.008	
	(0.011)		(0.008)		(0.011)		(0.011)		(0.017)		(0.008)	
Racial/ethnic composition and distribution												
Ethnic heterogeneity	0.269		0.190	†	0.424	*	0.126		0.879	**	0.354	**
	(0.167)		(0.101)		(0.168)		(0.160)		(0.183)		(0.113)	
African-American	1.137	**	0.022		0.869	**	1.057	**	1.434	**	0.255	*
	(0.181)		(0.111)		(0.188)		(0.170)		(0.180)		(0.124)	
Latino	0.617	*	0.373	*	-0.120		1.171	**	1.247	**	0.892	**
	(0.287)		(0.172)		(0.274)		(0.280)		(0.257)		(0.191)	
Asian	-0.443		-0.299		-0.781	†	-0.992	*	-0.085		-0.587	†
	(0.479)		(0.299)		(0.452)		(0.467)		(0.605)		(0.326)	
Other race	0.263		-0.467		-0.217		0.663		-0.153		-0.310	
	(0.690)		(0.545)		(0.632)		(0.667)		(0.849)		(0.475)	
Control variables												
Owners	0.348		0.382	*	0.234		0.315		-0.986	**	0.470	*
	(0.272)		(0.187)		(0.276)		(0.261)		(0.304)		(0.184)	
Occupied units	-0.708	**	-0.135		-0.024		-0.426	†	-0.634	*	-0.960	**
	(0.226)		(0.149)		(0.239)		(0.229)		(0.249)		(0.167)	
Divorced	-0.363	†	-0.353	**	0.008		-0.274		0.295		-0.032	
	(0.192)		(0.127)		(0.187)		(0.182)		(0.214)		(0.132)	
Unemployment rate	0.493	†	-0.315	†	-0.091		-0.061		0.630	*	-0.550	**
	(0.273)		(0.175)		(0.271)		(0.254)		(0.315)		(0.184)	
Average length of residence	2.991	**	-0.192		2.480	**	1.800	*	4.027	**	0.703	
	(0.951)		(0.617)		(0.924)		(0.894)		(1.012)		(0.645)	
Bars/liquor stores per capita	0.025		0.013		0.016		0.035	†	0.043	†	0.028	*
	(0.017)		(0.012)		(0.018)		(0.018)		(0.026)		(0.012)	
Retail establishments per capita	0.039		0.165	**	0.067		0.072		-0.001		0.066	†
	(0.050)		(0.035)		(0.054)		(0.054)		(0.074)		(0.035)	
R-square, second wave	0.96		0.97		0.94		0.93		0.65		0.96	
R-square, first wave	0.80		0.94		0.89		0.92		0.63		0.92	
N	2,880		2,370		2,186		2,524		4,240		2,711	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses*

Table 4.9. Fixed effects models predicting the change in violent crime for several cities over various decades spanning the 1970-2000 period, comparing the effects of various forms of inequality and heterogeneity

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Economic resources and distribution														
Inequality	0.563	†							0.471		0.675	*		
	(0.339)								(0.402)		(0.340)			
Inequality within race			0.349						0.141				0.401	†
			(0.238)						(0.281)				(0.237)	
Inequality between blacks/whites					0.349	**	0.313	**			0.364	**	0.349	**
					(0.083)		(0.085)				(0.083)		(0.083)	
Inequality between Latinos/whites					0.181		0.162				0.161		0.181	
					(0.298)		(0.305)				(0.297)		(0.297)	
Inequality between blacks/whites X ethnic heterogeneity							-0.979	*						
							(0.420)							
Inequality between Latinos/whites X ethnic heterogeneity							1.982							
							(1.592)							
At/below 125% of poverty	-0.371		-0.296		-0.293		-0.323		-0.354		-0.440	†	-0.349	
	(0.254)		(0.249)		(0.244)		(0.244)		(0.254)		(0.254)		(0.248)	
Average household income	-0.028	**	-0.032	**	-0.043	**	-0.045	**	-0.029	**	-0.044	**	-0.047	**
	(0.011)		(0.011)		(0.011)		(0.011)		(0.011)		(0.011)		(0.011)	
Racial/ethnic composition and distribution														
Ethnic heterogeneity	0.279	†	0.293	†	0.150		0.145		0.289	†	0.150		0.169	
	(0.167)		(0.167)		(0.169)		(0.172)		(0.167)		(0.169)		(0.169)	
African-American	1.120	**	1.088	**	1.039	**	1.102	**	1.097	**	1.042	**	1.008	**
	(0.181)		(0.181)		(0.181)		(0.183)		(0.181)		(0.181)		(0.181)	
Latino	0.657	*	0.622	*	0.594	*	0.692	*	0.652	*	0.653	*	0.611	*
	(0.288)		(0.288)		(0.286)		(0.289)		(0.288)		(0.287)		(0.287)	
Asian	-0.468		-0.482		-0.389		-0.228		-0.452		-0.417		-0.431	
	(0.479)		(0.480)		(0.478)		(0.482)		(0.480)		(0.479)		(0.479)	
Other race	0.194		0.162		-0.026		0.287		0.179		-0.034		-0.072	
	(0.690)		(0.691)		(0.690)		(0.701)		(0.691)		(0.689)		(0.690)	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. All models control for percent owners, percent occupied units, percent divorced, unemployment rate, average length of residence, bars/liquor stores per capita, retail establishments per capita, and indicator variables for each city year. N=2,880*

Table 4.10. Fixed effects models predicting the change in property crime for several cities over various decades spanning the 1970-2000 period, comparing the effects of various forms of inequality and heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economic resources and distribution							
Inequality	0.055				0.341	0.108	
	(0.223)				(0.278)	(0.223)	
Inequality within race		0.115			-0.361 †		0.13
		(0.157)			(0.209)		(0.157)
Inequality between blacks/whites			0.15 **	0.11 *		0.151 **	0.142 **
			(0.049)	(0.050)		(0.049)	(0.049)
Inequality between Latinos/whites			0.247	0.237		0.237	0.254
			(0.181)	(0.187)		(0.180)	(0.181)
Inequality between blacks/whites X ethnic heterogeneity				-1.137 **			
				(0.249)			
Inequality between Latinos/whites X ethnic heterogeneity				0.726			
				(0.979)			
At/below 125% of poverty	0.175	0.213	0.149	0.088	0.187	0.122	0.169
	(0.165)	(0.161)	(0.157)	(0.157)	(0.165)	(0.165)	(0.161)
Average household income	-0.016 *	-0.016 *	-0.023 **	-0.025 **	-0.012	-0.024 **	-0.023 **
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Racial/ethnic composition and distribution							
Ethnic heterogeneity	0.192 †	0.2 *	0.136	0.164	0.192 †	0.138	0.147
	(0.101)	(0.101)	(0.103)	(0.103)	(0.101)	(0.103)	(0.103)
African-American	0.032	0.006	-0.014	0.042	0.041	-0.003	-0.029
	(0.110)	(0.111)	(0.111)	(0.111)	(0.111)	(0.110)	(0.111)
Latino	0.374 *	0.356 *	0.37 *	0.499 **	0.341 *	0.374 *	0.355 *
	(0.172)	(0.172)	(0.172)	(0.174)	(0.173)	(0.172)	(0.172)
Asian	-0.318	-0.336	-0.277	-0.115	-0.324	-0.292	-0.306
	(0.300)	(0.298)	(0.297)	(0.298)	(0.299)	(0.298)	(0.297)
Other race	-0.473	-0.467	-0.606	-0.026	-0.483	-0.606	-0.596
	(0.545)	(0.545)	(0.545)	(0.557)	(0.544)	(0.544)	(0.545)

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test). Standard errors in parentheses. All models control for percent owners, percent occupied units, percent divorced, unemployment rate, average length of residence, bars/liquor stores per capita, retail establishments per capita, and indicator variables for each city year. N=2,370*

Table 4.11. Fixed effects models predicting the change in various types of crime for several cities over various decades spanning the 1970-2000 period, comparing the effects of various forms of inequality and heterogeneity

Table 4.11. Fixed effects models predicting various types of crime over decades for three types of inequality

	Aggravated assault		Robbery		Murder		Burglary	
	(A)	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**
Economic resources and distribution								
Inequality	0.247		0.552 †		0.259		0.212	
	(0.325)		(0.323)		(0.389)		(0.231)	
Inequality within race		0.051		0.248		-0.194		0.203
		(0.233)		(0.209)		(0.222)		(0.153)
Inequality between blacks/whites	0.371 **	0.364 **	0.186 *	0.179 *	0.861 **	0.846 **	0.073	0.061
	(0.082)	(0.082)	(0.088)	(0.088)	(0.139)	(0.140)	(0.060)	(0.059)
Inequality between Latinos/whites	-0.219	-0.173	0.722 *	0.786 *	0.357	0.364	0.043	0.053
	(0.309)	(0.309)	(0.308)	(0.308)	(0.434)	(0.432)	(0.213)	(0.213)
Inequality between blacks/whites X ethnic heterogeneity	-2.396 **	-2.360 **	-1.223 **	-1.144 *	0.604	0.575	-1.743 **	-1.717 **
	(0.404)	(0.403)	(0.457)	(0.458)	(0.704)	(0.703)	(0.292)	(0.292)
Inequality between Latinos/whites X ethnic heterogeneity	-0.906	-0.796	-1.129	-0.751	2.621	2.757	-0.529	-0.504
	(1.617)	(1.616)	(1.592)	(1.595)	(2.195)	(2.195)	(1.100)	(1.101)
At/below 125% of poverty	-0.008	0.058	0.309	0.378	0.204	0.293	-0.006	-0.009
	(0.246)	(0.241)	(0.235)	(0.231)	(0.267)	(0.257)	(0.169)	(0.166)
Average household income	-0.029 *	-0.029 *	-0.050 **	-0.053 **	-0.017	-0.012	-0.017 *	-0.018 *
	(0.011)	(0.011)	(0.012)	(0.012)	(0.017)	(0.017)	(0.008)	(0.009)

(continued)

	Aggravated assault		Robbery		Murder		Burglary	
	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)
Racial/ethnic composition and distribution								
Ethnic heterogeneity	0.336 †	0.339 *	0.104	0.106	0.605 **	0.601 **	0.392 **	0.390 **
	(0.172)	(0.173)	(0.166)	(0.166)	(0.191)	(0.191)	(0.116)	(0.116)
African-American	0.950 **	0.924 **	1.088 **	1.048 **	1.404 **	1.410 **	0.334 **	0.325 **
	(0.186)	(0.187)	(0.171)	(0.172)	(0.182)	(0.182)	(0.124)	(0.124)
Latino	0.185	0.130	1.388 **	1.341 **	1.323 **	1.310 **	1.095 **	1.080 **
	(0.274)	(0.274)	(0.283)	(0.284)	(0.259)	(0.259)	(0.193)	(0.193)
Asian	-0.169	-0.187	-0.689	-0.658	0.015	0.067	-0.274	-0.271
	(0.456)	(0.457)	(0.477)	(0.478)	(0.612)	(0.612)	(0.329)	(0.329)
Other race	0.448	0.411	0.937	0.889	-0.102	-0.111	0.148	0.124
	(0.632)	(0.634)	(0.680)	(0.683)	(0.860)	(0.862)	(0.480)	(0.480)
N	2,186	2,186	2,524	2,524	4,240	4,240	2,711	2,711

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

Figure 4.1. Effect of interaction between ethnic heterogeneity and inequality between African-Americans and whites from fixed effects models predicting the change in violent crime for several cities over various decades spanning the 1970-2000 period

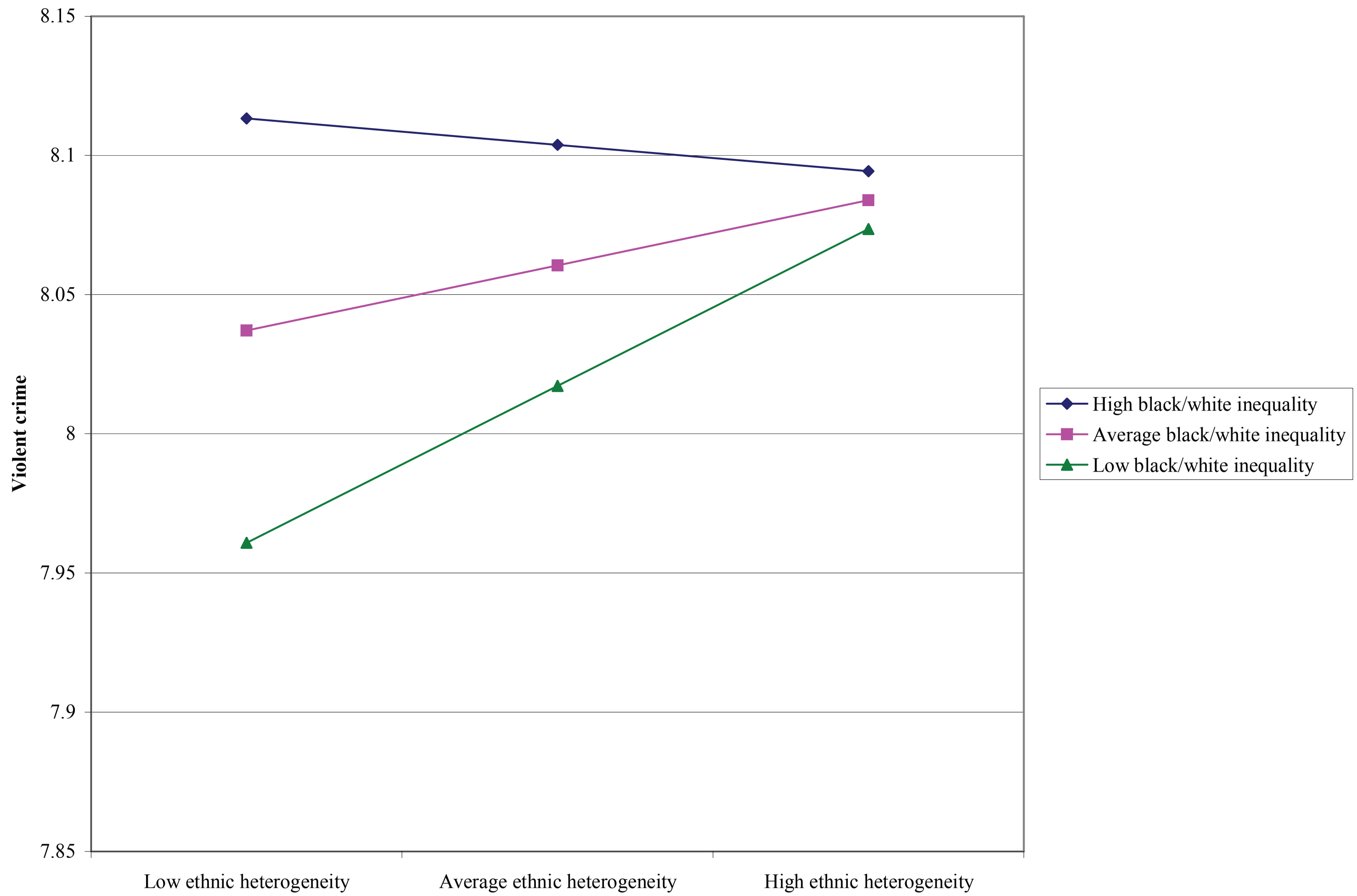


Figure 4.2. Effect of interaction between ethnic heterogeneity and inequality between African-Americans and whites from fixed effects models predicting the change in property crime for several cities over various decades spanning the 1970-2000 period

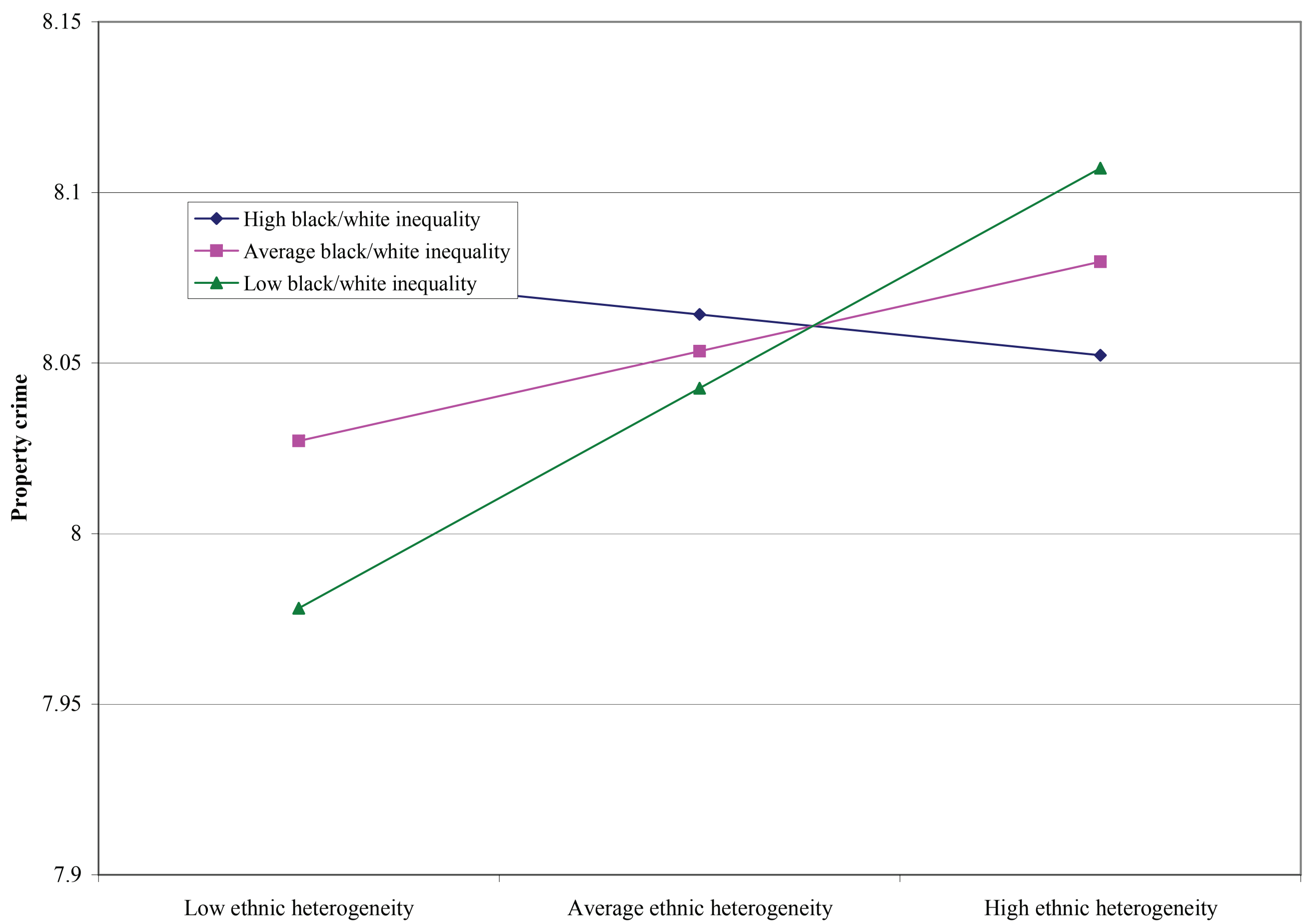
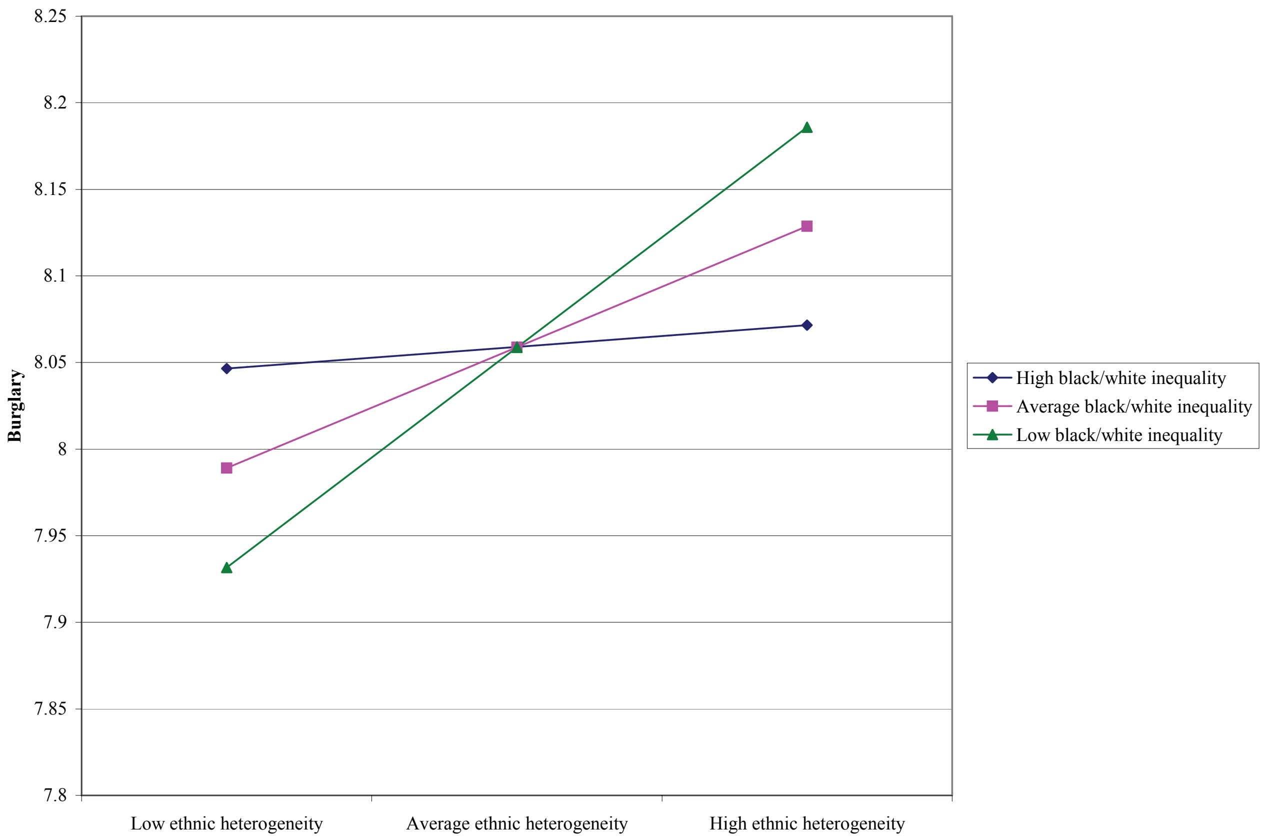


Figure 4.3. Effect of interaction between ethnic heterogeneity and inequality between African-Americans and whites from fixed effects models predicting the change in burglary for several cities over various decades spanning the 1970-2000 period



V. Conclusion

This dissertation has focused on neighborhood change and the intertwining roles of social distance between residents, residential mobility decisions and their implications for the structural characteristics of neighborhoods, and crime. The chapters in this dissertation had several overarching themes.

First, these three different chapters have highlighted the importance of social distance (as measured by the social categories residents are part of) for neighborhoods. Social distance as measured along the category of race/ethnicity was particularly important: block-level ethnic heterogeneity was positively related to a neighborhood's common perception of crime in chapter two's cross-sectional analysis, both block- and tract-level ethnic heterogeneity were positively related to a neighborhood's common perception of crime four years later in the dynamic analyses of chapter three, and tract level ethnic heterogeneity was positively related to crime in both cross-sectional analyses and in fixed effects analyses over a ten-year time period in chapter four. Thus, these results were found for a national sample of non-rural blocks in chapters two and three, and a sample of tracts in several metropolitan areas in chapter four, illustrating the robustness of these findings. In addition, the cross-sectional findings from chapter two suggested that the reason block-level ethnic heterogeneity reduces neighborhood satisfaction is entirely because it increases the crime and disorder of the block.

These chapters also highlighted that social distance beyond simple racial/ethnic differences is important. For instance, chapter two showed that social distance measured at the *individual-level* strongly affects perceived crime and disorder in blocks—but only when social distance is measured using a number of different constructs rather than just race/ethnicity. This suggests that social distance should not be measured just along race/ethnicity, but also along socio-economic characteristics as well as such demographic characteristics as age, marital status, and presence of children. Chapter four highlighted the importance of socio-economic distance, as the fixed effects models found that tracts experiencing increasing inequality across race/ethnicity—thus distance along both race and socio-economic status simultaneously—experienced increasing levels of nearly all types of crime.

But while this dissertation consistently showed that social distance has strong effects on neighborhood crime rates, the effects of race/ethnicity as the proportion minority members in the neighborhood were mixed. On the one hand, the presence of more African-Americans and Latinos was associated with higher rates of neighborhood perceived crime in the cross-sectional analyses of chapter two, and likewise for most of the crime types in the fixed effects analyses of chapter four. Little effect, however, was found in chapter three for the dynamic analyses predicting neighborhood perceived crime four years later. This, accompanied with the findings in chapter three that neighborhoods with higher perceived crime are more likely to see a housing unit transition to an African-American or Latino household, and less likely to see a transition to a white household, raises the possibility that at least some of this relationship between minority groups and crime is due to mobility into neighborhoods, rather than a causal effect from such groups to crime.

While the possibility of reciprocal effects between crime and racial/ethnic composition poses an avenue for future research, a key theme of this dissertation was viewing the possibly reciprocal relationship between crime and residential instability. While chapter three specifically focused on this possible reciprocal relationship, the findings from this dissertation were broader: specifically, a consistent finding was the *lack* of importance of residential stability for reducing crime rates. Instead, we frequently saw that residential stability was associated with *higher* rates of crime. The dynamic models of chapter three found that residential stability actually had a modest positive effect on crime, and both the cross-sectional and the fixed effects models of chapter four found a positive relationship between residential stability and various types of crime. These results from two very different data sets—one a national data set, and the other a collection of eleven different cities over a long period of time—pose a strong challenge to the social disorganization hypothesis that residential stability will reduce crime by increasing neighborhood ties. The results here suggest, at minimum, a need for theorists to specify the reduced scope under which this relationship would operate.

Instead, the results here generally supported one aspect of the theoretical model I developed in chapter three building on the notions of exit, voice, loyalty and neglect: the implication that homeownership may be important for combating crime. While a common strategy of most research in the neighborhood literature is to combine the percent homeowners and the average length of residence in a neighborhood into a composite measure labeled "residential stability," the findings from all three chapters of this dissertation point out that these are indeed two distinct constructs, thus highlighting the need to disentangle them in analyses. Whereas I found residential stability (as measured by average length of residence) often *increased* crime, I found that percent homeowners often *decreased* crime. The percent homeowners on the block was negatively related to the block common perception of crime in the cross-sectional analyses of chapter two, it was negatively related to block common perception of crime four years later in the dynamic analyses of chapter three, and the percent homeowners in the tract was negatively related to both property and violent crime in the cross-sectional analyses of chapter four. The lone exception were the fixed effects models of chapter four—though it should be highlighted that in these models focusing only on change within tracts that the very high stability over time in the percent homeowners in tracts (a correlation of .96 over the decades) suggests there is very little power in these models to detect such effects since there is almost no change within a neighborhood in percent homeowners. These results, along with the positive relationship between percent homeowners and aggregate neighborhood satisfaction in chapter two, suggest that homeownership may be a particularly important characteristic for understanding how neighborhoods evolve over time.

Although less novel, another common theme in this dissertation was the importance of social disadvantage for neighborhoods and their crime rates. Even so, measurement and conceptual issues surround this measure. While neighborhood studies frequently employ the strategy of exploratory factor analysis to combine several variables into a measure of social disadvantage (i.e., percent in poverty, median income, percent with a bachelor's degree, percent divorced families, and percent single parent families), I adopted the strategy of separately estimating the effects of these various components. The results generally supported the importance of economic factors for affecting crime: average neighborhood income was negatively associated with crime and disorder in the cross-sectional analyses of chapter two, and had a negative effect on various types of crime in the fixed effects models of chapter four. As well, the percent on the block below poverty had a positive effect on neighborhood perceived crime four years later in the dynamic models of chapter three, and was positively related to rates of various crime types in the cross-sectional analyses of chapter four. In contrast to these consistent findings for economic factors, the effects for broken families was less clear. While the percentage of single parent families was positively related to neighborhood perceived crime and disorder in the cross-sectional models of chapter two, no such effect was found in the dynamic models of chapter three predicting neighborhood perceived crime four years later, nor in the fixed effects models of chapter four. These differences are obscured in studies collapsing these separate measures into a single measure of disadvantage.

Directions for future research

A key direction for future research is exploring the mechanisms underlying some of the empirical relationships observed here. For instance, the question of what measures to combine into a construct labeled "disadvantage" requires considering the how these various mechanisms work. If high poverty rates increase crime because they reduce access to the resources that would otherwise help combat crime, while broken families increase crime because of a lack of parental monitoring, combining these into a single measure potentially obscures understanding how these processes work given the different mechanisms involved. This has important policy implications, as interventions aimed at providing a substitute for a lack of parental monitoring likely differ from interventions aimed at providing more general resources to a neighborhood. Additionally, the fact that the size of the effect for poverty diminished in the chapter four fixed effects models when including inequality across race suggests yet one more possible mechanism through which poverty might work: instead of poverty increasing crime by reducing access to resources from the larger community, it may be that such neighborhoods simply have more inequality across race/ethnicity, and this is what increases crime. However, even here the mechanism is uncertain as chapter four highlighted: does inequality across race increase crime because it reduces interaction among residents, or because it creates a sense of unfairness and enmity, leading to a violent response? Again, actually measuring these mechanisms is an important next step. Studies that include a linear measure of racial composition in such measures of disadvantage may further confound matters: to the extent that minority groups are hypothesized to cause more crime for various cultural reasons, this suggests yet one more mechanism through which such a composite measure of disadvantage would work. And to the extent that crime itself causes racial/ethnic transformation, as suggested by this dissertation, cross-sectional studies finding a relationship between composite disadvantage and crime—when including racial/ethnic composition as a component of disadvantage—may be particularly unhelpful.

And while this dissertation highlighted the importance of social distance for neighborhood crime and satisfaction—and provided various theoretical rationales for why we should see such a relationship—future research will need to explore more closely the actual mechanisms through which social distance works. One possibility put forth here is that social distance works by reducing the interaction among residents—this clearly raises the need for studies to explore this possible mechanism. While clearly challenging—as this requires collecting information on the demographic, racial/ethnic, and socio-economic characteristics of residents as well as their network linkages with their neighbors—such analyses would provide key insight into this possible mechanism.

Closely related to understanding the *mechanisms* of social distance is understanding the *determinants* of social distance. We need to understand what causes perceived social distance in order to explore its effects. This dissertation took the approach of measuring social distance as a single individual-level construct in which I combined several determinants of social distance into a single observed variable: finding that this measure led to greater perception of crime and disorder in the neighborhood. A natural next direction for research is to explore whether any of these determinants are particularly important for fostering this social distance. That is, while past research has often simply assumed that distance along race/ethnicity is most important, perhaps difference along age or the presence of children is more important. There are certainly important policy implications for understanding which determinants of social distance are most important: an uncomfortable implication of these findings are that certain types of segregation may be preferable for some households. Given the likely controversial nature of such an implication, understanding precisely what sort of social distance is problematic is particularly important. For instance, if distance created by the presence or lack of children is important for creating social distance, this would imply that households with children would prefer to live near other households with children, and households without children would prefer living near like households. This may not be terribly surprising or controversial: anecdotally, we know that certain housing developments are populated with more households containing children, whereas certain condominium developments are populated by young singles and couples without children. Likewise, if age is particularly important for fostering social distance, this would comport with the observation that retirement communities exist in most cities—a form of age segregation.

But the results for the effect of racial/ethnic heterogeneity are potentially more troubling. If it is indeed the case that this racial/ethnic difference reduces interaction, which then leads to more crime, this suggests that policy interventions might focus on bridging the effects this distance might otherwise have on such social interactions. But an additional area of fruitful research would be to determine the effects of this racial/ethnic difference over time, and whether it might diminish. This links with the contact hypothesis literature (Belanger and Pinard 1991; Lee, Farrell, and Link 2004; Powers and Ellison 1995; Quillian and Campbell 2003), which hypothesizes that prolonged periods of interaction will break down such social distance. This suggests the need to model the effects of social distance in a neighborhood over a period of time. And while this might imply that racial/ethnic distance will "cure" itself over time, the mixed results for the contact hypothesis, as well as the possibility that social distance might cause residents to flee a neighborhood before the contact hypothesis could take effect, suggest another fruitful avenue for research.

Besides studying social distance longitudinally, future research will also want to study it contextually. That is, the finding in this dissertation that inequality across race/ethnicities had a strong positive effect on crime in the fixed effects models suggests that reducing the economic inequality across race/ethnicities may be a first step towards reducing the effects of racial/ethnic social distance. If this is indeed the case, various manners of reducing this inequality across racial/ethnic groups would be a natural point of intervention for policy makers. While the distribution of income across racial/ethnic groups may accentuate the distance effects of race/ethnicity, another possibility worth exploring is whether the aggregate level of economic resources can reduce the effect of this racial/ethnic social distance. That is, the context of higher income areas may minimize the distance otherwise fostered by racial/ethnic difference. This suggests an "all boats rise together" framework, and that any inequality would be more tolerable in an environment of greater wealth. While clearly speculative, exploring such a possibility would provide one more possible intervention point for policy makers.

One surprising result of this dissertation was how little effect residential instability had on crime rates. This poses a considerable challenge to the social disorganization theoretical model. And while residential stability had the positive relationship with overall neighborhood satisfaction predicted by the systemic model (Kasarda and Janowitz 1974) in the cross-sectional models of chapter two, it is important to note that the causal direction of this relationship may in fact be reversed. That is, to the extent that household level neighborhood satisfaction may be important for residential mobility decisions (Speare 1974), this presumed causal effect of the systemic model may be called into question. Exploring this possible reciprocal relationship between neighborhood satisfaction and residential stability suggests another fruitful direction for future research using longitudinal data.

But while there was little evidence that the residential instability caused by mobility decisions affects crime rates, an alternative possibility suggested by these results is that the presence of unoccupied units caused by residential mobility decisions may be important. That is, when a household chooses to leave a neighborhood, there are two possible outcomes for the housing unit they leave: 1) they are replaced by another household, hence increasing the amount of residential instability; 2) they are not replaced at all, thus increasing the vacancy rate in the neighborhood. And this may not be a trivial issue: in this dissertation neighborhoods with higher vacancy rates had higher levels of perceived crime and disorder in the cross-sectional models of chapter two, and also had a generally positive effect on different crime types in the fixed effects models of chapter four. While no such effect was found between vacancy rates and perceived crime in the dynamic models of chapter three, the overall findings here nonetheless suggest that this would be a useful possible direction to explore. The fact that higher vacancy rates led to greater residential instability in the dynamic models of chapter three also has important implications for theoretical models of neighborhood change: this suggests the possibility that a household abandoning a neighborhood—and not replaced by another—may trigger a chain reaction where these higher vacancy rates cause more crime, and the crime and vacancy rates then induce more mobility that continues the downward cycle. This suggests that abandoned units can have consequences for neighboring units. The externalities implied by these vacant units suggest a possible important policy intervention point. At a minimum, this suggests the need to further explore this possible interrelationship between crime, residential instability, and abandoned units.

Finally, the results of this dissertation highlighted that not only can crime rates in neighborhoods affect mobility decisions on the part of their residents, but also that crime rates affect who chooses to move into such neighborhoods. In particular, the models from chapter three suggested that the common perception of neighborhood crime engenders racial/ethnic transformation in neighborhoods. Whereas a household is more likely to become occupied by an African-American or a Latino household if it is in a block with a higher level of perceived crime, a household in the same block is *less* likely to become occupied by a white household. This suggests a particularly important mechanism through which neighborhood racial/ethnic transformation may occur, and highlights that the relationship between the racial/ethnic composition of a neighborhood and the crime rate may be more nuanced. Future research will need to explore how strong this effect is, and what the implications are for theories proposing that higher levels of minority residents in a neighborhood cause greater levels of crime.

APPENDIX A: Combining spatial data into common units over time

For the aggregate spatial data I used, it is necessary to place the data into common units over time. Since some of the data is aggregated to different units to begin with, this requires 1) placing the data into a common unit at a particular point in time (I used census tracts); and then 2) combining these census tracts over time into a common unit (I used 1990 census tracts for the Chapter 3 analyses, and 1980 census tracts for the Chapter 1 and 2 analyses since the American Housing Survey respondents are placed into 1980 tracts). I use 1990 tracts in the Chapter 3 analyses because: 1) most of my data are for the years 1990 and 2000; 2) since more tracts in the U.S. are experiencing increasing population and hence splitting rather than experiencing shrinking population and hence collapsing with other tracts, using 1990 tracts requires fewer assumptions, as I elaborate at the end of this appendix.

Placing the data into a common unit at a particular point in time

When collapsing data from any non-tract unit into census tracts, a distinction needs to be made between count data and per capita data. Consider Figure A1, which illustrates a hypothetical situation in which two zip codes (or any other type of unit) overlap with six tracts. Tracts 1 and 2 are both entirely contained within zip code A (containing perpendicular lines), while tracts 5 and 6 are both entirely contained within zip code B (containing diagonal lines). Tracts 3 and 4 overlap with both zip codes. Suppose we have count data (e.g., the number of retail establishments) for the zip codes. If we assume a homogeneous condition in which a retail establishment is equally likely in any location of the zip code, then we can proportionately assign the number of retail establishments to the tract. To do this, we calculate the proportion of the zip code which each tract constitutes. Thus,

(1) $$X_i = \sum_{j=1}^{J} X_j (P_{ij} / P_j)$$

where X_i represents the count of the variable of interest in the tract which we are estimating, X_j represents the count of the variable of interest in the j=1 to J zip codes the tract lies within, P_{ij} represents the population of tract *i* contained within zip code *j*, and P_j represents the population of zip code *j* (note that for certain measures it was necessary for me to substitute the area of the tracts and zip codes rather than the population for P). For instance, if tract 1 constitutes 30% of zip code A, then we multiply the number of retail establishments in zip code A by .3 to obtain an estimate of the number of retail establishments in tract 1. For tract 3, we multiply the number of retail establishments in zip code A by the proportion of zip code A constituted by tract 3, and sum this with number of retail establishments in zip code B multiplied by the proportion of zip code B constituted by tract 3.

The calculation is different for per capita measures, such as the number of retail establishments per 1,000 population. In this instance, we calculate the proportion of the tract contained within each zip code:

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

where X_i represents the per capita measure of the variable of interest in the tract which we are estimating, X_j represents the per capita measure of the variable of interest in the j=1 to J zip codes the tract overlaps, P_{ji} represents the population of zip code *j* contained within tract *i*, and P_i represents the population of tract *i*. For instance, in Figure A1, since 100% of tract 1 lies within zip code A it is given the same value of X as zip code A (given our homogeneity assumption within a zip code, we assume that the per capita rate for any variable would be the same for a tract lying entirely within the zip code). On the other hand, for tract 3 we would multiply the proportion of tract 3's population in zip code A by the per capita measure of the variable of interest, sum this with the product of the proportion of tract 3's population in zip code B and the per capita measure of the variable of interest, and divide this by 2 (that is, J—the number of zip codes with which tract 3 overlaps). Thus, we compute the mean of the zip code values weighted by the proportion of the tract contained within each zip code.

I used this general procedure for each of the different aggregated units.

Zip Codes into tracts

To place 1982 and 1987 economic census data into 1980 tracts I used the Master Area Reference File (Census 1980). This provides me with estimates of the population per tract for 1980, and I use this to weight the zip code data into tracts, as describe above. To place 1992 and 1997 economic census data into 1990 tracts I used the MABLE/GEOCORR website at the University of Missouri that places zip codes into tracts based on population (http://mcdc2.missouri.edu/websas/geocorr90.shtml).

School district data into tracts

This school district data was taken from the Local Education Agency (School District) Universe Survey Longitudinal Data File: 1986-1997 (Education 2001). To place this data into 1980 census tracts to match with the AHS, I obtained shape files for school districts in 2000 from the Census Bureau website (www.census.gov), and intersected these with the shape files for 1980 census tracts (these shape files for 1980 census tracts were obtained from the Geolytics CD-ROM for 1980 census data). Thus, I was able to determine the overlap in area between a given tract and a school district, and I used the amount of area as the weighting when using equations 1 and 2 to place the school district data into tracts.

Neighborhood data into tracts

The Baltimore crime data comes from the "Crime Changes in Baltimore, 1970-1994" (CCIB) study. This study measures the amount of crime in various Baltimore neighborhoods over this period of time. Thus, I needed to place this neighborhood crime data into tracts. Fortunately, there is considerable overlap between these neighborhoods and census tracts in Baltimore. To determine the degree of overlap: 1) I obtained shape file information on the boundaries of neighborhoods in 1990 from the Johns Hopkins website (http://webapps.jhu.edu/census/); 2) I then visually reconciled this listing of neighborhoods with a hard copy map of the neighborhoods used in the CCIB study (contained in Taylor, Brower, and Drain 1979). It was necessary for me to collapse a few of the neighborhoods in the CCIB study to match them up with the neighborhoods mapped in 1990. Once reconciling the neighborhoods over time, I was then able to use ArcView to determine the degree of overlap between neighborhoods and tracts based on area, and used equations 1 and 2 above to place the crime data into tracts.

Combining these census tracts into a common unit over time

The second issue is taking into account tracts that change boundaries over time. Tracts generally change in one of two ways: 1) those experiencing population increases will split over time into multiple tracts; 2) those experiencing population decreases will consolidate over time into fewer tracts.[83] Consider the top panel of Figure A2, which illustrates situation 1: tract A at time one has split into two tracts (A1 and A2) at time two. Also consider the bottom panel of Figure A2, which illustrates situation 2: Tracts A and B at

[83] To place year 2000 tracts into 1990 tracts, I used the Census Tract Relationship File (Census 2000). To place 1980 tracts into 1990 tracts, I used the TIGER/Census Tract Comparability File (Census 1990). To place 1970 tracts in 1980 tracts, I used the 1980-1970 tract comparability file (Census 1987).

time one have collapsed into tract 1 at time two. Suppose we want to use the common geography over time of tracts at the first time point. Of course, since the time one data are already in the correct tracts we need not adjust these data at all. However, we must adjust the time two data. To calculate the value of a count variable at time 2, we sum the values of the tracts at time two by the proportion of the tract in the full tract at time one:

(3) $$X_i = \sum_{j=1}^{J} X_j (P_j / P_{ji})$$

where X_i represents the count of the variable of interest at time two in the time one tract boundaries which we are estimating of the i-th tract at time one, X_j represents the count of the variable of interest in the j=1 to J tracts at time two lying within the time one boundary, P_j represents the population of the time two tract j, and P_{ji} represents the population of tract j contained within tract i at time one. Thus, we are weighting by the proportion of the time two tract lying within the time one tract. For instance, in the top panel of Figure A2, since 100% of tract A1 and A2 lie within tract A at time one, they are weighted at one, thus a simple sum of their values of X gives the total of X in tract "A" at time two (the hypothetical tract we are constructing). In the bottom panel of Figure A2, we must split the time two tract 1 into tracts "A" and "B": we do this by multiplying X (the value in tract 1) by the proportion of the population constituted by the two tracts at time one. Suppose that at time one, 30% of the time two tract lay within tract A and 70% lay within tract B. We then multiply X by each of these proportions to get the values for tracts "A" and "B" at time two.

Again, things are slightly different when dealing with per capita variables rather than counts, as we must again take a mean value:

(4) $$X_i = \frac{1}{J} \sum_{j=1}^{J} X_j (P_j / P_{ij})$$

where X_i represents the per capita value of the variable of interest at time two in the time one tract boundaries which we are estimating of the *i*-th tract at time one, X_j represents the per capita value of the variable of interest in the j=1 to J tracts at time two lying within the time one boundary, P_j represents the population of the time two tract *j*, P_{ij} represents the population of tract j in the time one (*i*) boundaries, and we now are taking the mean value of the per capita variable (since we are dividing by J). Thus, in the top panel of Figure A2, to calculate the value of tract "A" at time two we weight the per capita values of tracts 1 and 2 by the proportion of the tract "A" population they represent at time two. The per capita value of tract A1 is weighted by the proportion of the population in tract "A" it represents, and likewise for tract A2. In the bottom panel of Figure A2, we must split the time two tract 1 into tracts "A" and "B": since we assume homogeneity within this area, each tract receives the same per capita value.

While the assumption of homogeneity is certainly not ideal, lacking additional information on these tracts I have little choice. Nonetheless, there is reason to suspect that this is a fairly reasonable assumption, given that there is considerable evidence of spatial contiguity of many demographic variables in cities. I tested this by viewing the data used in my chapter 4 analyses, finding considerable spatial autocorrelation for these measures. For instance, I calculated the Moran's I statistic for several of the variables in 2000 for four different cities in the sample: Baltimore, Cleveland, Denver, and Milwaukee. The lowest Moran's I values were for percent occupied units variable, with values of .363, .331, and .266 for the cumulative distance bands of 2/3 mile, 1 1/3 mile, and 2 miles respectively.[84] The

[84] Moran's I statistics generally range from –1 to +1, and are somewhat analogous to correlation coefficients. The band size groups together tracts based within that particular distance, and then compares the covariation within these bands to the overall covariation in the sample. Intuitively, when more similar tracts are located close together, the covariation within these bands of tracts will be higher than the overall covariation.

average income variable had similar values (.413, .337, .249), suggesting a fair degree of clustering even for these measures. And the other measures showed even stronger spatial correlation, with percent owners (.604, .469, .384), bars/liquor stores employees per capita (.638, .562, .422), and retail shop employees (.605, .482, .328) showing similar degrees of spatial autocorrelation. And the percent African-American variable showed the strongest degree of autocorrelation (.79, .695, .565). This suggests considerable geographic contiguity for these measures, suggesting that the homogeneity assumption is not too unreasonable.

Second, there is considerable consistency over time in these measures for tracts that do not change boundaries. For instance, the summary statistics shown in Table 4.3 for chapter 4 show that the correlations over the decade for many of these measures range from .60 to .95. While not evidence of homogeneity geographically, this does attest to the general stability of these measures. This is useful given that the sources of data do not always come from the same year: this temporal stability suggests that being off a couple years likely does not cause many problems.

Finally, given that nearly all of the variables I use in the analyses are per capita measures, I point out an implication of my decision to place the data into 1990 tracts. As noted above, most of my data are for the years 1990 and 2000. If I had instead chosen to place the data into year 2000 tracts, I would need to adopt this homogeneity assumption of the 1990 tract for a particular variable in any tract that split during this time period when apportioning it to the various new tracts. However, by using 1990 tracts, I am instead combining the various year 2000 tracts together—this gives me an accurate estimate of the variable without having to assume homogeneity (a downside is that this approach results in fewer tracts, but the size of my sample allows me to adopt this strategy).

Figure A1. Collapsing other geographic units into tracts

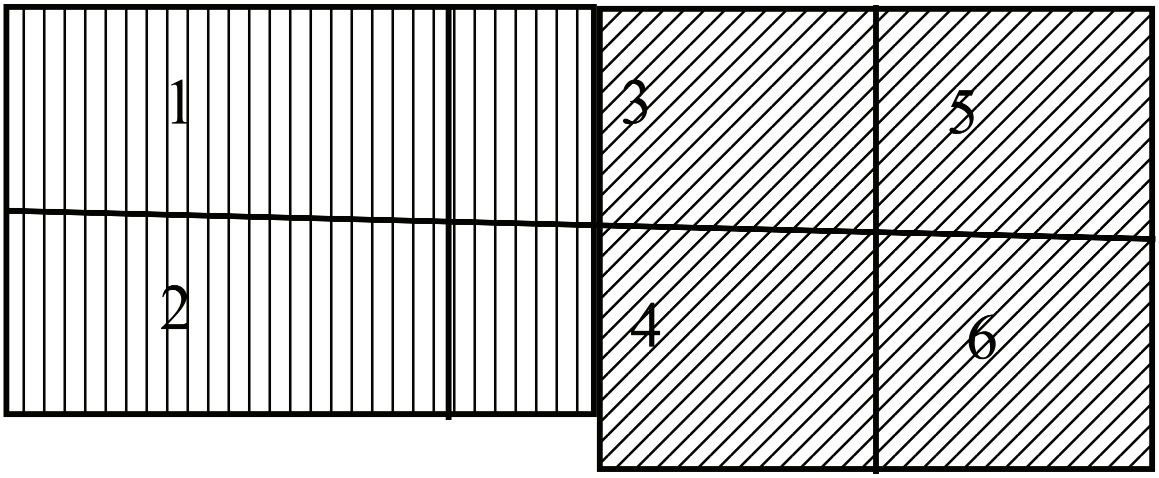
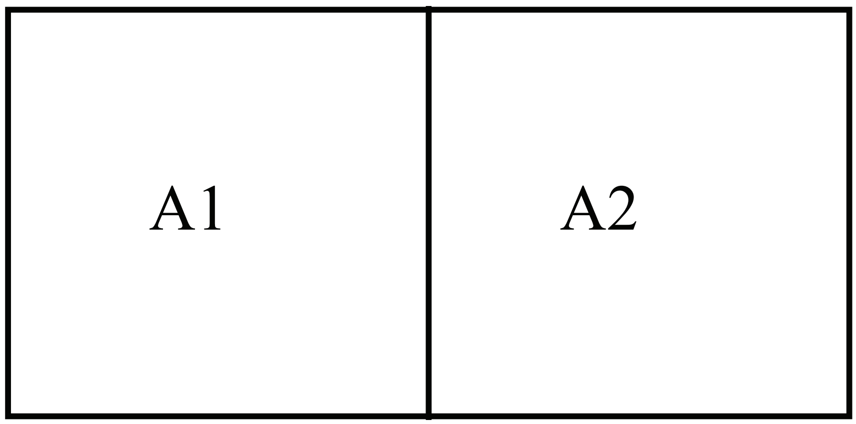
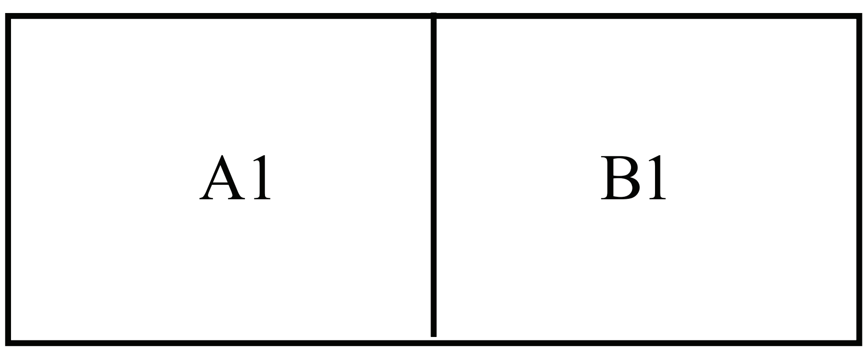


Figure A2. Tracts changing over time

Case 1: Tract A at time one has split into two tracts (A1 and A2) at time two



Case 2: Tracts A and B at time one have collapsed into tract 1 at time two



APPENDIX B: Detecting spatial effects in models, and estimation of spatial effects models

A complication for analyses of neighborhoods in cities is that neighborhoods are adjacent to one another. This raises the possibility of spatial autocorrelation or spatial lag. Morenoff et al (2001) posit three theoretical reasons for spatial effects: 1) there is an inexact correspondence between neighborhood boundaries of census geography and the ecological properties that shape social interaction; 2) offenders are disproportionately involved in delinquent acts near their homes; 3) interpersonal crimes are based on social interaction and thus subject to diffusion processes. Indeed, past studies have found spatial effects for race when employing such data: a study of 74 local community areas in Chicago found a spatial effect where "if one area increases its nonwhite composition, adjoining areas are also likely to" (Heitgerd and Robert J. Bursik 1987). Another study found that integrated neighborhoods primarily function as border zones separating more segregated areas (Kenyon 1976). Other studies have shown a spatial effect for crime rates between neighborhoods (Kubrin and Herting 2003; Morenoff, Sampson, and Raudenbush 2001; Nielsen and Martinez 2003; Roncek and Maier 1991; Smith, Frazee, and Davison 2000).

The first issue for assessing possible spatial effects is determining what constitutes "close" neighborhoods (or any other unit of analysis in a spatial model). This choice is not straightforward, and evidence suggests that this decision can have serious ramifications for estimates (Anselin 1988; Anselin 2002; Florax and Rey 1995; Leenders 2002). There are two dominant approaches. The first is based on contiguity, and determines closeness based on sharing a border. Researchers adopting such an approach will sometimes simply count the neighborhoods that share a border with the neighborhood of interest, or sometimes they will weight the adjacent neighborhoods based on the proportion of the border they share with the focal neighborhood. Researchers adopting the second dominant approach utilize some type of distance decay function in measuring the distance of surrounding neighborhoods from the focal neighborhood. Most commonly, they will calculate the inverse distance of the other neighborhoods from the focal neighborhood, and generally employ a particular cutoff point at which the weight is given a value of zero. This resulting weight matrix (W) is usually then row-standardized (that is, the distance of the nearby neighborhoods from the focal neighborhood sums to one). In this study, I adopted the latter approach, employing a distance decay function with a cutoff at two miles (beyond which the neighborhoods have a value of zero in the W matrix). Given that past studies have suggested a distance decay function for offenders (Rengert, Piquero, and Jones 1999), with an average distance traveled between 1 to 2.5 miles (Pyle 1974), this seems a reasonable choice for a weight matrix.

Given a W matrix indicating "close" neighborhoods, we can then specify either a spatial autocorrelation or a spatial lag model. A spatial autocorrelation (or spatial error) model can be specified as:

$$Y = XB + \varepsilon$$

where $\varepsilon = \lambda W\varepsilon + \mu$, Y is a vector of the outcome measure, X is a matrix of predictors that have B effect on y, λ represents the spatial autoregressive parameter, and μ is a vector of homoskedastic and uncorrelated errors.

Alternatively, we can specify a spatial lag model:

$$Y = \rho WY + XB + \mu$$

where ρ represents the spatial autoregressive parameter, WY represents the spatially lagged dependent variable, and all other terms are as defined before.

Detection of spatial autocorrelation or spatial lag in models

Considerable recent work has been done on the question of detecting the presence of spatial autocorrelation (λ in the above equations) or spatial lag (ρ in the above equations) in models. This endeavor is challenging, given the possible confounding of the other effect when testing one effect. For instance, the most common approach uses the Lagrange Multiplier. In this approach the standard ordinary least squares model is estimated (assuming that λ and ρ are zero), and diagnostics are then performed on these residuals (Anselin 1988; Anselin, Bera, Florax, and Yoon 1996; Anselin and Florax 1995). However, when testing $\lambda = 0$, such tests will respond to nonzero ρ. Conversely, Lagrange Multiplier tests of $\rho = 0$ will respond to nonzero λ. This raised a need for tests that are robust to such confounding effects, and Anselin et. al. (1996) devised such "robust" LM tests, as they referred to them. Monte Carlo simulations suggested that these robust LM tests perform reasonably well (for details on this test procedure and the simulation results, see Anselin, Bera, Florax, and Yoon 1996).

Thus a problem I encountered when performing these tests is my large sample size. In the fixed effects models looking at change in neighborhoods I had between 2,000 and 3,000 cases. In the cross-sectional models, I had 5,000 cases. Since the spatial tests require the use of the X matrix, which grows exponentially with sample size, this poses memory problems. I therefore took the approach of performing the tests for each city separately (since there would be no spatial effects *across* cities). As noted in chapter four, there is much less reason to expect spatial effects in the fixed effects model, since taking into account unchanging characteristics of the tract also takes into account unchanging spatial effects. In support of this, there seems to be considerable evidence of spatial lag effects in the cross-sectional data, but little evidence of spatial error or spatial lag effects for the fixed effects model for violent crime, as presented in Table A1. This table presents the results of the robust LM tests for both spatial correlation and spatial lag(Anselin, Bera, Florax, and Yoon 1996). The general pattern shows that spatial lag is much more of a threat in these data than spatial error, as the effects for spatial lag are nearly always stronger. Note that for the fixed effects models, only three cities show appreciable evidence of spatial lag effects (Milwaukee in 1990-2000, and Seattle and Baltimore from 1970-80). Two other cities are just barely significant for a spatial lag effect. Thus, in most of these cities there is no evidence of spatial lag effects when taking into account the unobserved fixed effects of these tracts. In sharp contrast, for the cross-sectional models, 10 of the 12 cities show significant evidence of spatial lag effects, and often very strong evidence. The spatial effects for property crime show a similar pattern, though the spatial effects are weaker for this type of crime. For property crime, just one city shows appreciable evidence of a spatial lag effect (Baltimore from 1990-2000), and two others are marginally significant. Again, there is much stronger evidence for a spatial lag effect in the cross-sectional model, as 6 of the 9 cities show considerable spatial effects.

As a further diagnostic, I also estimated maximum likelihood models for each city taking into account spatial lag, and compared these results to OLS models ignoring this possible spatial effect. In the cross-sectional models for violent crime, the average bias of coefficients was 21.0% (as measured by the absolute difference of the two coefficients divided by the coefficient from the OLS model, and taking an average over all significant coefficients), and the typical coefficient was overestimated in the OLS models by 31.0% (as measured by dividing the coefficient from the OLS model by the coefficient from the spatial lag model, and taking an average over all significant coefficients).[85] In contrast, there was much less evidence of bias present in the fixed effects models for violent crime, as the significant coefficients had an average bias of just 3.7%, and the average coefficient overestimate in the models without spatial effects was just 2.4%. The pattern of stronger spatial effects for the cross-sectional models was again evident when using property crime as the outcome, as the cross-sectional models showed average bias of 10.5% and on average overestimated coefficients by 4.5%. These numbers were again smaller for the fixed effects models, with average bias of just 2.8%, and overestimating coefficients by just 1.8% when failing to take into account possible spatial effects. Again, this highlights that taking into account the unobserved fixed effects of tracts largely eliminates spatial effects.

Estimation of models with spatial autocorrelation or spatial lag

While there are various strategies for estimating models with spatial autocorrelation and spatial lag, many of these are not explicitly tailored to multivariate modeling. A common approach is a maximum likelihood strategy to handle various types of spatial heterogeneity, autocorrelation, and lag (Anselin 1988). However, such an approach is computationally intensive, and is difficult to apply to multivariate analysis. It is particularly unwieldy for a sample the size of the one here. An alternative strategy utilizes the two-stage least squares approach suggested by Anselin (1988) and modified by Land and Deane (1992). Land and Deane (1992: 221) suggest that this 2SLS strategy is "much more computationally efficient than the ML estimator and yields numerical estimates of comparable statistical efficiency." They argue that their approach will perform relatively well in large samples

[85] I only compare significant coefficients for this contrast----very small insignificant coefficients can show very high proportional variability simply because they are estimated so close to zero.

when good exogenous identifying variables are available, and showed in a particular example that the estimates obtained both through 2SLS and ML were very similar.

The key for any two-stage least squares approach is obtaining appropriate instrumental variables. That is, the researcher needs to find variables that are uncorrelated with the disturbance term in the equation of interest, but nonetheless correlated with the endogenous variable. In this instance, the endogenous variable is the spatially lagged y-variable for neighboring tracts to the tract of interest. There are at least three different two-stage least squares approaches to handling spatial lag effects. In these models, y* represents the value of y in the nearby neighborhoods. The 2SLS approach estimates $\hat{y}*$ in a first stage, and then includes this estimate in the final model. As mentioned above, various W matrices can be created.

One approach was proposed by Anselin (1988), and entails first estimating $\hat{y}*$ by regressing y on all of the x-variables in the model. This estimate of $\hat{y}*$ is then multiplied by W to create $\hat{y}**$ (I denote this new estimate with double-asterisks). This $\hat{y}**$ is then included in the structural model of interest. Note that pre-multiplying $\hat{y}*$ by W provides the identification for this model; this is because this W varies across observations, breaking the otherwise perfect collinearity between X and the instruments.

A second approach was proposed by Anselin (1988) and Land and Deane (1992) and entails first creating a new variable, Wy*, by multiplying the amount of crime in a tract by its distance from the tract of interest. Land and Deane (1992) motivated this by comparison to the population potential model (Duncan, Cuzzort, and Duncan 1963). In this approach, the researcher first creates a W matrix of the distances of all the tracts in the city from one another. Then an estimate of $W\hat{y}^*$ is created by regressing Wy* on all of the x-variables in the model plus some additional exogenous predictors not in the model (these "instruments" provide the identification for the model). This $\hat{y}^*$ is then included in the structural model. A challenge for this approach is finding suitable instruments.

A third approach entails multiplying the matrix of X variables by the weight matrix (W) to create WX variables; these WX variables are then used as the instruments in the first stage equation predicting Wy*. This approach was suggested by Anselin (1995), and employed by Morenoff (2003) in a study of Chicago neighborhoods. Note that this approach assumes that whereas the value of X in a neighboring tract has a direct effect on that tract's crime, it has no direct effect on the crime rate in the tract of interest. Indeed, this is how the initial model is specified (of course, the value of X in these neighboring tracts would have an indirect effect on the Y in the tract of interest, but this does not disqualify them as instruments since they do not have a posited direct effect).

I adopted the third 2SLS approach in this study for the cross-sectional models. This estimator for the cross-sectional models was generally well-behaved: for instance, in the violent crime model the R-square for the first stage regression was .68, suggesting that I am getting a rather reasonable estimate of the $\hat{y}^*$ that I am including in the structural model. In the property crime model, the first stage R-square was .66. Also important is that these instruments help to uniquely explain this $\hat{y}^*$ from the X variables in the structural equation: I tested for collinearity by regressing this $\hat{y}^*$ on the X variables in the structural equation and found an R-square of .89 in the violent crime model and .92 in the property crime model. While relatively high as both are near the suggested cutoff of values of .90, they suggest a decent job of creating an independent estimate of the spatial effects. It is also instructive to contrast these results when estimating a spatial 2SLS for the fixed effects model (which show little spatial effects), as the collinearity of the $\hat{y}*$ with the predictors in the model is much higher: .96 in both the violent crime and property crime models.

Table A1. Tests for spatial error and spatial lag in two types of models: fixed effects models for change in the decade, and OLS models for a single point in time. Models for two outcomes: violent crime and property crime

		Fixed effects models				Cross-sectional OLS models			
		Robust LM test for spatial error		Robust LM test for spatial lag		Robust LM test for spatial error		Robust LM test for spatial lag	
City	Years	Test	P-value	Test	P-value	Test	P-value	Test	P-value
Violent crime models									
Denver	1990-2000	0.032	0.859	0.424	0.515	2.400	0.121	25.565	0.000
Milwaukee	1990-2000	8.764	0.003	17.047	0.000	12.926	0.000	29.091	0.000
Sacramento	1990-2000	1.009	0.315	0.163	0.687	0.356	0.551	64.157	0.000
Indianapolis	1990-2000	1.990	0.158	3.028	0.082	5.290	0.021	8.525	0.004
Cleveland	1990-2000	4.201	0.040	4.155	0.042	0.354	0.552	0.371	0.542
Washington	1990-2000	0.024	0.878	0.092	0.762	9.444	0.002	25.195	0.000
Baltimore	1990-2000	3.285	0.070	4.724	0.030	3.263	0.071	16.552	0.000
Washington	1980-1990	0.729	0.393	1.786	0.181	9.521	0.002	60.198	0.000
Baltimore	1980-1990	2.768	0.096	1.803	0.179	9.991	0.002	18.118	0.000
Seattle	1970-1980	7.807	0.005	8.876	0.003	1.844	0.174	1.867	0.172
St. Louis	1970-1980	3.508	0.061	1.875	0.171	2.253	0.133	19.013	0.000
Baltimore	1970-1980	7.922	0.005	9.443	0.002	3.154	0.076	16.968	0.000
Property crime models									
Denver	1990-2000	0.589	0.443	0.043	0.836	3.016	0.082	12.833	0.000
Milwaukee	1990-2000	1.528	0.216	2.524	0.112	8.837	0.003	11.933	0.001
Sacramento	1990-2000	0.258	0.612	0.546	0.460	0.000	0.994	59.197	0.000
Indianapolis	1990-2000	2.540	0.011	1.078	0.299	4.209	0.040	6.736	0.009
Cleveland	1990-2000	3.639	0.056	4.205	0.040	0.094	0.759	0.064	0.800
Baltimore	1990-2000	13.487	0.000	14.377	0.000	3.346	0.067	21.707	0.000
Baltimore	1980-1990	0.013	0.910	0.000	0.988	4.944	0.026	9.837	0.002
St. Louis	1970-1980	3.027	0.082	4.079	0.043	0.401	0.527	0.167	0.683
Baltimore	1970-1980	0.753	0.386	1.473	0.225	3.298	0.069	2.836	0.092

Note: All tests are chi-square distributed with 1 degree of freedom

References

Adams, Richard E. 1992. "Is happiness a home in the suburbs?: The influence of urban versus suburban neighborhoods on psychological health." *Journal of Community Psychology* 20:353-371.

Agency, Environmental Protection. 2005. "The toxics release inventory (TRI) and factors to consider when using TRI data." Environmental Protection Agency, Washington, D.C.

Agency, United States Environmental Protection. 2004. "EPA's risk-screening environmental indicators (RSEI) chronic human health methodology." Washington, D.C.

Aigner, Dennis J. and Arther S. Goldberger. 1970. "Estimation of Pareto's law from grouped observations." *Journal of the American Statistical Association* 65:712-723.

Alaniz, Maria Luisa, Randi S. Cartmill, and Robert Nash Parker. 1998. "Immigrants and violence: The importance of neighborhood context." *Hispanic Journal of Behavioral Sciences* 20:155-175.

Alba, Richard D. and John R. Logan. 1992. "Analyzing locational attainments: Constructing individual-level regression models using aggregate data." *Sociological Methods & Research* 20:367-397.

Alba, Richard D., John R. Logan, and Paul E. Bellair. 1994. "Living with crime: The implications of racial/ethnic differences in suburban location." *Social Forces* 73:395-434.

Aldrich, Howard. 1975. "Ecological succession in racially changing neighborhoods: A review of the literature." *Urban Affairs Quarterly* 10:327-348.

Aldrich, Howard, John Cater, Trevor Jones, David McEvoy, and Paul Velleman. 1985. "Ethnic residential concentration and the protected market hypothesis." *Social Forces* 63:996-1009.

Allison, Paul D. 1978. "Measures of inequality." *American Sociological Review* 43:865-880.

—. 2000. "Combchi." Philadelphia, PA: University of Pennsylvania.

Allison, Paul D. and Kennth A. Bollen. 1997. "Change scores, fixed effects, and random effects: A structural equation approach." in *American Socioogical Association Convention*. Toronto, Ontario, Canada.

Alwin, Duane F. 1987. "Distributive justice and satisfaction with material well-being." *American Sociological Review* 52:83-95.

Anselin, Luc. 1988. *Spatial econometrics: Methods and models*. Boston: Springer.

—. 1995. *Spacestat version 1.80 user's guide*. Urbana, IL: University of Illinois.

—. 2002. "Under the hood. Issues in the specification and interpretation of spatial regression models." *Agricultural Economics*:27:247-267.

Anselin, Luc, Anil K. Bera, Raymond Florax, and Mann J. Yoon. 1996. "Simple diagnostic tests for spatial dependence." *Regional Science and Urban Economics* 26:77-104.

Anselin, Luc and Raymond J.G.M. Florax. 1995. "Small sample properties of tests for spatial dependence in regression models: Some further results." Pp. 21-74 in *New directions in spatial econometrics*, edited by L. Anselin and R. J. G. M. Florax. New York: Springer.

Arguea, Nestor M. and Cheng Hsiao. 2000. "Market values of environmental amenities: A latent variable approach." *Journal of Housing Economics* 9:104-126.

Aristotle. 1946. *The politics*, Edited by E. Barker. London: Oxford.

Austin, D. Mark and Yoko Baba. 1990. "Social determinants of neighborhood attachment." *Sociological Spectrum* 10:59-78.

Austin, D. Mark, L. Allen Furr, and Michael Spine. 2002. "The effects of neighborhood conditions on perceptions of safety." *Journal of Criminal Justice* 30:417-427.

Balkwell, James W. 1990. "Ethnic inequality and the rate of homicide." *Social Forces* 69:53-70.

Bauman, Karl E. 1968. "Status inconsistency, satisfactory social interaction, and community satisfaction in an area of rapid growth." *Social Forces* 47:45-52.

Belanger, Sarah and Maurice Pinard. 1991. "Ethnic movements and the competition model: Some missing links." *American Sociological Review* 56:446-457.

Bellair, Paul E. 1997. "Social interaction and community crime: Examining the importance of neighbor networks." *Criminology* 35:677-703.

—. 2000. "Informal surveillance and street crime: A complex relationship." *Criminology* 38:137-167.

Bernaards, Coen A. and Robert I. Jennrich. 2005. "Gradient projection algorithms and software for arbitrary rotation criteria in factor analysis." *Educational and Psychological Measurement* 65:676-696.

Berry, M. and F. Bove. 1997. "Birth weight reduction associated with residence near a hazardous waste landfill." *Environmental Health Perspectives* 105:856-861.

Beyerlein, Kraig and John R. Hipp. 2005. "Social capital, too much of a good thing? American religious traditions and community crime." *Social Forces* 84:995-1013.

Blau, Judith R. and Peter M. Blau. 1982. "The cost of inequality: Metropolitan structure and violent crime." *American Sociological Review* 47:114-129.

Blau, Peter M. 1977. "A macrosociological theory of social structure." *American Journal of Sociology* 83:26-54.

—. 1987. *Inequality and heterogeneity : A primitive theory of social structure*. New York: Free Press.

Blau, Peter M. and Reid M. Golden. 1986. "Metropolitan structure and criminal violence." *The Sociological Quarterly* 27:15-26.

Blumer, Herbert. 1958. "Race prejudice as a sense of group position." *Pacific Sociological Review* 1:3-7.

Bobo, Lawrence and Vincent L. Hutchings. 1996. "Perceptions of racial group competition: Extending Blumer's theory of group position to a multiracial social context." *American Sociological Review* 61:951-972.

Bogardus, Emory S. 1947. "Measurement of personal-group relations." *Sociometry* 10:306-311.

Bolan, Marc. 1997. "The mobility experience and neighborhood attachment." *Demography* 34:225-237.

Bollen, Kenneth A. 1989. *Structural equations with latent variables*. New York: John Wiley & Sons.

Bollen, Kenneth A. and J. Scott Long. 1993. "Testing structural equation models." Newbury Park, CA: Sage.

Bourdieu, Pierre. 1984. *Distinction*. Cambridge, MA: Harvard University Press.

Bourguignon, Francois. 1979. "Decomposable income inequality measures." *Econometrica* 47:901-920.

Braun, Denny. 1988. "Multiple measurements of U.S. Income inequality." *The Review of Economics and Statistics* 70:398-405.

Breton, Raymond. 1964. "Institutional completeness of ethnic communities and the personal relations of immigrants." *American Journal of Sociology* 70:193-205.

Browne, Michael and Robert Cudeck. 1993. "Alternative ways to assessing model fit." in *Testing structural equation models*, edited by K. Bollen and S. Long. Newbury Park, CA: Sage.

Browning, Christopher R. and Kathleen A. Cagney. 2002. "Neighborhood structural disadvantage, collective efficacy, and self-rated physical health in an urban setting." *Journal of Health and Social Behavior* 43:383-399.

Browning, Christopher R., Seth L. Feinberg, and Robert D. Dietz. 2004. "The paradox of social organization: Networks, collective efficacy, and violent crime in urban neighborhoods." *Social Forces* 83:503-534.

Bursik, Robert J. 1986. "Delinquency rates as sources of ecological change." Pp. 63-74 in *The social ecology*, edited by J. M. Byrne and R. J. Sampson. New York: Springer-Verlag.

Bursik, Robert J. and Harold G. Grasmick. 1993. *Neighborhoods and crime*. New York: Lexington.

Campbell, Karen E. and Barrett A. Lee. 1992. "Sources of personal neighbor networks: Social integration, need, or time?" *Social Forces* 70:1077-1100.

Caplow, Theodore and Robert Forman. 1950. "Neighborhood interaction in a homogeneous community." *American Sociological Review* 15:357-366.

Census, Bureau of the. 1987. "Census of population and housing, 1980: 1980-1970 tract comparability file." vol. 2005: Bureau of the Census: housed at the Odum Institute for Research in the Social Sciences, UNC-Chapel Hill.

—. 2000. "Census tract relationship file." vol. 2005: Bureau of the Census: housed at the Odum Institute for Research in the Social Sciences, UNC-Chapel Hill.

Census, of Population and Housing. 1980. "Zip code equivalency file (marf 5)." Washington: The Bureau. Housed at the Odum Institute for Research in the Social Sciences at UNC-Chapel Hill.

Census, United States Department of Commerce. Bureau of the. 1990. "Census of population and housing, 1990 [united states]: Tiger/census tract comparability file." vol. 2005: Washington, DC: U.S. Dept. of Commerce, Bureau of the Census [producer], 1992. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 1992.

Chamlin, Mitchell B. and John K. Cochran. 1997. "Social altruism and crime." *Criminology* 35:203-228.

Chilton, Roland J. 1964. "Continuity in delinquency area research: A comparison of studies for Baltimore, Detroit, and Indianapolis." *American Sociological Review* 29:71-83.

Christakopoulou, Sophia, Jon Dawson, and Aikaterini Gari. 2001. "The community well-being questionnaire: Theoretical context and initial assessment of its reliability and validity." *Social Indicators Research* 56:319-349.

Chwe, Michael Suk-Young. 1999. "Structure and strategy in collective action." *American Journal of Sociology* 105:128-156.

Clark, David E. and Willam E. Herrin. 2000. "The impact of public school attributes on home sale prices in California." *Growth and Change* 31:385-407.

Cohen, Lawrence E. and Marcus Felson. 1979. "Social change and crime rate trends: A routine activity approach." *American Sociological Review* 44:588-608.

Cohen, Lawrence E., Marcus Felson, and Kenneth C. Land. 1980. "Property crime rates in the united states: A macrodynamic analysis, 1947-1977; with ex ante forecasts for the mid-1980s." *American Journal of Sociology* 86:90-118.

Connerly, Charles E. and Robert W. Marans. 1985. "Comparing two global measures of perceived neighborhood quality." *Social Indicators Research* 17:29-47.

Crenshaw, Edward and Craig St. John. 1989. "The organizationally dependent community: A comparative study of neighborhood attachment." *Urban Affairs Quarterly* 24:412-434.

Croen, L., G. Shaw, L. Sanbonmatsu, S. Selvin, and P. Buffler. 1997. "Maternal residential proximity to hazardous waste sites and risk for selected congenital malformations." *Epidemiology* 8:347-354.

Crutchfield, Robert D. 1989. "Labor stratification and violent crime." *Social Forces* 68:489-512.

Crutchfield, Robert D., Ann Glusker, and George S. Bridges. 1999. "A tale of three cities: Labor markets and homicide." *Sociological Focus* 32:65-83.

Cullen, Julie Berry and Steven D. Levitt. 1996. "Crime, urban flight, and the consequences for cities." *NBER Working Paper 5737.*

Cutler, David M., Edward L. Glaeser, and Jacob L. Vigdor. 1999. "The rise and decline of the American ghetto." *The Journal of Political Economy* 107.

Dahlback, Olog. 1998. "Modelling the influence of societal factors on municipal theft rates in Sweden: Methodological concerns and substantive findings." *Acta Sociologica* 41:37-57.

Davis, Earl E. and Margret Fine-Davis. 1981. "Predictors of satisfaction with housing and neighbourhood: A nationwide study in the Republic of Ireland." *Social Indicators Research* 9:477-494.

Davis, James A. 1963. "Structural balance, mechanical solidarity, and interpersonal relations." *American Journal of Sociology* 68:444-462.

Dugan, Laura. 1999. "The effect of criminal victimization on a household's moving decision." *Criminology* 37:903-930.

Duncan, Otis Dudley, Ray P. Cuzzort, and Beverly Duncan. 1963. *Statistical geography*. New York: Free Press.

Durkheim, Emile. 1952 [1897]. *Suicide, a study in sociology*. Translated by J. A. Spaulding and G. Simpson. London: Routledge & Kegan Paul.

—. 1984 [1933]. *The division of labour in society*. Houndmills, Basingstoke, Hampshire: Macmillan.

Ebert, Udo. 1999. "Dual decomposable inequality measures." *The Canadian Journal of Economics* 32:234-246.

Education, U.S. Department of. 2001. "Local education agency (school district) universe survey longitudinal data file: 1986-1997." vol. 2004: National Center for Education Statistics.

Elder, Glen H. 1985. "Perspectives on the life course." Pp. 23-49 in *Life course dynamics: Trajectories and transitions, 1968-1980*, edited by G. H. Elder. Ithaca, NY: Cornell University Press.

—. 1999. *Children of the great depression: Social change in life experience*. Boulder, CO: Westview Press.

Elder, Glen H. Jr. 1998. "The life course and human development." Pp. 939-991 in *Handbook of child psychology*, vol. 1, edited by R. M. Lerner. New York: Wiley.

Ellison, Christopher G. 1991. "An eye for an eye? A note on the southern subculture of violence thesis." *Social Forces* 69:1223-1239.

Farley, Reynolds, Charlotte Steeh, Maria Krysan, Tara Jackson, and Keith Reeves. 1994. "Stereotypes and segregation: Neighborhoods in the Detroit area." *American Journal of Sociology* 100:750-780.

Feld, Scott L. 1982. "Social structural determinants of similarity among associates." *American Sociological Review* 47:797-801.

Fischer, Claude S. 1975. "Toward a subcultural theory of urbanism." *American Journal of Sociology* 80:1319-1341.

—. 1982. *To dwell among friends: Personal networks in town and city*. Chicago: University of Chicago.

Fischer, Mary J. and Douglas S. Massey. 2004. "The ecology of racial discrimination." *City and Community* 3:221-241.

Fleming, Monique A. and Richard E. Petty. 2000. "Identity and persuasion: An elaboration likelihood approach." Pp. 171-197 in *Attitudes, behavior, and social context: The role of norms and group membership*, edited by D. J. Terry and M. A. Hogg. Mahwah, NJ: Lawrence Erlbaum.

Florax, Raymond J.G.M. and Serge Rey. 1995. "The impacts of misspecified spatial interaction in linear regression models." Pp. 111-135 in *New directions in spatial econometrics*, edited by L. Anselin and R. J. G. M. Florax. New York: Springer.

Frank, Kenneth A. 1996. "Mapping interactions within and between cohesive subgroups." *Social Networks* 18:93-119.

Freudenburg, William R. 1986. "The density of acquaintanceship: An overlooked variable in community research?" *American Journal of Sociology* 92:27-63.

Frey, William H. 1979. "Central city white-flight: Racial and non-racial causes." *American Sociological Review* 44:425-448.

Frey, William H. and Reynolds Farley. 1996. "Latino, Asian, and black segregation in U.S. Metropolitan areas: Are multi-ethnic metros different?" *Demography* 33:35-50.

Friedkin, Noah E. 1999. "Choice shift and group polarization." *American Sociological Review* 64:856-875.

Friedman, Warren. 1998. "Volunteerism and the decline of violent crime." *The Journal of Criminal Law & Criminology* 88:1453-1474.

Geis, Karlyn J. and Catherine E. Ross. 1998. "A new look at urban alienation: The effect of neighborhood disorder on perceived powerlessness." *Social Psychology Quarterly* 61:232-246.

Gerson, Kathleen, C. Ann Stueve, and Claude S. Fischer. 1977. "Attachment to place." Pp. 139-161 in *Networks and places: Social relations in the urban setting*, edited by C. S. Fischer. New York: Free Press.

Gibbs, Jack P. and Walter T. Martin. 1962. "Urbanization, technology, and the division of labor: International patterns." *American Sociological Review* 27:667-677.

Glaeser, Edward L. and Bruce Sacerdote. 1999. "Why is there more crime in cities?" *The Journal of Political Economy* 107:S225-S258.

Golden, Reid M. and Steven F. Messner. 1987. "Dimensions of racial inequality and rates of violent crime." *Criminology* 25:525-541.

Gorman, Dennis M., Paul W. Speer, Paul J. Gruenewald, and Erich W. Labouvie. 2001. "Spatial dynamics of alcohol availability, neighborhood structure and violent crime." *Journal of Studies on Alcohol* 62:628-636.

Gove, Walter R., Michael Hughes, and Michael Geerken. 1985. "Are uniform crime reports a valid indicator of the index crime? An affirmative answer with minor qualifications." *Criminology* 23:451-501.

Grannis, Rick. 1998. "The importance of trivial streets: Residential streets and residential segregation." *American Journal of Sociology* 103:1530-1564.

Gray, Alan. 1987. "Intermarriage: Opportunity and preference." *Population Studies* 41:365-379.

Green, Donald P., Dara Z. Strolovitch, and Janelle S. Wong. 1998. "Defended neighborhoods, integration, and racially motivated crime." *American Journal of Sociology* 104:372-403.

Green, Howard Whipple and Leon E. Truesdell. 1937. *Census tracts in American cities*. Washington, D.C.: Dept. of Commerce, Bureau of the Census.

Greenberg, Michael R. 1999. "Improving neighborhood quality: A hierarchy of needs." *Housing Policy Debate* 10:601-624.

Greene, William H. 2000. *Econometric analysis*. Upper Saddle River, NJ: Prentice Hall.

Guest, Avery M. and R. S. Oropesa. 1984. "Problem-solving strategies of local areas in the metropolis." *American Sociological Review* 49:828-840.

Gyimah-Brempong, Kwabena. 2001. "Alcohol availability and crime: Evidence from census tract data." *Southern Economic Journal* 68:2-21.

Hadden, Louise and Mireille Leger. 1990. *Codebook for the American housing survey data base: 1973-1993*. Cambridge, MA: Abt Associates.

—. 1995. *Codebook for the American housing survey*, vol. 1. Cambridge, MA: Abt Associates.

Halaby, Charles N. 2004. "Panel models in sociological research: Theory into practice." *Annual Review of Sociology* 30:507-544.

Harer, Miles D. and Darrell Steffensmeier. 1992. "The differing effects of economic inequality on black and white rates of violence." *Social Forces* 70:1035-1054.

Harris, David R. 2001. "Why are whites and blacks averse to black neighbors?" *Social Science Research* 30:100-116.

Hartnagel, Timothy F. 1979. "The perception and fear of crime: Implications for neighborhood cohesion, social activity, and community affect." *Social Forces* 58:176-193.

Heitgerd, Janet L. and Jr. Robert J. Bursik. 1987. "Extracommunity dynamics and the ecology of delinquency." *American Journal of Sociology* 92:775-787.

Hipp, John R. 2003a. "If you don't do it, someone else might: Volunteering for neighborhood associations as a response to environmental change." *unpublished manuscript*.

—. 2003b. "Who you gonna believe---me, or your eyes? Accounting for measurement error in neighborhood assessment." *Presented at the American Sociological Society Annual Meeting, Atlanta, GA, August, 2003*.

Hirschfield, A. and K.J Bowers. 1997. "The effect of social cohesion on levels of recorded crime in disadvantaged areas." *Urban Studies* 34:1274-1294.

Hirschman, Albert O. 1970. *Exit, voice, and loyalty; responses to decline in firms, organizations, and states*. Cambridge, MA: Harvard.

Hogg, Michael A. 1992. *The social psychology of group cohesiveness: From attraction to social identity*. New York: NYU.

Homans, George Caspar. 1974. *Social behavior: Its elementary forms*. New York: Harcourt Brace Jovanovich.

Hunter, Albert. 1974. *Symbolic communities*. Chicago: University of Chicago.

—. 1975. "The loss of community: An empirical test through replication." *American Sociological Review* 40:537-552.

Hyman, Herbert H. 1942. "The psychology of status." *Archives of Psychology* 38:5-94.

Ioannides, Yannis M. and Jeffrey E. Zabel. 2002. "Interactions, neighborhood selection and housing demand." *The Center for Economic Studies Working Paper*:37.

Jagun, Adedokun, Diane R. Brown, Norweeta G. Milburn, and Lawrence E. Gary. 1990. "Residential satisfaction and socioeconomic and housing characteristics of urban black adults." *Journal of Black Studies* 21:40-51.

Jang, Sung Joon and Byron R. Johnson. 2001. "Neighborhood disorder, individual religiosity and adolescent use of illicit drugs: A test of multilevel hypotheses." *Criminology* 39:109-143.

Janowitz, Morris. 1952. *The community press in an urban setting*. Glencoe, IL: Free Press.

—. 1975. "Sociological theory and social control." *American Journal of Sociology* 81:82-108.

Jargowsky, Paul A. 1996. "Take the money and run: Economic segregation in U.S. Metropolitan areas." *American Sociological Review* 61:984-998.

Jasso, Guillermina. 1980. "A new theory of distributive justice." *American Sociological Review* 45:3-32.

Jones, F.L. 1991. "Ethnic intermarriage in Australia, 1950-52 to 1980-82: Models or indices?" *Population Studies* 45:27-42.

Kain, John F. and John M. Quigley. 1975. *Housing markets and racial discrimination: A microeconomic analysis*. New York: National Bureau of Economic Research.

Kakwani, N. C. and N. Podder. 1976. "Efficient estimation of the Lorenz curve and associated inequality measures from grouped observations." *Econometrica* 44:137-148.

Kandel, Denise B. 1978. "Homophily, selection, and socialization in adolescent friendships." *American Journal of Sociology* 84:427-436.

Kasarda, John D. and Morris Janowitz. 1974. "Community attachment in mass society." *American Sociological Review* 39:328-339.

Kenny, David A. and C. M. Judd. 1984. "Estimating the nonlinear and interactive effects of latent variables." *Psychological Bulletin* 96:201-210.

Kenyon, James B. 1976. "Spatial associations in the integration of the American city." *Economic Geography* 52:287-303.

Kiel, Katherine A. and Jeffrey E. Zabel. 1997. "Evaluating the usefulness of the American Housing Survey for creating house price indices." *Journal of Real Estate Finance and Economics* 14:189-202.

Klinenberg, Eric. 2002. *Heat wave : A social autopsy of disaster in Chicago*. Chicago: University of Chicago.

Knox, E.G. and E.A. Gilman. 1997. "Hazard proximities of childhood cancers in Great Britain from 1953-80." *Journal of Epidemiology and Community Health* 51:151-159.

Kovandzic, Tomislav V., Lynne M. Vieratis, and Mark R. Yeisley. 1998. "The structural covariates of urban homicide: Reassessing the impact of income inequality and poverty in the post-Reagan era." *Criminology* 36:569-599.

Kposowa, Augustine J., Kevin D. Breault, and Beatrice M. Harrison. 1995. "Reassessing the structural covariates of violent and property crimes in the USA: A county level analysis." *British Journal of Sociology* 46:79-105.

Krivo, Lauren J. and Ruth D. Peterson. 1996. "Extremely disadvantaged neighborhoods and urban crime." *Social Forces* 75:619-648.

Krysan, Maria. 2002. "Whites who say they'd flee: Who are they, and why would they leave?" *Demography* 39:675-696.

Kubrin, Charis E. and Jerald R. Herting. 2003. "Neighborhood correlates of homicide trends: An analysis using growth-curve modeling." *The Sociological Quarterly* 44:329-350.

La Gory, Mark and John Pipkin. 1981. *Urban social space*. Belmont, CA: Wadsworth.

LaFree, Gary and Kriss A. Drass. 1996. "The effect of changes in intraracial income inequality and educational attainment on changes in arrest rates for African Americans and whites, 1957-1990." *American Sociological Review* 61:614-634.

Lambert, Peter J. and J. Richard Aronson. 1993. "Inequality decomposition analysis and the Gini coefficient revisited." *The Economic Journal* 103:1221-1227.

Land, Kenneth C. and Glenn Deane. 1992. "On the large-sample estimation of regression models with spatial- or network-effects terms: A two-stage least squares approach." *Sociological Methodology* 22:221-248.

Land, Kenneth C., Patricia L. McCall, and Lawrence E. Cohen. 1990. "Structural covariates of homicide rates: Are there any invariances across time and social space?" *American Journal of Sociology* 95:922-963.

Landale, Nancy S. and Avery M. Guest. 1985. "Constraints, satisfaction and residential mobility: Speare's model reconsidered." *Demography* 22:199-222.

Lander, Bernard. 1954. *Towards an understanding of juvenile delinquency*. New York: Columbia.

Lau, Richard R. 1989. "Individual and contextual influences on group identification." *Social Psychology Quarterly* 52:220-231.

Lee, Barrett A., Karen E. Campbell, and Oscar Miller. 1991. "Racial differences in urban neighboring." *Sociological Forum* 6:525-550.

Lee, Barrett A., Chad R. Farrell, and Bruce G. Link. 2004. "Revisiting the contact hypothesis: The case of public exposure to homelessness." *American Sociological Review*:2004.

Leenders, Roger Th. A. J. 2002. "Modeling social influence through network autocorrelation: Constructing the weight matrix." *Social Networks* 24:21-47.

Lipton, Robert and Paul Gruenewald. 2002. "The spatial dynamics of violence and alcohol outlets." *Journal of Studies on Alcohol* 63:187-195.

Liska, Allen E. and Paul E. Bellair. 1995. "Violent-crime rates and racial composition: Convergence over time." *American Journal of Sociology* 101:578-610.

Liska, Allen E., John R. Logan, and Paul E. Bellair. 1998. "Race and violent crime in the suburbs." *American Sociological Review* 63:27-38.

Logan, John R., Richard D. Alba, and Shu Yin Leung. 1996. "Minority access to white suburbs: A multiregional comparison." *Social Forces* 74:851-881.

Logan, John R., Richard D. Alba, and Wenquan Zhang. 2002. "Immigrant enclaves and ethnic communities in New York and Los Angeles." *American Sociological Review* 67:299-322.

Logan, John R. and Glenna D. Spitze. 1994. "Family neighbors." *American Journal of Sociology* 100:453-476.

Lu, Max. 1998. "Analyzing migration decisionmaking: Relationships between residential satisfaction, mobility intentions, and moving behavior." *Environment And Planning A* 30:1473-1495.

—. 1999a. "Determinants of residential satisfaction: Ordered logit vs. Regression models." *Growth and Change* 30:264-287.

—. 1999b. "Do people move when they say they will? Inconsistencies in individual migration behavior." *Population and Environment* 20:467-488.

Lyons, William E. and David Lowery. 1986. "The organization of political space and citizen responses to dissatisfaction in urban communities: An integrative model." *The Journal of Politics* 48:321-346.

Markovsky, Barry. 1985. "Toward a multilevel distributive justice theory." *American Sociological Review* 50:822-839.

Markowitz, Fred E., Paul E. Bellair, Allen E. Liska, and Jianhong Liu. 2001. "Extending social disorganization theory: Modeling the relationships between cohesion, disorder, and fear." *Criminology* 39:293-319.

Marshall, Harvey. 1979. "White movement to the suburbs: A comparison of explanations." *American Sociological Review* 44:975-994.

Marullo, Sam. 1985. "Targets for racial invasion and reinvasion: Housing units where racial turnovers occurred, 1974-77." *Social Forces* 63:748-774.

Marx, Karl. 1978. *Capital, volume one*. New York: W.W. Norton.

Massey, Douglas S. and Nancy A. Denton. 1987. "Trends in the residential segregation of blacks, Hispanics, and Asians: 1970-1980." *American Sociological Review* 52:802-825.

—. 1993. *American apartheid: Segregation and the making of the underclass*. Cambridge, MA: Harvard.

Massey, Douglas S. and Eric Fong. 1990. "Segregation and neighborhood quality: Blacks, Hispanics, and Asians in the San Francisco metropolitan area." *Social Forces* 69:15-32.

Massey, Douglas S., Andrew B. Gross, and Kumiko Shibuya. 1994. "Migration, segregation, and the geographic concentration of poverty." *American Sociological Review* 59:425-445.

Mayhew, Bruce H., J. Miller McPherson, Thomas Rotolo, and Lynn Smith Lovin. 1995. "Sex and race homogeneity in naturally occurring groups." *Social Forces* 74:15-52.

McAuley, William J. and Cheri L. Nutty. 1982. "Residential preferences and moving behavior: A family life-cycle analysis." *Journal of Marriage and the Family* 44:301-309.

McClain, Paula D. 1989. "Urban black neighborhood environment and homicide: A research note on a decade of change in four cities--1970 to 1980." *Urban Affairs Quarterly* 24:584-596.

McHugh, Kevin E., Patricia Gober, and Neil Reid. 1990. "Determinants of short- and long-term mobility expectations for home owners and renters." *Demography* 27:81-95.

McNulty, Thomas L. 2001. "Assessing the race-violence relationship at the macro level: The assumption of racial invariance and the problem of restricted distributions." *Criminology* 39:467-489.

McNulty, Thomas L. and Steven R. Holloway. 2000. "Race, crime, and public housing in Atlanta: Testing a conditional effect hypothesis." *Social Forces* 79:707-729.

McPherson, J. Miller and James R. Ranger-Moore. 1991. "Evolution on a dancing landscape: Organizations and networks in dynamic Blau space." *Social Forces* 70:19-42.

McPherson, J. Miller and Lynn Smith-Lovin. 1987. "Homophily in voluntary organizations: Status distance and the composition of face-to-face groups." *American Sociological Review* 52:370-379.

McPherson, Miller, Lynn Smith-Lovin, and James M Cook. 2001. "Birds of a feather: Homophily in social networks." *Annual Review of Sociology* 27:415-444.

Merton, Robert K. 1968. *Social theory and social structure*. New York: The Free Press.

Messner, Steven F. and Kenneth Tardiff. 1986. "Economic inequality and levels of homicide: An analysis of urban neighborhoods." *Criminology* 24:297-317.

Michelson, William H. 1976. *Man and his urban environment: A sociological approach*. Reading, MA: Addison-Wesley.

Miethe, Terance D., Michael Hughes, and David McDowall. 1991. "Social change and crime rates: An evaluation of alternative theoretical approaches." *Social Forces* 70:165-185.

Mills, Jeffrey A. and Sourushe Zandvakili. 1997. "Statistical inference via bootstrapping for measures of inequality." *Journal of Applied Econometrics* 12:133-150.

Miner, Sonia and Stewart Tolnay. 1998. "Barriers to voluntary organization membership: An examination of race and cohort differences." *Journal of Gerontology* 53B:S241-S248.

Morenoff, Jeffrey D , Robert J. Sampson, and Stephen W. Raudenbush. 2001. "Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence." *Criminology* 39:517-559.

Morenoff, Jeffrey D. 2003. "Neighborhood mechanisms and the spatial dynamics of birth weight." *American Journal of Sociology* 108:976-1017.

Mouw, Ted and Barbara Entwisle. 2006. "Residential segregation and interracial friendship in schools." *American Journal of Sociology* Forthcoming.

Mroz, Thomas A., Kenneth A. Bollen, Ilene S. Speizer, and Dominic J. Mancini. 1999. "Quality, accessibility, and contraceptive use in rural Tanzania." *Demography* 36:23-40.

Nielsen, Amie L. and Ramiro Martinez. 2003. "Reassessing the alcohol-violence linkage: Results from a multiethnic city." *Justice Quarterly* 20:445-469.

Nielsen, Francois and Arthur S. Alderson. 1997. "The Kuznets curve and the great u-turn: Income inequality in U.S. Counties, 1970 to 1990." *American Sociological Review* 62:12-33.

Oliver, J. Eric. 2000. "City size and civic involvement in metropolitan America." *American Political Science Review* 94:361-373.

Oliver, Pamela. 1984. ""If you don't do it, nobody else will"." *American Sociological Review* 49:601-610.

Olson, Mancur. 1971. *The logic of collective action*. Cambridge, MA: Harvard University Press.

Orbell, John M. and Toru Uno. 1972. "A theory of neighborhood problem solving: Political action vs. Residential mobility." *The American Political Science Review* 66:471-489.

Ouimet, Marc. 2000. "Aggregation bias in ecological research: How social disorganization and criminal opportunities shape the spatial distribution of juvenile delinquency in montreal." *Canadian Journal of Criminology* 42:135-156.

Ousey, Graham C. 1999. "Homicide, structural factors, and the racial invariance assumption." *Criminology* 37:405-426.

Park, Robert E. and Ernest W. Burgess. 1921. *Introduction to the science of sociology*. Chicago: University of Chicago.

Parkes, Alison, Ade Kearns, and Rowland Atkinson. 2002. "What makes people dissatisfied with their neighborhoods?" *Urban Studies* 39:2413-2438.

Pastor, Manuel Jr., Jim Sadd, and John Hipp. 2001. "Which came first? Toxic facilities, minority move-in, and environmental justice." *Journal of Urban Affairs* 23:1-21.

Pastor, Manuel and Justin Scoggins. 2003. "Income forecasting at the small area level for southern California: Issues, methods, and projections: Final report to the southern California association of governments."6.

Pattillo, Mary E. 1998. "Sweet mothers and gangbangers: Managing crime in a black middle-class neighborhood." *Social Forces* 76:747-774.

Payne, M. Carr Jr., C. Michael York, and Joen Fagan. 1974. "Changes in measured social distance over time." *Sociometry* 37:131-136.

Pedersen, Axel West. 2004. "Inequality as relative deprivation: A sociological approach to inequality measurement." *Acta Sociologica* 47:31-49.

Perkins, Douglas D., Paul Florin, Richard C. Rich, Abraham Wandersman, and David M. Chavis. 1990. "Participation and the social and physical environment of residential blocks: Crime and community context." *American Journal of Community Psychology* 18:83-115.

Peterson, Ruth D. and Lauren J. Krivo. 1993. "Racial segregation and black urban homicide." *Social Forces* 71:1001-1026.

Peterson, Ruth D., Lauren J. Krivo, and Mark A. Harris. 2000. "Disadvantage and neighborhood violent crime: Do local institutions matter?" *Journal of Research in Crime and Delinquency* 37:31-63.

Poole, Willard C. Jr. 1927. "Distance in sociology." *The American Journal of Sociology* 33:99-104.

Powers, Daniel A. and Christopher G. Ellison. 1995. "Interracial contact and black racial attitudes: The contact hypothesis and selectivity bias." *Social Forces* 74:205-226.

Putnam, Robert D. 2000. *Bowling alone: The collapse and revival of American community*. New York: Simon & Schuster.

Pyle, Gerald F. 1974. *The spatial dynamics of crime*, vol. 159. Chicago: University of Chicago, Dept. of Geography.

Quillian, Lincoln. 1995. "Prejudice as a response to perceived group threat: Population composition and anti-immigrant and racial prejudice in Europe." *American Sociological Review* 60:586-611.

—. 1999. "Migration patterns and the growth of high-poverty neighborhoods, 1970-1990." *American Journal of Sociology* 105:1-37.

Quillian, Lincoln and Mary E. Campbell. 2003. "Beyond black and white: The present and future of multiracial friendship segregation." *American Sociological Review* 68:540-566.

Quillian, Lincoln and Devah Pager. 2001. "Black neighbors, higher crime? The role of racial stereotypes in evaluations of neighborhood crime." *American Journal of Sociology* 107:717-767.

Raudenbush, Stephen W. and Anthony S. Bryk. 2002. *Hierarchical linear models: Applications and data analysis*, vol. 1, Edited by J. DeLeeuw and R. A. Berk. Thousand Oaks: Sage.

Reed, John Shelton. 1972. *The enduring south: Subcultural persistence in mass society*. Lexington, MA: Lexington Books.

Reiss, Albert J. Jr. 1951. "Delinquency as the failure of personal and social controls." *American Sociological Review* 16:196-207.

Rengert, George F., Alex R. Piquero, and Peter R. Jones. 1999. "Distance decay reexamined." *Criminology* 37:427-445.

Rice, Tom W. and Brent Steele. 2001. "White ethnic diversity and community attachment in small Iowa towns." *Social Science Quarterly* 82:397-407.

Roncek, Dennis W. 1981. "Dangerous places: Crime and residential environment." *Social Forces* 60:74-96.

Roncek, Dennis W. and Pamela A. Maier. 1991. "Bars, blocks, and crimes revisited: Linking the theory of routine activities to the empiricism of 'hot spots'." *Criminology* 29:725-753.

Rosenbaum, Emily. 1992. "Race and ethnicity in housing: Turnover in New York City, 1978-1987." *Demography* 29:467-486.

—. 1994. "The constraints on minority housing choices, New York City 1978-1987." *Social Forces* 72:725-747.

Ross, Catherine E. and Sung Joon Jang. 2000. "Neighborhood disorder, fear, and mistrust: The buffering role of social ties with neighbors." *American Journal of Community Psychology* 28:401-420.

Ross, Catherine E. and John Mirowsky. 1999. "Disorder and decay." *Urban Affairs Review* 34:412-432.

—. 2001. "Neighborhood disadvantage, disorder, and health." *Journal of Health and Social Behavior* 42:258-276.

Rossi, Peter H. 1955. *Why families move: A study in the social psychology of urban residential mobility*. Glencoe, IL: The Free Press.

Rountree, Pamela Wilcox and Barbara D Warner. 1999. "Social ties and crime: Is the relationship gendered?" *Criminology* 37:789-813.

Sampson, Robert J. 1984. "Group size, heterogeneity, and intergroup conflict: A test of Blau's inequality and heterogeneity." *Social Forces* 62:618-639.

—. 1985. "Neighborhood and crime: The structural determinants of personal victimization." *Journal of Research in Crime and Delinquency* 22:7--40.

—. 1988. "Local friendship ties and community attachment in mass society: A multilevel systemic model." *American Sociological Review* 53:766-779.

—. 1991. "Linking the micro- and macrolevel dimensions of community social organization." *Social Forces* 70:43-64.

Sampson, Robert J. and W. Byron Groves. 1989. "Community structure and crime: Testing social-disorganization theory." *American Journal of Sociology* 94:774-802.

Sampson, Robert J., Jeffrey D. Morenoff, and Felton Earls. 1999. "Beyond social capital: Spatial dynamics of collective efficacy for children." *American Sociological Review* 64:633-660.

Sampson, Robert J. and Stephen W. Raudenbush. 1999. "Systematic social observation of public spaces: A new look at disorder in urban neighborhoods." *American Journal of Sociology* 105:603-651.

—. 2004. "Seeing disorder: Neighborhood stigma and the social construction of "broken windows"." *Social Psychology Quarterly* 67:319-342.

Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. "Neighborhoods and violent crime: A multilevel study of collective efficacy." *Science* 277:918-924.

Sampson, Robert J. and William Julius Wilson. 1995. "Toward a theory of race, crime, and urban inequality." Pp. 37-54 in *Crime and inequality*, edited by J. Hagan and R. D. Peterson. Stanford, CA: Stanford.

Schafer, Joseph L. 1997. *Analysis of incomplete multivariate data*. New York: Chapman and Hall.

Schelling, Thomas C. 1978. *Micromotives and macrobehavior*. New York: W.W. Norton & Co.

Scherzer, Kenneth A. 1992. *The unbounded community: Neighborhood life and social structure in new york city, 1830-1875*. Durham, NC: Duke University Press.

Shaw, Clifford and Henry D. McKay. 1942. *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.

Shaw, G.M., J. Schulman, J.D. Frisch, S.K. Cummins, and J.A. Harris. 1992. "Congenital malformations and birthweight in areas with potential environmental contamination." *Architectual Environmental Health* 47:147-154.

Shihadeh, Edward S. and Graham C. Ousey. 1996. "Metropolitan expansion and black social dislocation: The link between suburbanization and center-city crime." *Social Forces* 75:649-666.

Shorrocks, Anthony F. 1984. "Inequality decomposition by population subgroups." *Econometrica* 52:1369-1386.

Simcha-Fagan, O. and J. Schwartz. 1986. "Neighborhood and delinquency: An assessment of contextual effects." *Criminology* 24:667-704.

Simmel, Georg. 1908. *Soziologie*. Leipzig: Duncker & Humblot.

—. 1955. *"Conflict" and "The web of group-affiliations"*. Glencoe, IL: The Free Press.

—. 1971. "The metropolis and mental life." in *Georg Simmel: On individuality and social forms*, edited by D. N. Levine. Chicago: University of Chicago.

Simon, Bernd, Claudia Hastedt, and Birgit Aufderheide. 1997. "When self-categorization makes sense: The role of meaningful social categorization in minority and majority members' self-perception." *Journal of Personality and Social Psychology* 73:310-320.

Simpson, Miles E. 1985. "Violent crime, income inequality, and regional culture: Another look." *Sociological Focus* 18:199-208.

Skogan, Wesley G. 1989. "Communities, crime, and neighborhood organization." *Crime & Delinquency* 35:437-457.

—. 1990. *Disorder and decline: Crime and the spiral of decay in American neighborhoods*. New York: Free Press.

Skvoretz, John. 1983. "Salience, heterogeneity and consolidation of parameters: Civilizing Blau's primitive theory." *American Sociological Review* 48:360-375.

Smith, Douglas A and G Roger Jarjoura. 1988. "Social structure and criminal victimization." *The Journal of Research in Crime and Delinquency* 25:27-52.

Smith, William R., Sharon Glave Frazee, and Elizabeth L. Davison. 2000. "Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process." *Criminology* 38:489-523.

South, Scott J. and Kyle D. Crowder. 1997a. "Escaping distressed neighborhoods: Individual, community, and metropolitan influences." *American Journal of Sociology* 102:1040-1084.

—. 1997b. "Residential mobility between cities and suburbs: Race, suburbanization, and back-to-the-city moves." *Demography* 34:525-538.

South, Scott J. and Glenn D. Deane. 1993. "Race and residential mobility: Individual determinants and structural constraints." *Social Forces* 72:147-167.

South, Scott J. and Steven F. Messner. 1986. "Structural determinants of intergroup association: Interracial marriage and crime." *American Journal of Sociology* 91:1409-1430.

—. 2000. "Crime and demography: Multiple linkages, reciprocal relations." *Annual Review of Sociology* 26:83-106.

Speare, Alden Jr. 1974. "Residential satisfaction as an intervening variable in residential mobility." *Demography* 11:173-188.

Speare, Alden Jr., Frances Kobrin, and Ward Kingkade. 1982. "The influence of socioeconomic bonds and satisfaction on interstate migration." *Social Forces* 61:551-574.

Speizer, Ilene S. and Kenneth A. Bollen. 2000. "How well do perceptions of family planning service quality correspond to objective measures? Evidence from Tanzania." *Studies in Family Planning* 31:163-177.

Stipak, Brian and Carl Hensler. 1983. "Effect of neighborhood racial and socio-economic composition on urban residents' evaluations of their neighborhoods." *Social Indicators Research* 12:311-320.

Stueve, C. Ann and Kathleen Gerson. 1977. "Personal relations across the life-cycle." Pp. 79-98 in *Networks and places: Social relations in the urban setting*, edited by C. S. Fischer. New York: Free Press.

Tajfel, Henry and John C. Turner. 1986. "The social identity theory of intergroup behavior." Pp. 7-24 in *Psychology of intergroup relations*, edited by S. Worchel and W. G. Austin. Chicago: Nelson-Hall.

Taub, Richard P., George P. Surgeon, Sara Lindholm, Phyllis Betts Otti, and Amy Bridges. 1977. "Urban voluntary associations, locality based and externally induced." *American Journal of Sociology* 83:425-442.

Taub, Richard P., D. Garth Taylor, and Jan D. Dunham. 1984. *Paths of neighborhood change: Race and crime in urban America*. Chicago: University of Chicago.

Taylor, Ralph B. 1996. "Neighborhood responses to disorder and local attachments: The systemic model of attachment, social disorganization, and neighborhood use value." *Sociological Forum* 11:41-74.

—. 2001. *Breaking away from broken windows: Baltimore neighborhoods and the nationwide fight against crime, grime, fear, and decline*. Boulder, CO: Westview.

Taylor, Ralph B., Sidney N. Brower, and Whit Drain. 1979. *Toward a neighborhood-based data file: A map of Baltimore neighborhoods*. Baltimore, MD: Center for Metropolitan Planning and Research.

Turner, John C. 1987. *Rediscovering the social group: A self-categorization theory*. New York: Basil Blackwell.

Van Valey, Thomas L., Wade Clark Roof, and Jerome E. Wilcox. 1977. "Trends in residential segregation: 1960-1970." *American Journal of Sociology* 82:826-844.

Veysey, Bonita M. and Steven F. Messner. 1999. "Further testing of social disorganization theory: An elaboration of Sampson and Groves's 'community structure and crime'." *Journal of Research in Crime and Delinquency* 36:156-174.

Ward, Russell A., Mark LaGory, and Susan R. Sherman. 1985. "Neighborhood and network age concentration: Does age homogeneity matter for older people?" *Social Psychology Quarterly* 48:138-149.

Warner, Barbara D. 2003. "The role of attenuated culture in social disorganization theory." *Criminology* 41:73-97.

Warner, Barbara D. and Glenn L. Pierce. 1993. "Reexamining social disorganization theory using calls to the police as a measure of crime." *Criminology* 31:493-517.

Warner, Barbara D. and Pamela Wilcox Rountree. 1997. "Local social ties in a community and crime model: Questioning the systemic nature of informal social control." *Social Problems* 44:520-536.

Wasserman, Stanley and Katherine Faust. 1994. *Social network analysis: Methods and applications*. New York: Cambridge.

Weber, Max. 1968. *Economy and society: An outline of interpretive sociology*, vol. 1, Edited by G. Roth and C. Wittich. Translated by E. F. a. others. New York: Bedminster.

Wilcox, Pamela, Kenneth C. Land, and Scott A. Hunt. 2003. *Criminal circumstance: A dynamic multicontextual criminal opportunity theory*. New York: Aldine de Gruyter.

Wilson, William J. 1987. *The truly disadvantaged: The inner city, the underclass, and public policy*. Chicago: University of Chicago Press.

Wirth, Louis. 1956a. "Life in the city." Pp. 206-217 in *Community life and social policy*, edited by L. Wirth. Chicago: University of Chicago Press.

—. 1956b. "Urbanism as a way of life." Pp. 58-82 in *Metropolis: Center and symbol of our times*, edited by P. Kasinitz. New York: New York University.

Woldoff, Rachael A. 2002. "The effects of local stressors on neighborhood attachment." *Social Forces* 81:87-116.

Yitzhaki, Shlomo. 1979. "Relative deprivation and the Gini coefficient." *The Quarterly Journal of Economics* 93:321-324.