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ABSTRACT

The relationships between neighborhood structural conditions and crime have been extensively studied, but recent scholarship has suggested that important questions remain unanswered regarding (1) variation in the cross-sectional relationships between structural conditions and crime across neighborhoods and (2) the temporal nature of the social processes linking structure to crime. Much of the communities and crime research relies heavily on cross-sectional, non-spatial examinations of key relationships between concentrated disadvantage, social processes like collective efficacy, and crime outcomes. This is somewhat surprising given the theoretically important role of stability and change in ecological perspectives on crime. Key processes mediating the structure-crime relationship are inherently time-dependent, requiring time to develop (or weaken/strengthen) in response to changing structural conditions, while the influence they exert on crime-related outcomes similarly takes time to emerge (e.g. through building or limiting informal social control).

Using multiple years of decennial census data, information on neighborhood social conditions from the Project on Human Development in Chicago Neighborhoods Community Survey (PHDCN-CS), and homicide data collected by the Chicago Police Department, this dissertation combines these foci – historical time and geographical space – into an exploration of 1) how neighborhood histories of concentrated disadvantage influence neighborhood homicide rates; 2) how neighborhood histories of concentrated disadvantage influence neighborhood levels of collective efficacy; and 3) how the influence of change or stability in neighborhood concentrated disadvantage on neighborhood homicide rates is channeled
through collective efficacy, an important theoretical mediator of the concentrated disadvantage-crime association.

The major findings fall into four general categories. First, the cross-sectional relationship between the level of neighborhood concentrated disadvantage and homicide rates significantly varies across Chicago neighborhoods in cross-section in 1990. The same was found for the relationship between the level of concentrated disadvantage and neighborhood collective efficacy. Second, in both cases the cross-sectional relationship became spatially invariant once a measure of historical within-neighborhood changes in concentrated disadvantage was added to the models. It appears that there are significant differences in homicide rates across neighborhoods which share a similar level of disadvantage in cross-section but have dissimilar histories of disadvantage in the preceding decades.

Third, while the previous results suggest that within-neighborhood changes in concentrated disadvantage are “disruptive” in terms of contributing to higher homicide rates and lower levels of collective efficacy, it also appears that within-neighborhood historical stability interacts with the cross-sectional level of concentrated disadvantage. The negative effects of high disadvantage are exacerbated under stable historical conditions, at least as far as being significantly related to higher homicide rates. It appears that the detrimental effects of high levels of disadvantage “accumulate” under stable conditions. However, this was not the case in when collective efficacy was the outcome modeled; it does not appear that the harmful effects of concentrated disadvantage on collective efficacy “accumulate” under stable historical conditions.
Finally, it does not appear that the effects of within-neighborhood change (or stability) are mediated by the collective efficacy mechanism. While collective efficacy does mediate the cross-sectional relationship between concentrated disadvantage and homicide rates to some extent, it does not explain the spatial variation in the relationship. It is only after accounting for within-neighborhood change in the model that the cross-sectional relationship between disadvantage and neighborhood homicide rates becomes spatially invariant.

The key contribution of this research was to demonstrate that within-neighborhood stability and change in concentrated disadvantage plays an important role in the production of neighborhood collective efficacy, as well as significantly contributes to the prediction of neighborhood homicide rates. This realistic representation of neighborhoods as both spatial and temporal units adds to the growing body of work that considers neighborhoods from a developmental or life-course perspective. It should be extended by considering what other social processes – besides collective efficacy – may mediate the impact of within-neighborhood structural change, as well as with explorations of other sources of within-neighborhood change like immigration concentration.
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CHAPTER 1. THE LIFE-COURSE OF THE NEIGHBORHOOD: DISADVANTAGE, SOCIAL DISORGANIZATION, AND CRIME

Introduction

“In the absence of any precedent let us tentatively define human ecology as a study of the spatial and temporal relations of human beings as affected by the selective, distributive, and accommodative forces of the environment.”

This declaration by Roderick D. McKenzie, in comparing the well-established sciences of plant and animal ecology to the “practically...unsurveyed field” of human ecology, speaks directly to the importance of spatial and temporal dynamics for sociological investigations of human communities (Park, Burgess, and McKenzie 1967, pp. 63-64). One of the key insights of the original social ecologists of the Chicago School – Robert E. Park, Ernest W. Burgess, McKenzie, Louis Wirth, and W.I. Thomas, among others – was to view the growth of the city not simply as an aggregation of the population into urban areas, but the outcome of a multiplicity of forces, institutions and social processes like industrialization, immigration, labor specialization, social bonds, religion, and the family. Critical to the emerging paradigm of social or human ecology was an understanding that cities and urban communities and neighborhoods were embedded in complex economic and social systems which both drove urban growth and change and were the product of it. Geographical space and, perhaps more importantly, time played a crucial role in this growth and change. The terms “process” and “change” occur often in Burgess’s discussion of the growth of the city, where he suggests viewing social organization and
disorganization as macro-sociological processes which parallel the biological "processes of metabolism" in the human body (Park, Burgess, and McKenzie 1967, p. 53).

It is on this foundation that the current research rests, in the hopes that I can encourage a more holistic approach to the investigation of structural conditions and crime in the modern era. In our pursuit of methodological innovation, better predictive models, and more universal (yet parsimonious) theories of crime, I believe macro-criminological research has unintentionally limited the scope of its vision. Neighborhoods do not spring into existence fully formed, with a particular set of structural conditions. Neither do these conditions – poverty or concentrated disadvantage, racial/ethnic homogeneity, residential instability, and the like – immediately generate the theoretical social processes and interactions that are the proximal causes of many macro-level outcomes like crime rates. It is logical that the 'present' of a neighborhood is dependent on its 'past' much like those of an individual.

A key word in the previous quotation is "processes." Social outcomes, whether negative or positive, do not emerge within neighborhoods and cities out of whole cloth but are the result of ongoing social processes which link structural conditions to crime. When research focuses on the relationships between structural conditions like concentrated disadvantage and crime at a single point in time, it conceptually restricts the scope of the questions to be asked, and naturally the answers that follow. That is not to say that such studies are flawed, but simply to point out that the complex relationships between neighborhood conditions and social outcomes described by the original Chicago School have been to some extent set aside in the interests of theoretical parsimony or practical considerations like data availability. It is the goal of this dissertation to return to a somewhat more complex (and more complete)
conceptualization of the links between neighborhood conditions, social processes, and outcomes as described by Parks, Burgess and others. In particular, the role of social change—and its inverse, stability\(^1\)—over time has important implications for the theoretical relationships hypothesized to link structural conditions and crime.

By assuming that aggregate units like cities—and by extension, neighborhoods—are embedded in “metabolic” processes of stability, growth, and change, it is possible to view them from a developmental or life-course perspective. Like individuals, cities are “born,” grow or decline, and in general change (or not) over time. Though it may be more difficult to see, the dynamics of cities and neighborhoods are analogous to the dynamics of the individual’s life-course. Cities and neighborhoods follow “trajectories” of development over time, they face “transitions” embedded in these trajectories that mark changes in structural conditions, and some of these transitions may act as “turning points” that redirect the developmental trajectory of the city or neighborhood. Sampson and Laub’s age-graded theory of informal social control speaks to “continuity and change over the life course” of the individual and its influence on individual-level stability and change in crime (Sampson and Laub 1993, p. 9; emphasis in original), by and large channeled through the informal social control stemming (or not) from informal social ties. If the life-course of the individual plays a role in explaining individual offending and desistance, it seems likely that the “life-course” of the neighborhood would play a similar role.

\(^{1}\) When using the terms “instability” or “stability,” I am referring in a general sense to the degree of change—or lack of it—within a neighborhood over time. This should not be confused with the term “residential instability,” which refers specifically to a measure of residential turnover within a neighborhood (described in more detail in Chapter 2). For the sake of clarity, when referring to the latter concept I will always employ the full term (“residential instability”).
In this sense, neighborhood **history** is the macro-level analogue to individual **biography**. There is a long tradition of criminological research on social disorganization and its modern counterparts with roots in social ecology. Drawing in part on recent advances in spatial methodologies, current research on neighborhoods and crime hints at a more complex theoretical model, and I believe a project exploring the influence of within-neighborhood continuity and change on neighborhood crime rates is called for. Several of the general principles of neighborhood criminology laid out by Robert Sampson in his recent presidential address to the American Society of Criminology speak to this point (2013). He stresses the importance of both continuity (stability) and change (instability) in neighborhoods and argues that criminology must cultivate a “life course of place” (p. 12) aimed at answering the basic but difficult question of how a neighborhood’s past impacts its present (also see Sampson, Morenoff, and Gannon-Rowley 2002). It is my intent here to take up that suggestion, and by incorporating the individual-level logic of the “life course” with macro-level theorizing on the social ecology of the neighborhood, begin to explore if and how neighborhood history matters for its present.

Beginning with the work of Shaw and McKay (1969) and their intellectual predecessors in human/social ecology, the study of crime at the neighborhood level has a long and complex history. That there are important relationships between neighborhood conditions – such as poverty, racial/ethnic heterogeneity, and residential stability, among others – and crime outcomes is not in question. However, important questions remain over the precise form, causal ordering, and emergence of the socially-embedded mechanisms that produce these relationships, in addition to other methodological and theoretical debates. It is the goal of this
dissertation to shed light on some of these issues and attempt to answer several questions about the nature of the relationship between a key structural variable – concentrated disadvantage – and neighborhood crime rates. I tie together several threads in the sociological and criminological literature on neighborhood structure, concentrated disadvantage, social capital, spatial effects, and the developmental/life-course perspective to present a model of collective efficacy that incorporates geographical space and temporal processes. The model of neighborhood conditions and crime that emerges is dynamic, and I believe it is a more accurate representation of the processes which link the two, moving beyond the largely cross-sectional perspective of previous work in this area. In this manner, I hope to stress the importance of two understudied factors in neighborhood crime research – geographical space and time-dependent social processes – and recognize area crime rates not as the outcome of static relationships but of dynamic histories of change (or continuity) over the “life course” of neighborhoods.

The dissertation is organized into five major parts. The remainder of Chapter 1 discusses several areas of neighborhood research relevant to this project. These include the origins of social disorganization theory in the Chicago School tradition, discussions of “concentrated disadvantage” in urban sociology, and the importance of this concept for collective efficacy theory, a modern evolution of social disorganization. While this literature does not deny the dynamic nature of neighborhoods or the potential for change within them, it often focuses only on the degree to which neighborhoods experience disadvantage at a single point in time and fails to consider the role of stability or instability in that condition over time. Recently, however, some scholars have begun to explore change – in both structural conditions and crime-related
outcomes – within neighborhoods, leading some to call for a developmental or life-course orientation to studying neighborhoods. I go on to describe how recent methodological advances in spatial analysis have begun to be applied to macro-level criminological research and the implications of these studies for larger theoretical questions. Throughout the chapter I point out important contributions of the dissertation to criminology and sociology more generally, situating the current work within existing historical and contemporary research on neighborhood conditions and crime.

Chapter 2 describes the data sources for the project, including the Project on Human Development and Chicago Neighborhoods Community Survey (PHDCN-CS), the analytic sample and the construction of the variables, and briefly outlines the methodological approaches used here. Chapters 3 through 5 constitute the bulk of the dissertation, where in each chapter I present a set of empirical analyses oriented around a particular question or issue. Beginning with the examination of the spatial invariance assumption in Chapter 3 and what the findings suggest about the theoretical relationships between concentrated disadvantage and homicide rates, each subsequent chapter builds upon the findings of the previous one and attempts to answer new questions which are raised. Finally, Chapter 6 summarizes the findings of the empirical analyses and uses them to formulate a model of collective efficacy that explicitly recognizes the inherent dynamism of the relationships between neighborhood structural conditions, the creation, maintenance, and exercise of collective efficacy within neighborhoods, and rates of crime within those neighborhoods.
The Social Ecology of the Neighborhood

By and large, the genesis of neighborhood-level crime research rests with the work of Clifford Shaw and Henry McKay. Their landmark text, *Juvenile Delinquency and Urban Areas* (1969), represents one of the first major theoretical and empirical research projects to move beyond individual-level explanations of criminal behavior to focus on the relationships between neighborhood structural conditions and rates of crime and juvenile delinquency. Before outlining the important contributions of Shaw and McKay, however, it is necessary to briefly explain the broader sociological paradigm of the Chicago School of social ecology mentioned earlier. That this school of thought developed in the early decades of the 20th century is not surprising; it was an era of major changes in many facets of the American way of life including culture, economics, technology, and industry. The growth of the American city as the dominant form of social and political organization was recognized as a critical factor in changing patterns of individual behavior, interaction, and community organization.

These changing patterns were the result of a multiplicity of larger structural changes occurring within the United States at the time. Technological advancements made communication and transportation easier over longer distances, the Industrial Revolution moved the locus of production from agriculture to heavy industry and the influx of large immigrant populations into booming urban areas all contributed in some way to the growth of cities and metropolitan areas. Burgess describes the changes wrought by machine industry as “characteristically American” and attributes the spread of social problems like divorce and crime to the physical growth and expansion of cities (1967, p. 47). Expansion to this point was largely perceived as a practical issue; that is, the physical growth of the city required careful
urban planning, zoning, and so on. In the social ecological model of urban growth, however, expansion does not signify the physical growth of the city but rather a process of urban “metabolism” and mobility (p. 48). Within the city, each area must expand, which requires that different types of areas – industrial, commercial, blue-collar residential, middle-class residential, etc. – invade or spread into territory which was once dominated by another type of area. This model is exemplified by the classic “concentric zone” model of city growth, seen below in Figure 1.1. This idealized version of the city shows how each ring or zone invades its outward neighbor, and in turn forces that area to move outward also. This process of expansion produces a cycle of invasion and succession where each ring extends its area outwards until it completely replaces the function of the type of area which previously existed (e.g. industry replacing workingmen’s homes).
The urban life which results from this ecological process, according to Burgess, was “possible only through a tremendous development of communal existence” (p. 53). However, this was a qualitatively different type of cooperation among residents and the institutions that served them. Urban dwellers were more dependent on large-scale institutions and service providers, like utility companies and economic specialization, than ever before, and the influence of economic systems stripped away much of the spirit of “community” that was thought to dominate previous notions of cooperation. The effects of expansion were not limited to the physical and economic order of the city, but also played a key role in the social
organization – or disorganization – of the city. Viewed as a metabolic process, urban growth required that cities maintain some level of equilibrium; that is, they maintain a “natural but adequate readjustment in the social organization” (p. 53) to accompany its rate of expansion. An excessive increase in population or imbalance in the composition of the population (e.g. more males than females) relative to the “natural” metabolism of the city leads to social disorganization, or an inability to incorporate individuals into the fabric of urban culture and city life.

Importantly, social disorganization was not seen as pathological but normal. Disorganization did not represent an intractable breakdown of culture, social norms, and social equilibrium accompanied by perpetually high levels of social ills like juvenile delinquency and crime, but the predecessor to reorganization. Social disorganization was bound to organization in a reciprocal relationship that ensured the city would be constantly undergoing processes of adjustment towards maintaining a “moving equilibrium of social order” (p. 54). Prior to reorganization, however, it was likely that breakdowns in community social control would lead to increases in juvenile delinquency and crime. Higher levels of delinquency in urban communities were believed to be in part due to the movement from a “village” model of the community to an urban model. In the village community model, control was largely exercised at the family and neighborhood level and based on more personal, intimate relationships. In the urban model of community, given the larger divisions of labor, technological advances in communication and transportation, and much larger populations to be administrated, more rational institutional mechanisms of control were necessary. The power of *gemeinschaft*
relationships to control individual behavior were greatly weakened and replaced by a reliance on gesellschaft relationships (Park 1967).

The period where older informal systems of social control are supplanted is one example of the process of social disorganization. The definition of social disorganization, according to Robert Park, rests on change:

(W)ith movement and change that have come about with the multiplication of the means of transportation and communication, the old forms of social control represented by the family, the neighborhood, and the local community have been undermined and their influence greatly diminished. This process by which the authority and influence of an earlier culture and system of social control is undermined and eventually destroyed is described by Thomas – looking at it from the side of the individual – as a process of “individualization.” But looking at it from the point of view of society and the community it is social disorganization....Everything is in a state of agitation – everything seems to be undergoing a change (1967, p. 107).

Change is anathema to social organization; it is inevitable that change will – at least for a time – disrupt existing patterns of behavior and social routine. This does not, however, imply that disorganization and the social problems it generates are insoluble. Instead, this period of disruption is expected to be succeeded by a period of reorganization when and if the pace of change slows or desists. The increases in delinquency observed at this time in Chicago, attributed to (largely African-American) migrant and European immigrant groups, is the result of these groups’ inability to assimilate into a “relatively strange environment” (p. 108). It is implied that once the expansion of the city reaches some level of equilibrium, the routine of
social life will stabilize, and the social order which rests on such routine will also. This is a critical point for criminological theories of social disorganization, and one to which I now turn.

**Neighborhood Disorganization and Crime**

Park and Burgess theorized that the emerging metropolitan areas were characterized by ecological processes of growth, invasion, and succession which produced new forms of social interaction and rapid change within urban areas. Booming industry and its accompanying economic opportunities attracted high numbers of domestic migrants and foreign immigrants. These (im)migrants, lacking in economic and human capital (like formal education), settled in areas which allowed easy access to low-skill jobs, largely near city centers. However, these areas suffered from high levels of poverty, poor housing conditions, pollution, and other negative conditions. As the city expanded, each area of the city grew outward, invading and succeeding areas which were previously occupied by the next ‘level’ or type of area, exemplified by the concentric zone model of the city in Figure 1.1 above. Expanding upon their predecessors, Shaw and McKay conceived of the neighborhood (and by extension, any macro-level unit like a city) as a complex system of interrelated actors and social forces (Shaw and McKay 1969). Rather than a set of completely independent individuals, each of whom could exercise complete agency over his or her own behavior, larger institutions, contexts, and processes affected the extent and nature of individual behavior in important ways. While they did not deny the importance of individual choice and agency, Shaw and McKay realized that the opportunities for behavior (both criminal and pro-social) could be influenced by neighborhood
conditions, such that the choices available to an individual in a given neighborhood were qualitatively different than the choices available to a resident in a different neighborhood.

This “neighborhood effect” was clearly apparent when Shaw and McKay described not only the differences in crime rates between neighborhoods at a single point in time, but the stability in crime rates within neighborhoods over time. In the presence of relatively rapid change in neighborhood composition – high levels of residential instability, the succession of different racial/ethnic groups – within a substantial number of Chicago neighborhoods, they found that structural conditions at the aggregate level remained relatively stable, as did rates of juvenile delinquency and related behavior (e.g. truancy). The same neighborhoods, regardless of which individuals lived there at a given point in time, produced rates of deviant behavior that were remarkably similar over long periods. This was a substantial shift in the way people thought about crime and its causes. Rather than suggest crime was produced by a particular type of person (e.g. young, male, racial/ethnic minority, low IQ, etc.), Shaw and McKay proposed that certain types of places produced high levels of crime.

They argued that a dynamic process, itself part of the larger trend of city growth and expansion described by Park and Burgess, produced certain neighborhoods with stable levels of high poverty. New immigrants, usually lacking substantial economic or social capital, were forced to settle in the least desirable areas of the city. This ongoing process produced a distinct spatial pattern of structural conditions, because the initial destinations of migrant and immigrant groups were likely to be close to industrial areas near the city center and characterized by high poverty, poor living conditions, substandard housing, pollution, and the like. Given the ability to be economically, socially, and spatially mobile (as characterized by the
“American Dream” both now and then), when individuals or groups attained the necessary level of capital they left these neighborhoods for more desirable ones. In turn, these people were replaced by more recent migrants and/or new immigrant groups. This cycle had the effect of producing neighborhoods that were not only consistently high in poverty, but also had a great deal of residential instability and racial/ethnic heterogeneity over time. These three key structural features produced what Shaw and McKay labeled “socially disorganized” neighborhoods, where the intrinsic social instability of this process prevented or greatly limited the assimilation of individuals and groups into their neighborhood environment.

Since the instability and change within these neighborhoods was ongoing, it was unlikely that the reorganization process described by earlier social ecologists would take place. The “authority and influence” (Park 1967, p. 107) of earlier systems of social control, largely based on informal, personal relationships like families and neighbors was lacking and needed to give way to some new form of control that was more appropriate to urban life. Endemic change, instability and heterogeneity made it difficult to establish a stable, universal, and urban-centric set of norms and develop the mechanisms to enforce them. Delinquency was not initially the result of deviant norms and values but sprang from the absence of social controls prohibiting criminal and delinquent behavior. Over time, this lack of control coupled with the reality of limited economic opportunity and social mobility led to the creation of unconventional, often delinquent, subcultures. These incorporated the goals and expectations of conventional society and were also oriented around economic success, but developed new and potentially deviant means to achieve these goals. Once established, the justifications for and methods of delinquency and crime were transmitted from older residents – juveniles and adults – to newer
residents, perpetuating high levels of delinquency in these neighborhoods and firmly establishing a deviant subculture in these areas. With stable levels of disadvantage and ongoing processes of expansion and change, this cycle was maintained over time regardless of the composition of the individuals residing in the neighborhood. It was the structural conditions at the neighborhood level and continued social disorganization which produced crime, not the demographic makeup of the individuals within the neighborhood. A visual representation of Shaw and McKay’s model is shown in Figure 1.2, depicting structural conditions as endogenous factors whose influence are mediated by the process of disorganization they engender, both through a lack of social control and the development of delinquent or deviant subcultures.

![Figure 1.2. Shaw & McKay’s Social Disorganization Model](image)

I should stress here that Shaw and McKay certainly did not dismiss the potential for reorganization in neighborhoods undergoing change. Rather, they described stable high levels of delinquency in certain areas to be the result of constant high levels of instability and change. The urban environment did not represent a qualitative shift away from notions of community, personal attachments, and social solidarity. A shift towards urban living necessitated some period of disorganization as a prerequisite for reorganization into more efficient and appropriate systems of cultural and social control, as Park and Burgess pointed out, but this did not require a complete reorientation of social life. Disorganization and reorganization were
simply stages in the life-cycle of the community stemming from ecological, institutional, and cultural shifts over time.

However, this perspective was not without its naysayers. Another Chicago School scholar, Louis Wirth, saw urbanization as a substantive change in the character of community life. He believed that urbanization did not represent a relatively brief period of disorganization and reorganization but a qualitative transformation in social relationships. Wirth theorized that the much larger populations, higher population density, and greater racial/ethnic heterogeneity evidenced in the growth of cities were accompanied by “profound changes in every phase of social life” (1938, p. 2). The size of the population increased individual variation across “personal traits, the cultural life, and the ideas of the members” (p. 11), which led to greater spatial segregation by race/ethnicity, economic class, and other characteristics. The primary social bonds arising from kinship and “neighborliness” based on commonalities among community members that were typical of less urbanized places were weakened and to a great extent replaced with secondary social bonds largely based on economic associations and formal social control, or rules that dictated the relationships between members. Larger populations also promoted more anonymity among residents; this was not to say that urban-dwellers knew fewer of their fellow residents, but a smaller proportion of the whole, and of whom they have less personal knowledge. All told, relationships within the city “may indeed be face to face, but they are nevertheless impersonal, superficial, transitory, and segmental” (p. 12).

The increase in social distance among residents was coupled with higher population density, creating “a spirit of competition, aggrandizement, and mutual exploitation” (p. 15) and a reliance on formal social controls to maintain order. Informal rules and enforcement
mechanisms were no longer adequate for such large populations, characterized by diversification, specialization, frequent but impersonal contact, and “glaring contrasts” (p. 14) among residents, which promoted segregation along economic, social, and cultural dimensions. Population heterogeneity was similarly supposed to weaken the importance of local communities and groups. Because “the individual acquires membership in widely divergent groups, each of which functions only with reference to a single segment of his personality” (p. 16), and these memberships are likely to change often according to that persons interests, the institutions supporting city living must be tailored to the average resident rather than a specific individual or group. This implied that the organization of urban life was elevated beyond the local community and came to rest at the city level, where social, political, and economic institutions (e.g. public utilities, schools, and voting) could meet this need most effectively. The end result of this process of urbanism were weaker social bonds between individuals, the dominance of secondary (gesellschaft) relationships over primary (gemeinschaft) relationships, and a decline in the importance of the local community or neighborhood.

These two contrasting views on the nature of urban social life and forms of social interaction and community attachment had very different implications for theories of social disorganization and crime. The perspective of Shaw and McKay (1969), rooted in Park and Burgess, held that disorganization was the product of processes of city growth and expansion. Disorganization and its related social ills were not intractable but would diminish over time as growth slowed and communities reorganized. Wirth, on the other hand, suggested that there was something fundamental to urban life that created disorganization, namely the loss of social bonds and an increasing reliance on formal social control (1938). The stability of high-
delinquency neighborhoods in Chicago described by Shaw and McKay was not the result of ongoing structural instability and a yet-to-occur reorganization process, but instead a breakdown in the sense of community endemic to city life. Debates over the Shaw and McKay model, disagreement over the key mechanisms linking structural conditions to crime, and a waning interest in macro-level criminological theory led to an extended lull in this area of research. In the late 1970s, however, a new impetus was given to this ecological tradition with the work of Kornhauser (1978) who reframed social disorganization purely in terms of social control. Her work drew heavily from advancements in urban sociology and human ecology, particularly the development of the “systemic model” of community attachment by Kasarda and Janowitz (1974). While not criminological in nature, their landmark study examining the implications of these competing perspectives for community attachment was critical in the evolution of social disorganization theory.

In their work, Kasarda and Janowitz derived a number of hypotheses from both the “linear development model” of Wirth and the “systemic model” of Park and Burgess. They argued that in the linear development model increasing population size, density, and heterogeneity were negatively related to community attachment. In the systemic model, on the other hand, community organization was an “essential aspect of mass society” (p. 329). Local communities were socially constructed according to ecological, institutional, and normative conditions, with disorganization only one part of the community “life-cycle” (p. 328). According to Kasarda and Janowitz, the local community represented a “complex system of friendship and kinship networks and formal and informal associational ties rooted in family life and on-going socialization processes” (p. 329). Here the key variable predicting community
sentiment/attachment was an individual’s length of residence, because it was hypothesized to positively influence local social bonds or networks and participation in local community associations (e.g. clubs, politics, charities, etc.). Their findings strongly supported the systemic model of community attachment: length of residence positively predicted social bonds, and thus community attachment, while population size and density were not related to a substitution of secondary for primary social contacts. In fact, they found that formal ties promoted more primary contacts in the community, contrary to the expectations of the linear development model.

Particularly important to the current research is Kasarda and Janowitz’s discussion of the disparity between Wirth’s model and their findings:

Wirth no doubt was aware of the elements of intense social cohesion which developed in the urban community. But in the dense inner city, he saw what he thought was a lack of integration or assimilation of these population groups into the social fabric of the urban community. In retrospect, he failed to give sufficient emphasis to the temporal sequence of assimilation; while he focused on increased population size and density, variables which operate continuously and with a time lag (1974, p. 338; emphasis added).

Their usage of terms like community “life-cycle,” development, and temporal sequence make it clear that the link between structural conditions and neighborhood outcomes is some type of social process that occurs over time. For Kasarda and Janowitz, community attachment was produced through the creation of social networks and bonds and local associations that were positively tied to one’s length of residence. Similar inferences exist in Shaw and McKay’s model
of social disorganization and crime: poverty is linked to population instability (turnover and
heterogeneity) which inhibits social control and contributes to the generation of a delinquent
subculture (1969). In neither case does the ultimate outcome (attachment or delinquency)
emerge out of whole cloth, but is completely dependent on some temporally-bound social
process mediating the relationships between neighborhood structural conditions and a given
consequence.

Empirical tests of the systemic model of social disorganization that followed were
largely supported; the effects of structural conditions on crime and delinquency were largely
mediated by the density of social networks, levels of community attachment, and the
supervision of teenage peer groups (Bellair 1997; Bursik and Grasmick 1993; Sampson and
Groves 1989; Taylor 1996; Warner and Rountree 1997). Neighborhood factors original to the
Shaw and McKay model – poverty, residential instability, and racial/ethnic heterogeneity –
remained the distal causes of high crime and delinquency rates but now exerted their influence
through negatively affecting community ties, attachment, and the exercise of informal social
control. Systemic ties within the neighborhood promoted a mutual working trust among co-
residents and increased the ability of the community to monitor the behavior of its members
(and others who entered the neighborhood). These ties created stronger levels of “private”
control within small primary groups like the family as well as “parochial” control within middle-
range groups and institutions like schools and churches (Bursik and Grasmick 1993). External
systemic ties were also beneficial because they linked neighborhood residents to institutions
rooted outside the community or at a higher level of incorporation, like the police or city-wide
politics, and elevated levels of “public” control. At the private and parochial levels, systemic ties
allowed communities to exercise largely informal social control over their own members, while at the public level they could provide more formal social control if and when more local, informal mechanisms did not suffice.

The focus on the density or strength of systemic ties later shifted to studies of what these ties actually provided. Work on the role of social networks (Granovetter 1973) suggested that not only were primary or “strong” ties important to generating social control, but secondary or “weak” social ties were also crucial. The systemic ties within and between groups (or neighborhoods) were not themselves social capital, but provided channels through which social capital was exchanged. This social capital took the form of social cohesion and mutual trust, combined with a willingness to intervene when behavioral norms were violated. Together, cohesion/trust and the ability to exert informal social control determined the level of “collective efficacy” in a neighborhood (Morenoff, Sampson, and Raudenbush 2001; Sampson, Raudenbush, and Earls 1997). Produced by both strong and weak ties, collective efficacy mediated the relationship between structural conditions and crime rates, and empirical research has by and large supported this model of structural conditions, informal social control, and crime (though there is some evidence the model may be less applicable to non-U.S. neighborhoods; see Bruinsma, Pauwels, Weerman, and Bernasco 2013).

More recent work, however, has called attention to the downside of the social capital channeled through systemic networks. Drawing on a conceptualization of “bridging” and “bonding” social capital, Browning and others have found that the effects of collective efficacy on crime are moderated by the type of systemic ties within a neighborhood (Browning 2009; Browning, Feinberg, and Dietz 2004). Bridging social capital connects different groups, based on
less personal or weaker systemic ties, while bonding social capital exists within a group and is rooted in stronger personal relationships. Collective efficacy is suggested to be largely the result of bridging social capital, where a number of groups are able to trust each other, agree on a set of social norms to be enforced, and exert informal social control over members of all groups. Bonding social capital, however, is rooted in expectations of reciprocated exchange between individuals who share strong ties, with the implication that the personal ties between individuals may take precedence over the interests of the larger community. In this “negotiated coexistence” model, network ties were found to attenuate the effects of collective efficacy on crime; higher levels of collective efficacy produce lower levels of property and violent crime as expected, but strong networks weakened the relationship. This is logical, given that individuals who commit crime are likely embedded in neighborhoods and networks alongside non-criminal individuals. Criminals are likely to draw on rules of reciprocated exchange within their networks to protect themselves from the informal social control mechanisms of collective efficacy.

The negotiated coexistence model speaks to an important long-standing criticism of social disorganization theory, and points up the reality of how complex the social processes linking neighborhood conditions to crime likely are. Shaw and McKay’s original formulation of social disorganization theory was thought by some to paint with too broad a brush, given it could not explain the existence of organization within impoverished neighborhoods. William Whyte, a contemporary of Shaw and McKay, argued in his review of the social disorganization literature to date that an inaccurate middle-class normative standard had been used to portray poor neighborhoods as “disorganized” (1943). Instead, Whyte saw slum neighborhoods as organized along a qualitatively different standard, but organized nonetheless. He pointed out
that these neighborhoods may already be in the end stages of social reorganization, in an environment where old groups and standards of behavior have broken down and “new groupings and standards have arisen” (p. 38). More recent quantitative and qualitative work on disadvantaged neighborhoods has reached similar conclusions. Mary Pattillo has shown that the incorporation of deviant individuals like gang members and drug dealers into largely pro-social networks of residents can prevent social networks from being completely efficacious (1998). As a corollary, she points out that even criminal or delinquent community members are not always and everywhere deviant. While their ties to law-abiding residents may weaken collective efficacy to some extent (as suggested by the negotiated coexistence model), all residents share a desire for some level of social organization. Criminals are still community members embedded into family and neighborhood social networks who share “mainstream desires for neighborhood order, albeit by different means” but are “given a degree of latitude to operate in the neighborhood” (p. 770).

This last point is an important piece of social disorganization theory in all its forms. It has come to be generally understood that social (dis)organization is not necessarily an objective concept; while most agree that levels of disorganization are distributed over some scale, the scale itself can be subjective to some degree. Contemporary scholars in this area describe social disorganization as the neighborhood’s inability to regulate its members’ social behavior, relative to some set of agreed upon norms and expectations. Cast as a pure social control theory, recent evolutions of social disorganization theory clearly understand that the standard against which “disorganization” is measured is to some extent dependent on the expectations and norms of the neighborhood itself. This is explicit in Sampson and colleagues’ discussion of
collective efficacy (Sampson 2002a; Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997). Efficacy, it is argued, only exists relative to some particular goal or effect, in this case the maintenance of an “acceptable” level of crime within a neighborhood. It does not seem controversial to say that within all neighborhoods, residents generally agree that no crime is better than some and less crime desirable over more. However, neighborhoods that lack the economic and social resources to formally and informally inhibit all crime (a rare if impossible feat in reality) are likely to realize the futility of this goal, and will instead work to limit crime as much as possible. It is also likely that they would seek out or establish alternative methods of social control which are not as dependent on traditional sources of social and economic capital like political connections or formal institutions like the police; a salient example in the form of gang member “Lance,” is given by Pattillo-McCoy (1999).

I believe that the somewhat subjective nature of social disorganization (or its inverse, collective efficacy) is important because it is closely related to the temporal nature of the social process linking structural conditions and crime outcomes. The links between poverty, residential instability, racial/ethnic heterogeneity and disorganization/collective efficacy take some degree of time to emerge, as does the relationship between disorganization/collective efficacy and crime. These links in and of themselves may also be strongly dependent on the amount of time a neighborhood has experienced or avoided these structural conditions. This moves the perspective of social disorganization and collective efficacy theory away from explaining between-neighborhood differences at a single point in time and towards a “life course” explanation of within-neighborhood development, change, and stability over time. This is certainly not to argue that the level of a particular structural condition does not matter. I
agree that at any given point in time a neighborhood with higher levels of disadvantage will almost certainly have more crime and other social problems than a less-impoverished neighborhood. However, I argue here it is not only the level but also the stability of a particular condition that matters. Thinking about how long a neighborhood has experienced a condition at a given level requires one to think in terms of a history of structural conditions at the neighborhood level. Given the theoretical importance of (in)stability to the generation and operation of the social processes that link structural conditions to crime, it is probable that neighborhoods with similar levels of some condition in the present but different histories in the past will have significantly different levels of social cohesion/trust and ability to exercise social control over individuals within the neighborhood – the two key components of collective efficacy (Sampson, Raudenbush, and Earls 1997).

**Neighborhoods in Time and Space**

Two critical pieces of Shaw and McKay’s theory of social disorganization were the role of spatial organization and time. This is readily apparent in Burgess’s introduction to the first edition of *Juvenile Delinquency*, where he describes the first major finding of the book to be that “the distribution of juvenile delinquents in space and time follows the pattern...of the social organization of the American city” (Shaw and McKay 1969, p. xxv; italics added). The spatial dimension was somewhat more explicit; the “concentric zone” model of Chicago neighborhoods relied on an understanding of the physical geography of Chicago and the economic and cultural processes underpinning social and spatial mobility (i.e. rising out of poverty and moving out of poor neighborhoods). Later studies of other cities, like Boston,
Cleveland, and Richmond, evidenced similar patterns of spatial relationships. Poor neighborhoods tended to be in close geographic proximity to each other, and thus high rates of crime and delinquency (as well as high rates of related problems like poor health) clustered as well. Contemporary research has also found that geographical space plays a role in the generation of neighborhood crime, though uncertainty remains over the correct form of spatial relationships (Baller, Anselin, Messner, Deane, and Hawkins 2001; Bruinsma, Pauwels, Weerman, and Bernasco 2013; Light and Harris 2012; Morenoff, Sampson, and Raudenbush 2001; Tita and Cohen 2004). The same neighborhoods also appear to be remarkably stable over time in both their levels of a particular structural factor like poverty and a number of crime measures including interpersonal violence and property crime (Sampson 2009; Sampson 2012).

However, while the “Chicago School” of social ecology has produced an extensive literature exploring the role of time and change, it is largely limited to urban sociology and demography rather than urban criminology. Numerous theories have been developed to explain processes of change in neighborhoods, including invasion-succession models based on the work of Park and Burgess (Park, Burgess, and McKenzie 1967) and the life-cycle model of Hoover and Vernon (1959; also see Birch 1971) among others (Schwirian 1983; Schwab 1987). The life-cycle model of neighborhoods in particular has been applied to a variety of topics, including the aging of neighborhood populations and housing stock (Wiesel 2012), neighborhood “status shifts” (Guest 1974; Choldin and Hanson 1982), household decision-making (Little 1976), urban planning and public policy (Roberts 1991; Metzger 2000), and “shrinking cities” (Martinez-Fernandez et al. 2012). Interest in the neighborhood life-cycle in urban sociology has been relatively steady (if somewhat sporadic) since the middle of the 20th
century, with recent research exploring the wide variety of change possible within neighborhoods and finding a complexity of forces at work simultaneously (Wei and Knox forthcoming; Owens 2012).

The temporal dimension of Shaw and McKay’s social disorganization model of neighborhood crime (Shaw and McKay 1969) and its modern counterpart in Sampson et al.’s collective efficacy model (Sampson, Raudenbush, and Earls 1997), on the other hand, has received much less attention in recent criminological research. Beyond suggesting that the stability of high crime rates over time in certain neighborhoods is attributable to the stability of the structural conditions believed to cause them, studies of neighborhood conditions and crime rarely address temporal changes in structural conditions or the social process hypothesized to link them with crime (though see Bursik 1986; Bursik and Webb 1982; Schuerman and Kobrin 1986; Sampson 1993). Given the critical role of structural instability and change in generating disorganization, I believe that this has produced a significant gap in our understanding of how neighborhood crime is linked to structural conditions over time. The mechanisms implicated in the generation, transmission, and replication of social disorganization or collective efficacy within certain neighborhoods are time-dependent; that is, they are processes embedded in the social fabric of the neighborhood. Poverty does not instantly create neighborhoods with high levels of residential mobility and ethnic heterogeneity, but rather generates these characteristics over time through forces of social, economic, and spatial mobility. In turn, this mobility – should it be maintained long enough – creates neighborhoods which are more or less disorganized and having more or less agreement upon and enforcement of behavioral norms, values, etc. In the short term, high poverty rates did not ensure residential instability and ethnic
heterogeneity, and the accompanying social disorganization of a neighborhood. Instead, it was
the fact that high poverty rates *endured over time* that allowed the process of social
disorganization to both emerge and continue to function. This results in disorganization
theories often being applied to explain differences in rates of crime and delinquency *between*
neighborhoods at a single point in time, while much less attention is paid to *within-
neighborhood change over time* by researchers. This shortcoming is one of the major points of
Sampson’s recent summary of the “hard questions” for future criminologists; he argues that in
moving forward we must start to consider neighborhoods as dynamic and possessing life
courses analogous to the individual (Sampson 2012; Sampson 2013).

There are certainly exceptions to this characterization of the literature, with a number
of researchers exploring crime trends over time, though none to my knowledge explores the
role of neighborhood histories of disadvantage in the presence or lack of collective efficacy. A
considerable amount of published work, both theoretical and empirical, describes and attempts
to account for the “Great American Crime Decline” during the 1990s (Fagan, Zimring, and Kim
1998; Friedman 1998; Gallo 1998; LaFree 1998; Maltz 1998; Parker and Cartmill 1998; Travis
and Waul 2002; Zimring 2007). Routine activity theorists have explored how changes in daily
activities affected the intersection of attractive targets with motivated offenders in the absence
of capable guardians (Cohen and Felson 1979; Felson 2002). Attempts have been made to
predict trends and within-community variation in homicide over time in Chicago (Stults 2010).
The related work of Weisburd, Groff, and others on Seattle is particularly relevant (Groff,
Weisburd, and Yang 2010; Groff, Weisburd, and Morris 2009; Weisburd, Morris, and Groff
2009). They link a growing (or re-emerging) interest in the policy implications of a place-
oriented (vs. person-oriented) perspective on crime prevention to stable concentrations of crime in particular places over time, echoing the work of Shaw and McKay decades earlier. While largely focused on the utility of smaller units of analysis like blocks, these authors make an important contribution to macro-criminological theory in how they apply trajectory analysis to aggregate units. As I will discuss briefly in Chapter 4, group-based trajectory analysis allows investigators to “uncover distinctive developmental trends” in a sample (Nagin 2005, p. 9). The developmental perspective in criminology has, by and large, been limited to the examination of individual-level trajectories as exemplified in life-course criminology (Laub and Sampson 2003; Moffitt 1993; Nagin, Farrington, and Moffitt 1995; Sampson and Laub 1992). However, I believe that this orientation is also appropriate to the examination of neighborhoods and other aggregate units, with “history” as a macro-level analogue to individual-level “biography.” Given the temporal nature of the processes linking structural conditions and crime within neighborhoods, it is likely that where a neighborhood is “located” in its history of poverty or disadvantage would impact the emergence and operation of collective efficacy (or its inverse disorganization) in a neighborhood.

This last point is particularly relevant in the light of a small but growing area of research employing geographically-weighted regression (GWR) to examine one key assumption of ordinary least-squares (OLS) regression models. As will be discussed in greater detail in Chapter 2, OLS and related regression methods generate a single “global” measure of the relationship between a given predictor like poverty and the dependent variable. This assumes that the global estimate of the effect is a relatively accurate assessment of the true relationship across all of the units in the analytic sample. In the case of neighborhood-level studies, this translates
to an assumption that the effects of the predictive variables are substantially the same across all places; for example, that the poverty-homicide relationship is the same in Los Angeles as Chicago, or in Brooklyn as in Queens. However, recent work has found that this assumption is likely flawed. The relationships between a variety of macro-level predictors and crime outcomes have been shown to significantly vary across aggregate units, including the proportion of foreign-born residents and language diversity across census tracts (Graif and Sampson 2009), a measure of structural disadvantage at the county level (Light and Harris 2012), and an index of social capital across counties (Deller and Deller 2012).

The findings of direct tests of the “spatial invariance” assumption are consistent with previous work on the role of neighborhood instability and change. Bursik and Grasmick (1992) found that increasing levels of stability within neighborhoods from 1930 to 1970 were significantly and positively related to declines in delinquency over time. Higher instability has also been linked to higher levels of violence in Baltimore (Covington and Taylor 1989; Taylor and Covington 1988), regardless of whether that change was positive (gentrification) or negative (increasing disadvantage). Gentrification, or neighborhood revitalization, is both an outcome and a process (Kreager, Lyons, and Hays 2011). On the face of it, improving conditions in neighborhoods are desirable, and Kreager et al. showed that Seattle tracts which gentrified in the 1990s experienced reductions in crime compared to non-gentrifying tracts. However, when exploring gentrification as a process, they found that mortgage investment had a curvilinear relationship to crime. This suggests that change, even positive change like gentrification, can generate disorganization or diminish informal social control in a neighborhood. Kreager et al. speculate that until some tipping point is reached and gentrification is completed, the
instability it generates may actually be criminogenic (p. 634). This is an important consideration because it demonstrates the importance of both the level of structural conditions and the stability of those conditions. It is possible that the spatially-varying relationships are attributable to the fact that some neighborhoods, while possessing similar levels of a given structural factor, have very different histories (i.e. of the degree of stability or change) of that same factor. Stults (2010) suggests viewing the relationship between stability (or instability) and crime through the lens of developmental theory, a strategy I endorse here. Like individuals, neighborhoods may evidence their own “criminal careers” (D’Unger, Land, McCall, and Nagin 1998; Eggleston and Laub 2002; Moffitt 1993; Nagin, Farrington, and Moffitt 1995).

While Stults and others typically employ trajectory modeling techniques to predict crime trends at the macro-level (Groff, Weisburd, and Yang 2010; Stults 2010), I believe these methods can be adapted not only to predict trends but also to account for spatial variation in the relationships between structural conditions and crime outcomes themselves in cross-section. In effect, the spatially-varying relationships between structural conditions and crime may be accounted for by the stability or instability over time of the condition itself. I have already discussed the importance of structural stability in social disorganization theory and the potential for reorganization when structural conditions stabilize, net of the level of those conditions. Since collective efficacy is essentially the inverse of disorganization, specified as a social process mediating the structure-crime relationship, I would expect the effects of stability and instability on collective efficacy to operate in much the same way. However, unlike the era of Shaw and McKay, where poverty initiated processes of residential instability and racial/ethnic heterogeneity and thus disorganization, deprivation in urban areas in the last
decades of the 20th century has transformed. This transformation, as described by William Julius Wilson (Wilson 1996; Wilson 1997), is critical to an understanding of collective efficacy theory. Before moving forward to a discussion of the implications of stability and instability for neighborhood collective efficacy and crime, it is necessary to first examine a concept that lies at the heart of the work of Sampson and others: concentrated disadvantage.

Concentrations of (Dis)advantage

Early sociological investigations of economic conditions in American cities almost exclusively relied on a single measure of deprivation – poverty – and its relationship to a host of social ills associated with the growth and nature of urban life, including breakdowns in social attachments (to individuals, organizations, and places), health, and crime. This orientation linked an objective lack of economic resources in neighborhoods to negative outcomes like high crime rates through social processes that were themselves dependent on economic conditions. Shaw and McKay’s model of poverty driving high residential instability and racial/ethnic heterogeneity described above is one example of such an orientation. There are several possible explanations for this historical focus on a single-factor orientation to deprivation. Certainly the collection of data on related structural factors like family structure, welfare, and employment within neighborhoods was not as advanced as we have come to expect, at least in terms of easily accessing and analyzing data. Furthermore, it is possible that the high correlations between related facets of structural disadvantage like poverty, family structure and welfare were simply not as strongly linked during the earliest years of studies into urban settings. Finally, the social mechanisms theorized to link deprivation to a given outcome
themselves relied on between-unit differences in levels of economic resources: Neighborhood
A had higher levels of residential instability than Neighborhood B because Neighborhood A
lacked some fixed level of economic capital to maintain desirable housing stock. Another
example in the criminological literature is from the “subculture of poverty” hypothesis, which
suggested that poor neighborhoods spawned a distinctive set of norms and behavioral
orientations promoting criminal behavior (Matza and Sykes 1961; Miller 1958). In either case, it
was economic capital, rather than social or human capital, which was the engine behind the
processes leading to social ills.

This focus on poverty as a singular structural factor was altered a great deal with the
work of William Julius Wilson. Beginning with his seminal work *The Truly Disadvantaged*
(Wilson 1996), Wilson described a new type of deprivation emerging in urban areas during
deindustrialization, stemming from not only poverty but a host of other structural conditions
within neighborhoods, including unemployment, single-parent (usually single mother) families,
and rising numbers of welfare recipients. In the last several decades of the 20th century, Wilson
argued, larger-scale social and economic processes at work in the United States led to a
concentration of not one or two of these factors but many of them, within particular
neighborhoods, creating a substantively different type of disadvantage than seen before. In
charting the rise of a new urban underclass of African-Americans, Wilson describes how the loss
of industry in cities and the relocation of jobs requiring less education to suburban areas
contributed to working- and middle-class black flight from city neighborhoods. Those
individuals who lacked the social, human, or economic capital to follow these jobs were forced
to remain in neighborhoods which now represented a “tangle of pathologies,” where structural
disadvantage across multiple factors was the norm (also see Wilson 1997). In the past, non-
poor black families were a “social buffer” for poor families, supporting local institutions and
acting as sources of neighborhood capital – not just economic, but social as well – from which
all co-residents could draw. With their exodus, however, these resources vanished, leaving
behind a concentration of disadvantage that was linked to a variety of negative social outcomes
including high levels of crime and violence.

For the purposes of the current research, there is one aspect of Wilson’s reasoning
which is critical. As Wilson describes it, the emergence of “concentrated disadvantage” is the
confluence in geographical space and historical time of multiple factors of disadvantage. In
other words, concentrated disadvantage is the product of several types of deprivation –
poverty, joblessness, female-headed households, welfare receipt – converging over time within
particular geographic locations, i.e. neighborhoods. It is not enough that there is loss of
industrial or low-education jobs within a larger economy like the United States; these jobs must
be lost mostly (or completely) from certain neighborhoods. Housing which is affordable to
impoverished or single-parent families is largely located in a few urban neighborhoods.
Moreover, these neighborhoods suffer from a lack of not only economic capital, but sources of
social and human capital as well. The institutions – churches, schools, local business
organizations, and the like – and roles models for pro-social social behavior are lost also. The
lack of social role models resulting from working- and middle-class black flight is greatest in the
same neighborhoods suffering losses in economic resources (Wilson 1996; 1997).

In each case, the neighborhoods losing economic capital – represented by rising
unemployment and poverty rates – are likely to be the same places losing social and human
capital in the form of social bonds and networks, cultural role-models, strong social institutions, and education. Losses of one type of resource cannot be assuaged by drawing on other types; instead, the neighborhood loses much of its economic, social, and human capital wholesale. Adding to Wilson’s arguments on the role of economic restructuring, Douglas Massey points out that racial/ethnic segregation interacts with economic segregation and contributes to the concentration of disadvantage in particular urban neighborhoods (Massey and Denton 1993). The end result is a set of neighborhoods which suffer from some of the greatest levels of disadvantage across multiple dimensions that has ever existed. The negative social outcomes that emerge in this same set of places or neighborhoods are theorized to be the result of this convergence in geographic space and time. Adding to this problem, the distribution of concentrated disadvantage appears to be remarkably stable over time. The most disadvantaged neighborhoods tend to remain the most disadvantaged relative to other areas; Sampson lays out a constellation of reasons this “tangle of pathology” (2012, p. 99; also see Sampson 2009) is durable, incorporating multiple levels of analysis and non-recursive relationships to explain the replication of place stratification over time. However, while the “rank ordering” of neighborhoods along the distribution of concentrated disadvantage appears stable, this does not automatically imply that there is no change within a particular neighborhood over time. Wilson’s description of this emergent form of concentrated disadvantage was of seminal importance in urban sociological research, but focused primarily on the creation and maintenance of extreme disadvantage in particular neighborhoods. Later research based on Wilson’s work has been similarly oriented and largely neglected the role of time-bound social processes linking structural conditions to the host of social ills that were found in
disadvantaged areas. By focusing only on between-neighborhood differences in disadvantage, the role of (in)stability over time represented by different histories of disadvantage has been to some extent ignored. The influence of Wilson’s work was not the only reason urban sociologists and criminologists turned to a multi-factor measure of disadvantage. At roughly the same time Wilson was describing the emergence of concentrated disadvantage, another debate in the criminological literature over the conceptualization of “deprivation” was ongoing, and (unintentionally) contributed to a focus on between-neighborhood differences to the exclusion of stability or instability within neighborhoods over time.

**Poverty vs. Inequality**

Around the same time Wilson was exploring the growth of concentrated disadvantage, a lively debate had emerged in the criminological literature regarding the conceptualization of a key predictor of macro-level crime rates: deprivation. Poverty had long been the standard measure of economic deprivation in sociological and criminological theory and empirical research. However, scholars had begun to reexamine the question of whether deprivation was more accurately conceived as an absolute measure – that is, deprivation measured against some objectively established standard level of economic well-being – or as a relative measure based on the distribution of economic resources within a population. This debate was in part prompted by criticisms of explanations of crime which relied on poverty to explain individual criminal behavior and aggregate crime rates, such as the “subculture of poverty” thesis (Matza and Sykes 1961; Miller 1958; Tittle 1989). Such theories, critics argued, might explain crime committed by the poor, or higher crime rates in poor neighborhoods, but could not account for
the criminal behavior of non-poor individuals or crime which occurred in affluent neighborhoods. At the individual level, non-poor individuals would lack the motivation to engage in criminal behavior; at the aggregate level, non-poor neighborhoods would have ample resources to control crime. A universal theory of crime would ideally account for both all types of criminal behavior at the individual level (e.g. economic crimes like robbery and violent crimes like assault) and aggregate crime rates. Regardless of whether the theory is oriented around motivation or social control, poverty-based explanations of crime lacked the ability to explain either in the absence of poverty.

In response to this critique, new theories of criminal behavior were developed that relied on mechanisms linked not to absolute deprivation, but relative deprivation. It was the inequality within a population that spawned the social processes that drove crime rates and criminal behavior, not an objective lack of economic resources. Merton’s structural strain theory focused on the disparity between culturally-defined success goals like wealth and access to the legitimate means of attaining those goals across class groups (determined in large part by the social structure). Higher rates of crime in the lower class were due to this group being relatively deprived of legitimate means compared to higher-class groups, and turning to illegitimate/criminal methods of attaining success (the "innovation" adaptation to strain; Merton 1938; Park, Burgess, and McKenzie 1967). The importance of this disparity in explaining crime was acknowledged by Shaw and McKay in their formulation of social disorganization theory:

(I)t is assumed that the differentiation of areas and the segregation of population within the city have resulted in wide variation of opportunities in the struggle for position
within our social order. The groups in the areas of lowest economic status find
themselves at a disadvantage in the struggle to achieve the goals idealized in our
civilization….Those persons who occupy a disadvantaged position are involved in a
conflict between the goals assumed to be attainable in a free society and those actually
attainable for a large proportion of the population. It is understandable, then, that the
economic position of persons living in the areas of least opportunity should be
translated at times into unconventional conduct, in an effort to reconcile the idealized
status and their practical prospects of attaining this status (1969, pp. 186-87).

In his work on general strain theory, Agnew describes negative emotional “affect,” including
depression and aggression, which emerges from falling short of cultural expectations of
economic success (1985; 1992). Individuals who fall short, he argues, are likely to manage their
negative affect through deviant behavior, including economic crime and violence. Related work
from Blau and Blau (1982) supported the importance of inequality in producing crime. In a
democratic context of attainment like the United States, it is assumed that all individuals have
an equal opportunity to achieve the goal of economic success and access to the means to attain
this success. Inequality based on ascribed characteristics like race, they argue, creates a
disjunction between goals and means and produces higher crime rates in areas with higher
ascribed inequality. While achieved inequality based on earned statuses like level of education
could also produce this disjunction or strain it was less likely to produce crime because it was
seen as an individual rather than structural failure.

Messner and Rosenfeld (2007) similarly conceptualize strain as rooted in macro-level
social structure. Their theory of “institutional anomie” posits that the primacy of economic
institutions and goals in the U.S. make it more likely that individuals would engage in deviant behavior to attain those goals when conventional means failed. Other social institutions like the family were of secondary importance relative to the economy and as such were less likely to be valued as indicators of achievement; it was less important to be a good husband and father, for example, than to be a good provider for one’s wife and child. Konty (2005) incorporated both macro- and micro-level elements into his theory of “microanomie.” In a synthesis of Blau and Blau’s relative deprivation theory with Messner and Rosenfeld’s institutional anomie, he suggested that cultural emphases on economic success and individualism at the aggregate level are replicated at the individual level, producing persons who value their own success more than the success of their society; they have fewer concerns for harm done to the group through their deviant behavior than the benefits such behavior may accrue to them. In any case, proponents of theories incorporating relative deprivation as the key predictor of the social process linking structural conditions to crime rates (or individual characteristics to behavior) argued that such theories were more accurate because they could account for crime and criminal behavior in the absence of poverty. The poverty-inequality debate in criminology spawned a tremendous amount of empirical research largely focused on the power of absolute vs. relative deprivation to explain crime rates across aggregate units. These comparisons often took the form of critical theoretical tests pitting poverty-based theories like social disorganization and the subculture of poverty against inequality-based theories such as relative deprivation. Interestingly, the results of studies comparing these factors were decidedly mixed; findings ranged from strong positive effects of poverty, inequality, or both to statistically insignificant relationships with crime rates.
In at least one case, the results contradicted theoretical expectations when poverty was found to have a significant negative effect on crime (Messner 1982).

The debate over these diverse findings culminated in a seminal piece by Land, McCall and Cohen (1990). The inconsistencies in the empirical literature over the respective roles of poverty and inequality, they argued, was possibly due to the wide variety of time periods, geographic units, and model specifications used across existing studies. Scholars have pointed out that multicollinearity between poverty, inequality, and other variables, as well as mis-specification of the relationships to crime outcomes (e.g. linear or non-linear) likely contribute to the variety of results in the literature (Patterson 1991; Williams 1984). Land et al. (1990) examined the potential for these statistical and methodological artifacts to explain the inconsistency, creating a baseline model of 11 structural covariates common to macro-criminological theory at several levels of measurement (including cities, metropolitan areas, and states) and at three different time periods (1960, '70, and '80). They found that the estimated relationships between structural conditions and crime were very unstable across models, and largely attributed it to the high levels of multicollinearity found among a number of the structural predictors. Employing principal component factor analysis, they simplified this set of 11 independent variables into two clusters. The “population structure” variable incorporated both population size and density, while the “resource deprivation/affluence” measure combined median family income, poverty rate, proportion black, proportion single-parent families, and the Gini measure of inequality. Re-estimation of the baseline model with the two factor variables (as well as the remaining “standalone” variables) indicated that the inconsistencies in the structure-crime relationships across levels of measurement and time
period were substantially reduced. Land et al. concluded that the effects of structural conditions on crime were invariant over time and social space, once multicollinearity among the predictors was accounted for. The effects of absolute and relative deprivation were not individually identifiable as they were too strongly related, but the strongest and most robust relationship in their model was of the resource deprivation/affluence index. This conclusion is in keeping with Wilson’s assertion (Wilson 1996) that the concentration of multiple dimensions of disadvantage, and the resulting social isolation of particular groups (e.g. poor African-Americans), was a key factor in the explanation of negative social outcomes at the aggregate level.

Histories of Disadvantage

While the work of Wilson, Massey and others in urban sociology and Messner, Blau and Blau, Land et al. and others in criminology was incredibly important for the evolution of studies of urban neighborhoods and crime, there was one unfortunate consequence for later research. By largely focusing only on the distribution of disadvantage across neighborhoods in cross-section (and to some extent on the methodological issue of building better predictive models), the crucial relationship between instability and disorganization originally posited by Shaw and McKay (1969) was ignored or forgotten. Remember that concentrated disadvantage (or any other structural condition) is linked to higher crime rates through social processes that are time-dependent. Poverty did not create disorganization except for contributing to residential instability and racial/ethnic heterogeneity.
The same logic applies to collective efficacy, which is essentially the inverse of disorganization. Neighborhood collective efficacy is the product of systemic ties (both strong and weak) among residents and to external actors and institutions that generate social capital for the neighborhood (Sampson 2012). This social capital takes the form of social cohesion, mutual trust, and shared expectations for social control within the neighborhood. Higher collective efficacy has been shown to predict lower crime rates (Browning 2009; Browning, Feinberg, and Dietz 2004; Morenoff, Sampson, and Raudenbush 2001; Sampson 2012; Sampson, Raudenbush, and Earls 1997), and the effects of concentrated disadvantage, residential instability, and population heterogeneity (typically represented by the proportion of Hispanic and foreign-born residents) on crime are mediated to a substantial degree by collective efficacy. Both social disorganization and collective efficacy, as the mediating mechanisms linking structural conditions to crime rates, are time-dependent. Systemic ties, social capital, and social control do not immediately emerge fully formed as determined by neighborhood structural conditions, but require some length of time to be created or formed. Similarly, the strength and/or degree of these mechanisms may wax and wane over time as neighborhood conditions change, but some length of time is necessary for these structural changes to be “translated” into changes in these social mechanisms.

The collective efficacy model of neighborhood conditions and crime is widely supported in the literature (see Sampson 2012). Though Sampson has greatly expanded the original model to include multiple levels of measurement and non-recursive relationships, at its core the role of concentrated disadvantage remains the same. Neighborhoods with higher levels of disadvantage are expected to have lower levels of collective efficacy, given the difficulty of
building social ties, establishing mutual trust and cohesion, and accruing social capital applicable to formal and informal social control in the face of serious disadvantage. Cross-sectional comparisons between neighborhoods with different levels of disadvantage bear this out (Sampson, Raudenbush, and Earls 1997), but there have been no studies (of which I am aware) that examine differences between neighborhoods that share similar levels of disadvantage at a given point in time but are temporally located at very different points along their internal histories of disadvantage. The concept of concentrated disadvantage, however, has much different implications for neighborhood stability than Shaw and McKay’s poverty. Unlike poverty, which was seen as the distal cause of an ecological process of instability through its relationship to residential turnover and racial/ethnic heterogeneity, and thus social disorganization in the neighborhood, the concept of concentrated disadvantage as described by Wilson and others implies that neighborhoods act as poverty “traps” (Massey and Denton 1993; Sampson 2009; Wilson 1996) and may actually promote structural stability to some degree. This mirrors earlier work on social disorganization in rural areas suggesting that poverty and stability were positively, not inversely, related in these areas (Osgood and Chambers 2000). The relationship between deprivation and stability in urban areas would be theoretically reversed, and it is appropriate to view the effects of concentrated disadvantage in terms of both its level and its historical stability. It is possible that while the level may evidence a negative relationship with collective efficacy, its stability over time may have a positive effect on collective efficacy and thus the eventual crime rate outcome. Alternatively, it is also possible that stable disadvantage has a cumulative negative effect on collective efficacy and crime where the relationship between disadvantage and collective efficacy becomes stronger over time.
I believe this is an important consideration for studies of neighborhood conditions and the mechanisms through which they inhibit or motivate crime. Two neighborhoods may share a similar level of disadvantage but not histories of disadvantage that precede it, and this reality is masked in cross-sectional data. Figure 1.3 presents a basic example of how neighborhoods may appear alike at a given point in time while at the same time existing along substantively different trajectories of disadvantage. The first set of neighborhoods all suffer from high levels of disadvantage. Neighborhood 1 previously experienced much higher levels and has recently seen disadvantage decline (for example, through gentrification). Neighborhood 2 has had a relatively stable level of disadvantage for some time, and Neighborhood 3 has seen disadvantage steadily rise for a number of years (say, due to the loss of an important local employer or neighborhood disinvestment). The second set of neighborhoods (#4-6) parallels these trajectories of disadvantage but at a lower average level. Research typically focuses on the relationship between disadvantage and crime at time $t$ but ignores the trajectories that each neighborhood travelled to reach that level of disadvantage. The first set of neighborhoods is expected to have higher crime rates than the second set, and this hypothesis is widely supported in the literature. Little is known, however, about differences within a given set of neighborhoods.
The overarching goal of this dissertation is to explore the relationship between stable or unstable histories of disadvantage with collective efficacy and crime rates. The “life course” of neighborhood disadvantage likely has important implications for the creation, maintenance and exercise of collective efficacy. Previous work suggests that there are several possible ways these histories could matter, net of the established negative effects of the level of concentrated disadvantage on collective efficacy. The first possibility is that structural stability contributes to increased collective efficacy within the neighborhood, regardless of its level of concentrated disadvantage. Stability has positive effects on social organization (Shaw and McKay 1969), and as concentrated disadvantage represents a “trap” for residents, the accrual of social capital through primary and secondary systemic networks into collective efficacy is more likely (even in
the face of undesirable conditions). It is also possible that stability allows the neighborhood to reorganize around different subjective expectations of social behavior in the neighborhood, as evidenced by the work of Pattillo (1999; 1998), Whyte (1943), Venkatesh (2000), and others. While crime rates would be higher relative to less disadvantaged neighborhoods, they would still be lower than one might expect given that the neighborhood has had time to re-establish a working level of mutual trust, cohesion, and social control. Neighborhoods experiencing recent changes – either increases or decreases – in concentrated disadvantage would find that collective efficacy is disrupted by such change, and crime rates would be higher than expected net of the current level of disadvantage. A similar explanation has been advance to account for a curvilinear relationship between gentrification and crime (Kreager, Lyons, and Hays 2011).

The second possibility is that the direction of change will affect the level of collective efficacy within a neighborhood. The ability of a neighborhood to establish trust and share expectations of informal social control exercised by residents is a form of social capital. Viewing social capital as analogous to financial capital, it is possible that neighborhoods experiencing increases in concentrated disadvantage over time have a reserve of social capital “savings” accrued in the less-disadvantaged past. As theoretically predicted, when neighborhood disadvantage rises systemic ties are eroded and previous feelings of social cohesion and willingness to exert social control based on these ties weaken. However, until this “savings” of social capital is depleted, there may be a lower-than-expected effect of disadvantage on collective efficacy. In cross-section, crime rates would be lower than the level of disadvantage alone would predict given that the relationship between disadvantage and collective efficacy is
– at least for a time – weaker than expected. The previous higher level of collective efficacy would act as a “parachute” to slow the increase in crime rates until that resource was depleted.

The reverse of this logic would apply to neighborhoods experiencing decreases in concentrated disadvantage. Unless these decreases were attributable to external influences like gentrification (which would be accounted for in the first scenario above), it seems unlikely that improvements in neighborhood conditions would be a detriment to collective efficacy. However, as a corollary to the preceding argument, there may be some degree of temporal lag between improving structural conditions and improving levels of collective efficacy. I have already discussed the importance of understanding the links between conditions and crime as a process, and there is likely to be some period of time required for higher levels of resources to be translated into social capital. Internal and external systemic ties and increased levels of trust and informal social control would take time to be established. In this case, the positive relationship between advantage and collective efficacy (rather than the negative relationship between disadvantage and collective efficacy discussed above) would be weaker than expected in cross-section. Neighborhoods with this historical trajectory would evidence higher crime rates than their level of disadvantage would predict.

A third possibility is that the effects of stability are dependent on the level of disadvantage. As others have noted (Sampson 2012; Sampson and Raudenbush 1999; Wodtke 2013; Wodtke, Harding, and Elwert 2011), it may be that stable high levels of disadvantage produce a cumulative negative effect over time. In this case, in disadvantaged neighborhoods the negative relationship between concentrated disadvantage and collective efficacy would become stronger over time. This implies that crime rates in these stable neighborhoods would
be higher than neighborhoods with similar levels of disadvantage at a given point in time but less stable histories. The inverse of this mechanism may also occur in neighborhoods with stable low levels of disadvantage, or high levels of concentrated advantage/affluence (Solari 2012). Over time, the positive relationship between advantage/affluence and collective efficacy would strengthen, and the crime rates in these neighborhoods would be lower than expected. Finally, a fourth possibility is that neighborhood histories of disadvantage have no significant effect on collective efficacy and crime rates. While this seems unlikely given the temporal dependency of the social process linking conditions to crime and the theoretical importance of structural stability, the amount of time necessary to produce, weaken, or strengthen collective efficacy could be relatively short. In this case, longer histories of disadvantage (or affluence) would not exert a substantial effect, and only the current level of disadvantage would be necessary to explain differences in collective efficacy and crime across neighborhoods.

**Research Strategy**

In this dissertation I explore the multiple possibilities laid out above, based on previous theoretical and empirical research in the social disorganization tradition. The conceptualization of neighborhoods within a developmental or life-course framework is relatively new, and my intent here is to make a major contribution to our understanding of how historical trajectories of neighborhoods impact the social processes linking structural conditions and crime. Existing work offers little guidance on what to expect as no one, to my knowledge, has examined the relationship between within-neighborhood historical changes in disadvantage and the level of neighborhood collective efficacy that emerges at a later point in time. Previous examinations of
neighborhood histories have been limited to accounts of trends in either structural conditions (such as the concentration of disadvantage) or the crime outcome itself (e.g. homicides over time). This dissertation represents an important step in the construction of a dynamic model of neighborhood conditions and crime that accounts for the temporal nature of the social processes linking the two.

This first chapter has laid out the theoretical reasoning behind the remainder of the dissertation, and made it clear why I expect neighborhood histories of disadvantage to matter. In Chapter 2 I describe my data sources, the sample used here, and how I constructed measures of structural conditions (both their level and degree of change over time), collective efficacy, and homicide rates. The rest of the dissertation is devoted to empirical analyses of critical relationships embedded in the model. Each of the three empirical chapters build upon the last, culminating in the construction of a unique dynamic model of neighborhood conditions, collective efficacy, and crime. I begin in Chapter 3 by testing the spatial invariance assumption mentioned earlier. If neighborhood histories matter for the creation, maintenance, and/or decline of collective efficacy, it is expected that the relationship between disadvantage and crime varies across neighborhoods at a given point in time. Previous work has found such spatial variation in the relationship, though with different units of analysis than the neighborhood clusters used here (Deller and Deller 2012; Graif and Sampson 2009; Light and Harris 2012). If the relationship between disadvantage and homicide does not vary across neighborhoods (implying that the disadvantage-collective efficacy relationship is similarly invariant), then it does not seem likely that neighborhoods’ structural stability matters. This assumes, of course, that there are different histories of disadvantage over the time period I
explore here, which as Wilson and others have shown is certainly the case (Papachristos, Smith, Scherer, and Fugiero 2011; Stults 2010; Wilson 1996) and basic descriptive statistics confirm here.

Chapter 4 describes the construction of a measure of neighborhood histories of disadvantage. I create a parsimonious but representative set of historical trends in disadvantage and classify all the sample neighborhoods as members in one of these groups. I then control for these groups and examine what effect, if any, this has on the spatial variation in the disadvantage-homicide relationship established in the previous chapter. In Chapter 5 I introduce a measure of collective efficacy to the model, which is expected to mediate the relationship between concentrated disadvantage and homicide. If the (in)stability of disadvantage within the neighborhood is important, it is not because it directly influences homicide rates (or other types of crime), but because structural (in)stability influences the strength of neighborhood collective efficacy. A number of comparisons between groups are examined, though a few of the possibilities discussed above are not testable given the divergence between the ideal model of historical trajectories described in Figure 1.3 and the actual trends found in the data. I conclude with a summary of my findings, the implications of these findings for both macro-criminological theory and practical application, and sketch out a basic model of dynamic neighborhood effects from a life-course/developmental perspective. I also suggest a number of avenues for future research, including several to address shortcomings encountered here.
CHAPTER 2. DATA SOURCES AND VARIABLE CONSTRUCTION

Data

In this dissertation I employ three independent sources of data to explore the dynamics of concentrated disadvantage, collective efficacy, and neighborhood homicide rates. Decennial census data from Chicago are used to measure the level and stability of neighborhood structural conditions, particularly concentrated disadvantage, over three decades including 1970, 1980, and 1990. The data was initially obtained at the tract level, which I then aggregated to represent “neighborhood clusters” (NCs), as I will explain in more depth below. Data on homicides – measured as events known to the police and geocoded by location – was obtained through the Chicago Police Department’s online database (CLEAR) and used to construct the average annual homicide rate per 10,000 residents during a five-year period between 2001 and 2005. Finally, I utilized the Project on Human Development in Chicago Neighborhoods Community Survey (PHDCN-CS) to create a measure of neighborhood collective efficacy in 1995, and also to guide the construction of NCs as the unit of analysis. While it is difficult to establish causal relationships in the social sciences, the models produced using these data sources at least ensure that the ordering of the variables is appropriate to a causal interpretation: structural conditions (measured from 1970-1990) precede the theoretical mediator of collective efficacy (measured in 1995), which in turn precedes the ultimate neighborhood homicide rate outcome (measured from 2001-2005). Each data source presented its own set of challenges, largely owing to the need for information on the spatial organization of the NCs over time and ensuring that identical units were being used over time; foremost among these challenges is the issue of changing spatial boundaries over time.
The boundaries of neighborhood clusters are determined by the outer boundaries of the tracts which comprise them; however, if the tract boundaries change across decennial censuses measures of structural conditions are no longer drawn from identical geographical units over each of the censuses. This is particularly important when performing spatial analyses that rely on geographic information (e.g. Cartesian coordinates or physical distance) to model relationships. Most changes in the boundaries over time are relatively minor and would in all likelihood not substantially alter the outcomes of my models, but in several cases the tract boundaries were considerably different across census years. In addition to changes in tract boundaries (e.g. one tract increasing in geographical size and a neighboring tract decreasing), a number of tracts were either combined or divided into two new tracts between censuses. All of these changes occurred within a given neighborhood cluster, however, so it was not necessary to partition or project the tract population (and other structural measures) across multiple NCs. To minimize the possibility that my results are influenced by errors introduced by using non-identical units over time, I employ data obtained from the Neighborhood Change Database (Geolytics) which standardizes multiple years of census data to 2000 Census tract boundaries. This strategy ensures that measures of structural conditions over time were drawn from identical geographical units. The tract boundaries and structural condition data was then aggregated to my neighborhood unit of analysis.

**Units of Analysis**

The ecological units used here are neighborhood clusters or “NCs” in the city of Chicago. Neighborhood clusters were defined by the authors of the PHDCN to create ecologically
meaningful units in the analysis of neighborhood conditions, social behavior, perceptions of community, and related issues (Earls, Brooks-Gunn, Raudenbush, and Sampson 2007). Empirical research on disadvantage, social control and disorganization, and crime has employed a diverse set of analytical units, including cities (Kovandzic, Vieraitis, and Yeisley 1998; Lee 2000; Oh 2005; Shihadeh and Steffensmeier 1994), census tracts (Graif and Sampson 2009; Kreager, Lyons, and Hays 2011; Krivo and Peterson 1996), face-blocks or street segments (Groff, Weisburd, and Yang 2010; Weisburd, Bushway, Lum, and Yang 2004), counties (Barnett and Mencken 2002; Lanier and Huff-Corzine 2006; Light and Harris 2012; Osgood and Chambers 2000), or metropolitan areas (Blau and Blau 1982; Kelly 2000; Williams 1984). The choice of which ecological unit to use is not a simple matter of picking one over another, but is both theoretically and methodologically important. Social disorganization and collective efficacy theories do not explicitly implicate any particular macro-level unit, and the mechanisms linking structural conditions to crime outcomes are not limited to any specific aggregate unit. However, the definition of the neighborhood must be separable from the social processes embedded within them to avoid a tautology; social processes like collective efficacy should not be confounded with the units within which they are embedded.

The solution to this problem is to conceptualize neighborhoods entirely in terms of geographic space. A spatial definition of place reduces the risk that the unit of analysis will be confounded with social mechanisms implicit in the concept of “community” (Sampson 2012). This is not to say that neighborhoods and communities are not interchangeable at times. Given the “complex social phenomenon” that is defining a neighborhood (p. 55), it is possible that the socially constructed community as understood by residents and non-residents is identical to the
institutionally determined spatial boundaries of the neighborhood. Rather than be tautological, however, the question of overlap can be empirically determined. The social processes theorized to link structural conditions to crime become separable from the geographic definition of the unit of analysis itself; levels of collective efficacy (or any social factor) can vary across units when those units are defined entirely in spatial terms. The result is a spatial definition of neighborhoods as “a collection of people and institutions occupying a subsection of a larger community” (Sampson, Raudenbush, and Earls 1997, p. 919). I should note here that this definition implies that neighborhoods in this sense are embedded within a larger structure. This nested conceptualization of neighborhoods recognizes that there are other levels – both larger and smaller – which also influence neighborhood-level outcomes, such as city- or county-wide political institutions and economics or block-group level physical disorder. As Sampson notes, however, ecological studies in this vein must start somewhere (Sampson 2012), and given the substantial amount of work that relies on the NC construction of neighborhoods and the PHDCN-CS data, I have chosen to also use this unit of analysis.

The original construction of the NCs in the PHDCN was driven largely by the desire to identify ecologically meaningful units based on several guidelines (for details, see Earls, Brooks-Gunn, Raudenbush, and Sampson 2007). The census tracts combined into an NC were geographically contiguous and produced a unit that was internally homogenous on a number of key census indicators, including race/ethnic and socioeconomic composition. Knowledge of the city itself and physical geographical boundaries like roads, parks, and transit lines also contributed to the construction of NCs. The result was a combination of 847 census tracts into 343 neighborhood clusters, each of which contained roughly 8000 residents. Within each NC a
representative sample of residents were surveyed (totaling 8782 individuals) on a variety of topics including physical and social conditions within the neighborhood. Their responses were then aggregated to the neighborhood cluster to create NC-level estimates of neighborhood conditions and social processes.²

The use of these NCs for the current work was complicated only slightly by the fact that NCs in the PHDCN-CS data are based on census tract boundaries from 1990. As I mentioned earlier, I needed to guarantee that the units being examined over time were geographically identical. Tract boundary changes between the 1990 and 2000 censuses were compared and checked for uniformity; in some cases the tract was split or re-numbered, but no major changes were found. Once the 1990 tracts were standardized to 2000 conventions, tract-level data on structural conditions was collected from the Neighborhood Change Database (Geolytics) from the 1970, 1980, 1990, and 2000 censuses. The Census and Chicago homicide data was compiled in ArcGIS mapping software using TIGER line files of Chicago census tract boundaries in 2000. I then aggregated the tract-level data to the NC level using “crosswalk” data supplied by the PHDCN, producing the basic map and database of Chicago I use for the bulk of the analyses here. The final sample includes 342 neighborhood clusters in Chicago.³

**Dependent Variable**

The outcome of interest throughout this dissertation is the five-year average homicide rate per 10,000 residents for each NC in Chicago. The Chicago Police Department’s online database

² Also see Sampson et al. (1997) and Sampson (2012) for descriptions of the PHDCN Community Survey.

³ Though the original PHDCN-CS data includes 343 neighborhood clusters, the missing NC is comprised of the area surrounding O’Hare International Airport, which lacks enough respondents to construct reliable measures (see Sampson, Morenoff, and Earls 1999)
(CLEAR) tracks crimes known to the police by type and year, and each “event” includes geographic information on where the crime occurred. All homicides from 2001 through 2005 were geocoded to the appropriate tract in ArcGIS and aggregated to the NC level. From this I calculated the average yearly number of homicides and constructed a rate per 10,000 residents (based on the 2000 decennial Census population). A multi-year average rate is commonly used to reduce potential bias introduced by year-to-year fluctuations in crime, especially relatively rare types like homicide (Krivo and Peterson 2000; Martinez Jr., Stowell, and Lee 2010). As the distribution of the homicide rate across NCs was substantially skewed, it was transformed using a natural log function, in keeping with previous work.

**Independent Variables**

Following in the footsteps of Land, McCall, and Cohen (1990) and Sampson, Raudenbush, and Earls (1997), contemporary research often focuses on three summary measures of neighborhood conditions: concentrated disadvantage, immigrant concentration (a modern analogue to Shaw and McKay’s measure of racial/ethnic heterogeneity), and residential instability. Several highly collinear univariate measures (e.g. poverty and female-headed households) are combined into a single conceptually-distinct measure of a particular structural condition using a principal-components factor regression procedure (for an example see Sampson, Raudenbush, and Earls 1997) This is a relatively straightforward strategy when examining a single year in cross-section, but more complicated when applied to multiple time points, because the factor regression procedure normalizes the resulting measure to have a mean of zero and a standard deviation of one.
In producing the factor regression score, each component variable is weighted by its factor loading (i.e. how strongly it is associated with the factor measure) and the distribution of values in the sample (through which the factor regression measure is normalized). Comparisons of the factor loadings of univariate measures of structural conditions across 1970-1990 showed the same components loaded together in substantively similar fashion over time; for example, “poverty” always loaded most strongly on the dimension of concentrated disadvantage. However, the distributions of the univariate measures changed considerably over time (e.g. the mean level of poverty in the sample in 1970 versus 1990). Because the final factor regression scores are normalized, direct comparisons over time are affected by shifts in the intercepts between years.

The intercept represents the mean level of a factor across the entire sample of NCs for a given year; for example, an NC with a level of concentrated disadvantage in 1970 equal to the mean disadvantage for the entire sample would have a standardized score of zero for 1970. The same NC could again have a level of disadvantage in 1990 equal to the sample mean and a standardized factor score of zero. If one were to only calculate the difference in the factor score between 1990 and 1970, concentrated disadvantage would not appear to have changed within this NC. However, if the mean level of disadvantage across all NCs in Chicago actually rose (or fell) in real terms, a change-score measure would be misleading. All it would indicate is whether an NC’s level of disadvantage, relative to the entire sample of Chicago NCs, changed over time. This is visualized in Figure 2.1, where each of the three curves represents the distribution of factor regression scores of concentrated disadvantage for a given year. In this hypothetical example, the order of NCs in the distribution is identical year to year, but the mean and the
distribution of the component measures (e.g. poverty) has risen. In real terms, concentrated disadvantage has gone up for all the NCs (represented by the shift in the curves from left to right), but because within each year the factor measure is standardized, each NC would have the same standardized score over time, giving a false impression of no change.

![Within-Year Distributions of Concentrated Disadvantage](image)

**Figure 2.1. Real Shifts in Concentrated Disadvantage Over Time**

To avoid this problem, I based the current factor regression scores on the factor loadings and distributions of the univariate measures across the entire period. The data was reshaped by NC-year, where each “unit” in the sample represented a given NC for a given year, and the variables themselves were no longer distinguished by census year.\(^4\) I then performed the factor regression analysis on the NC-year dataset, which produced rotated factor loadings of the component variables from 1970 through 1990, and normalized factor scores based on the distribution of the univariate measures over the entire time period. Essentially, the factor loadings and distribution of the new factor measures represent the “average” across all three

\(^4\) So rather than have three poverty measures (1970, ’80, and ’90) for a single NC, there is now a single measure of poverty for NC(1970), NC(1980), and NC(1990).
time periods. The rotated factor loadings, shown in Table 2.1, are consistent with previous work (Sampson, Raudenbush, and Earls 1997). The factor regression procedure produced a factor score for each NC-year “unit” and the dataset was then reshaped into its original form. The result is a dataset with 342 NC units in the sample and a factor measure of each structural condition for each year (e.g. concentrated disadvantage in 1970, 1980, and 1990). It is now possible to directly compare NC levels of disadvantage, immigrant concentration, and residential stability over time, as they are standardized to the average factor loadings and univariate distributions across all three time periods. The only remaining source of variation in the factor scores is the level of the univariate components at a given time point.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Factor Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentrated Disadvantage (α = .98)</td>
<td></td>
</tr>
<tr>
<td>Below poverty line</td>
<td>0.955</td>
</tr>
<tr>
<td>On public assistance</td>
<td>0.970</td>
</tr>
<tr>
<td>Female-headed households</td>
<td>0.901</td>
</tr>
<tr>
<td>Unemployed</td>
<td>0.969</td>
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<tr>
<td>Black</td>
<td>0.637</td>
</tr>
<tr>
<td>Immigrant Concentration (α = .80)</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.964</td>
</tr>
<tr>
<td>Foreign-born</td>
<td>0.821</td>
</tr>
<tr>
<td>Residential Stability (α = .64)</td>
<td></td>
</tr>
<tr>
<td>Same house as 5 years ago</td>
<td>0.943</td>
</tr>
<tr>
<td>Owner-occupied housing</td>
<td>0.756</td>
</tr>
</tbody>
</table>

The primary independent variable of interest, concentrated disadvantage, consists of the proportion of residents in an NC who are black, the proportion unemployed, and the proportion of households which are female-headed, below poverty, or on public assistance (α = .98). With the exception of “percentage black” each of these variables loaded very strongly onto this factor (> .90), and clearly taps into the larger concept of disadvantage. The other two
factor measures are employed as controls and constructed in a similar fashion. Immigrant concentration is determined by the proportion of Hispanic and foreign-born residents in the NC (\( \alpha = .80 \)), while residential stability is comprised of the proportion of residents living in the same location five years previously and the proportion of owner-occupied housing units (\( \alpha = .64 \)). Using these factor loadings, I constructed measures of the level of each structural condition in 1990, which will be used in Chapter 3 to predict neighborhood homicide rates and test the spatial invariance assumption.

Beginning in Chapter 4, I control for within-NC changes in concentrated disadvantage. While previous work has employed group-based trajectory models to characterize historical change within neighborhoods or other macro-level units (Groff, Weisburd, and Yang 2010; Stults 2010), I have chosen to use a somewhat simpler strategy. For reasons I will discuss at greater length in Chapter 4, I calculate a simple change score of concentrated disadvantage from 1970 to 1990; because the factor measure of concentrated disadvantage was standardized across all three time periods, this change score represents actual changes within each NC over time. I then separated the distribution of the change score into quartiles for the sake of parsimony. The general pattern in Chicago over this historical period was either steady or increasing levels of disadvantage; those NCs which experienced decreases (less than 5% of the sample) are captured in the lowest quartile of change. While actual trends in concentrated disadvantage do not completely conform to the ideal typology of level and change presented in Figure 1.3, it is still possible to explore differences across degrees of historical change. Examination of the change distribution suggests the first quartile represents very little or no change (including both slight increases and decreases), with each subsequent quartile
evidencing greater increases than the last. Dummy variables representing the four quartiles of change were calculated for each NC (1=yes, 0=no) to characterize historical shifts in the level of disadvantage over time.

The final variable of interest here is a measure of collective efficacy, which is theoretically expected to mediate the relationship between structural conditions (both the level and change) and the homicide rate. Collective efficacy is conceptualized as the intersection of social cohesion and mutual trust with the ability to exercise informal social control within a neighborhood. The PHDCN-CS data includes NC-level measures of both “informal social control” and “social cohesion and trust,” based on individual-level responses to a set of questions related to each dimension and measured on a Likert-type scale (see Sampson, Raudenbush, and Earls 1997). These two variables are strongly related and appear to tap into the same underlying latent variable ($r = .801, p < .001$). Following previous research, these two neighborhood-level measures were combined using factor regression into a summary measure of the level of collective efficacy in the neighborhood in 1995. Descriptive statistics for the 2001-2005 homicide rate, the 1990 structural predictors (the “level” variable), the dummy variables of changes in concentrated disadvantage over time (the “change” variable), and the level of neighborhood collective efficacy in 1995 are shown in Table 2.2.
Moving Forward

The section comprised of Chapters 3-5 starts by testing a basic assumption of cross-sectional models typically used in macro-level research. The “spatial invariance” assumption is simple enough, but whether or not this assumption holds has important ramifications for studies of neighborhoods and crime (or studies of neighborhoods in general). The bulk of Chapter 3 is oriented around a brief review of spatial effects in the criminological literature, including an explanation of the spatial invariance assumption leading up to a test of this assumption employing ordinary least-squares and geographically weighted regression models (OLS and GWR, respectively). While OLS regression is common and needs little explanation, GWR is much less so, though its use in criminology is slowly expanding. Part of Chapter 3 will be dedicated to an explanation of GWR models, how they are both similar to and different from OLS models, and why they are being used here. Briefly, the results of the GWR models and a direct test of the spatial invariance assumption suggest that concentrated disadvantage does not have the

<table>
<thead>
<tr>
<th>Table 2.2. Distribution of Neighborhood Homicide Rates, Structural Conditions, Changes in Disadvantage, and Collective Efficacy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Homicide Rate (2001-2005)</strong></td>
</tr>
<tr>
<td>(ln) Homicide rate</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.98</td>
</tr>
<tr>
<td><strong>Structural Conditions (1990)</strong></td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.39</td>
</tr>
<tr>
<td>Immigrant concentration</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.18</td>
</tr>
<tr>
<td>Residential stability</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.07</td>
</tr>
<tr>
<td><strong>Change in Disadvantage (1970-90)</strong></td>
</tr>
<tr>
<td>No change (Q1)</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.25</td>
</tr>
<tr>
<td>Minor increase (Q2)</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.25</td>
</tr>
<tr>
<td>Moderate increase (Q3)</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.25</td>
</tr>
<tr>
<td>Major increase (Q4)</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.25</td>
</tr>
<tr>
<td><strong>Collective Efficacy (1995)</strong></td>
</tr>
<tr>
<td>Collective efficacy</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>0.00</td>
</tr>
</tbody>
</table>

N = 342
same relationship with the homicide outcome across all the NCs in the dataset. This begs the question: why not?

I attempt to answer this basic but important question in Chapters 4 and 5, building on the findings of Chapter 3 to construct a model of neighborhood structural conditions, structural stability over time, collective efficacy, and neighborhood homicide rates. In Chapter 4 I examine two key relationships. First, I explore how within-NC structural stability (of concentrated disadvantage over the 1970-1990 time period) may explain spatial variation in the cross-sectional association between disadvantage and neighborhood homicide rates. As I argued in Chapter 1, internal stability should play an important role in the emergence and operation of the social processes linking structural conditions to crime outcomes. I hypothesize that within-NC stability (or inversely, change) will explain the spatial variation in the disadvantage-homicide relationship found in Chapter 3. The second key focus of Chapter 4 is on how historical change or stability in neighborhood disadvantage matters for its homicide rate at a given point in time. Do structurally stable neighborhoods experience higher or lower homicide rates than neighborhoods which have seen concentrated disadvantage increase in the past 20 years, net of concentrated disadvantage in 1990? While it is only possible with this data to compare relatively stable neighborhoods (in terms of concentrated disadvantage) to neighborhoods that experienced increases, the results of these comparisons – that the larger the increase (i.e. the higher the structural instability), the higher the homicide rate in 2001-2005 net of 1990 disadvantage – are very suggestive.

This leads into the final empirical stage of the current project. As within-neighborhood structural stability appears to influence the cross-sectional disadvantage-homicide relationship,
I hypothesize in Chapter 5 that this influence operates through the social process of collective efficacy. Neighborhood structural conditions do not directly affect crime, but are theoretically mediated by the level of collective efficacy in the neighborhood. I argue that structural instability, net of “current” conditions, influences the emergence and operation of collective efficacy, and thus the predicted level of homicide in the neighborhood. If the effects of historical change are “channeled” through collective efficacy, then controlling for collective efficacy should explain cross-sectional variation in the disadvantage-homicide relationship in cross-section (revealed in Chapter 3), without controlling for within-neighborhood changes in concentrated disadvantage (as I did in Chapter 4). I first examine collective efficacy as an outcome, in order to assess if the cross-sectional disadvantage-collective efficacy relationship is spatially invariant. I find that the relationship between concentrated disadvantage and collective efficacy varies across space in cross-section, and that structural change over time explains this variation, which is consistent with the possibility that collective efficacy mediates the effects of structural instability on neighborhood homicide rates. I then control for collective efficacy (in 1995) and see if the level of collective efficacy explains the spatial variation in the cross-sectional relationship between concentrated disadvantage and homicide rates.

Finally, I summarize my results and lay out a model of concentrated disadvantage (both its level and stability over time), collective efficacy, and neighborhood homicide rates in Chapter 6 that attempts to account for the inherently dynamic nature of neighborhoods. While structural stability and change appear to matter for the prediction of collective efficacy and homicide – in both cases it explains spatial variation between concentrated disadvantage and the outcome in cross-section – it does not appear as if the influence of historical conditions in
the neighborhood are completely a function of neighborhood collective efficacy. Even after controlling for this theoretical mediator, there is still spatial variation in the cross-sectional disadvantage-homicide relationship which can be explained with the measure of historical change. This may be the product of several empirical shortcomings of the study, which are considered here. It may also be the result of other theoretical social processes at work, mediating the relationship between neighborhood structural conditions and crime rates. Suggestions for future work, including tests of this basic framework employing other theoretical mediators, are also discussed.
CHAPTER 3. THE EFFECTS OF CONCENTRATED DISADVANTAGE ON HOMICIDE ACROSS SPACE: IN Variant OR HETEROGENEOUS?

Introduction

As discussed in Chapter 1, there is a long tradition of theoretical and empirical research on the relationships between structural contexts and levels of crime. Whether categorized as “social disorganization” (Shaw and McKay 1969), the “systemic model” (Bursik and Grasmick 1993), “collective efficacy” (Sampson, Raudenbush, and Earls 1997), or “negotiated coexistence” (Browning, Feinberg, and Dietz 2004), one thing which is shared by perspectives rooted in the ecological perspective of the Chicago School is the importance of some social process linking structural conditions with crime outcomes. However, there is a notable lack of theorizing on the role of space, and spatial influences, in research on structural conditions, intervening social processes, and crime outcome. Instead, notions of “space” are largely confounded with notions of “place”; that is, the spatial organization of aggregate units, whether counties, neighborhoods, tracts, or block groups, is largely ignored. It is likely, given the social ecological processes theorized to be at work, that attending to spatial relationships like distance or adjacency is warranted. Typical studies of structural conditions and crime, by ignoring the spatial dimension, treat all the observations in the sample (e.g. tracts) as discrete geographical units and rest on two key assumptions which are rarely made explicit: (1) spatial independence and (2) spatial invariance.

The first assumption, spatial independence, implies that structural conditions and crime outcomes within one geographic unit have no effect on crime in proximate geographic units. Its inverse, spatial dependence (or alternatively, spatial autocorrelation), can take two forms.
There can be a significant relationship between structural conditions and crime rates in a given neighborhood with the structural conditions and/or crime outcomes in neighboring areas, known as “spatial lag,” or there can be a relationship between unmeasured conditions in one area with unmeasured factors in neighboring areas, known as “spatial error” (since this relationship presents as spatially-correlated error terms). A rapidly growing literature addressing the spatial (in)dependence assumption finds substantial evidence that this assumption is largely unmet (Baller, Anselin, Messner, Deane, and Hawkins 2001; Messner and Anselin 2004). Instead, it appears that structural conditions and crime, and likely the social processes linking them, are interdependent among geographic units, though the exact form that this spatial dependence takes is still unclear (e.g. diffusion, exposure; see Morenoff, Sampson, and Raudenbush 2001).

While researchers have begun directing a considerable amount of attention to the issue of spatial dependence between geographic units, far less has been paid to the second assumption of spatial invariance. The spatial invariance assumption posits that the relationship between a given structural predictor and the crime outcome of interest is stable across space, or invariant (Graif and Sampson 2009). Traditional “global” (and aspatial) methods like OLS, logit, or seemingly-unrelated regression produce a single estimate (e.g. a $b$ coefficient) of the relationship between a predictor, such as concentrated disadvantage or racial/ethnic diversity, and the outcome. This coefficient represents the *average* effect of that variable across the entire sample and implies the relationship it signifies is relatively stable or invariant/stationary across the sample. This single, universal measure of the relationship may, however, mask

---

5 This is also referred to as a “stationary” relationship. The inverse, spatial variance, is also referred to as a spatially “heterogeneous” relationship.
substantial and statistically significant variation in both the strength and direction of the relationship between the two variables across geographic units. It is possible that the relationship varies across space, and is “non-stationary” or “spatially heterogeneous.” Thus, if the true relationship is spatially variant, empirical examinations of the relationship which assume spatially invariant effects may be substantially flawed via model misspecification. The global estimate of the relationship may misrepresent the true relationship in two particular ways. First, the global model may produce a null or non-significant relationship; if the true, spatially-variant relationship includes both significant negative and significant positive associations, these opposing forces may “wash out” and produce a Type II error. Second, there may be cases in the sample where the relationship is exceptionally strong in either a positive or negative direction. Like outliers in univariate distributions, which can substantially influence the mean value of a variable for a given sample, outlier relationships can alter the mean association of that variable with the outcome. Where the true relationship is non-significant, the presence of outliers in this sense may overestimate the mean relationship in a global model (in either a positive or negative direction) and produce a Type I error.

Historically, most research on communities and crime has sought to discover these “universal” relationships between structural conditions and crime (exemplified by Land, McCall, and Cohen 1990), and until recently it was extremely difficult to explicitly test the spatial invariance assumption. However, with the evolution of geographic information systems (GIS) and advances in statistical methodology like geographically weighted regression (GWR), it is now possible to assess “local,” as opposed to “global,” relationships between structural conditions and neighborhood crime rates. Limited extant research employing GIS and GWR
suggests that the effects of traditionally important structural conditions do, in fact, vary across spatial units (Graif and Sampson 2009; Light and Harris 2012). In this chapter, I will apply GIS and GWR techniques to the analysis of concentrated disadvantage and homicide rates in Chicago neighborhoods, comparing the results of these spatialized models to the findings of the extensive body of work on this relationship employing non-spatial methods discussed in Chapter 1.

Data

I use shape files of the city of Chicago to define spatial boundaries and derive geographic information (e.g. Cartesian coordinates and distances) for the units of analysis. I employ data drawn from several sources including independently collected homicide data from 2001-2005 (CLEAR) and 1990 decennial Census data (Geolytics), which provides information on the demographic characteristics and structural conditions of neighborhoods. In both cases, shape files and information on the variables of interest were initially measured at the census tract level and then aggregated to the neighborhood clusters (NCs) employed by the Project on Human Development in Chicago Neighborhoods (Earls, Brooks-Gunn, Raudenbush, and Sampson 2007). While not currently necessary, later analyses employ measures of collective efficacy (as both an outcome and a mediator of the concentrated disadvantage relationship), which is only available at the NC level. Using NCs across all three sets of empirical analyses allows each successive analysis to build on the last in a clear and straightforward manner. This also avoids to some extent criticisms based on the modifiable areal unit problem (MAUP) endemic to geographically-oriented research, where the level of measurement itself may
confound observed relationships (i.e. associations between variables are different at different levels of measurement like counties and census tracts). While this is still a concern, having the three empirical chapters share a common level of measurement ensures that whatever error may be introduced in this manner is at least identical across the analyses. Furthermore, there is a substantial body of work in the collective efficacy tradition by Sampson and others which employs the same geographic unit of analysis in a non-spatial manner (Browning 2002; Morenoff, Sampson, and Raudenbush 2001; Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997). Doing so here allows me to more readily compare the results of my non-spatial and spatial models of the relationships to previous findings. A more in-depth discussion of the choice of the unit of analysis and a description of the sample itself is available in Chapter 2.

**Dependent Variable**

The outcome in this set of analyses is the three-year average homicide rate per 10,000 by neighborhood cluster for the years 2001-2005. By using a five-year average, I can reduce the potential bias introduced by year-to-year fluctuations in the homicide rate and minimize the influence of an abnormally high- or low-rate single year. This strategy is often employed in macro-level crime research (Krivo and Peterson 2000; Martinez Jr., Stowell, and Lee 2010) and is particularly helpful when studying relatively rare crimes like homicide, where an absolute increase of a single homicide may represent a doubling of the previous year’s homicide count (and rate, given no change in the population size). An examination of the homicide rate across Chicago NCs indicated a substantially skewed distribution (given the tendency for crime in
general, and homicide in particular, to cluster close to zero), so was transformed using the natural log into a more normally distributed rate.

**Independent Variables**

My key focus throughout this chapter is on the relationship between neighborhood concentrated disadvantage in 1990 and the homicide rate (see Chapter 2 for a more in-depth discussion of how this and other independent variables were constructed). Following previous research (Krivo and Peterson 1996; Morenoff, Sampson, and Raudenbush 2001; Sampson 2009), concentrated disadvantage is a summary measure, produced here through an obliquely-rotated factor regression procedure applied to direct measures of theoretically-important structural conditions like the poverty rate (Sampson, Raudenbush, and Earls 1997). Unsurprisingly, a number of these direct measures were strongly multicollinear, and as suggested by previous studies loaded strongly onto a single conceptually-distinct factor or dimension of neighborhood conditions. The factor measure of concentrated disadvantage used here is strongly influenced by the proportion of female-headed households, high school graduates, unemployed, and black residents, as well as the proportion of households below poverty and on public assistance. The other two factor measures employed here are treated as controls and constructed in an identical fashion. Immigrant concentration is largely determined by the proportion Hispanic and foreign-born, while residential stability is driven primarily by the proportion of respondents living in the same location five years ago and the proportion of owner-occupied housing units. All three variables are constructed so that higher values
represent more of that particular dimension within a neighborhood cluster, e.g. higher levels of concentrated disadvantage or residential stability.

Analytic Strategy

In this chapter I explicitly test the assumption of a spatially-invariant relationship between neighborhood concentrated disadvantage and homicide rates in cross-section. The hypothesis tested here is a straightforward interpretation of the spatial invariance assumption:

**Hypothesis (1)** – The relationship between concentrated disadvantage and homicide rates in neighborhood clusters will be spatially invariant across the sample of Chicago NCs.

While simple, this hypothesis tests a basic and critical assumption of global models of structural relationships and crime. Theoretically, this assumption is a cornerstone of “global” conceptualizations of mediating social processes linking contexts and crime. A rejection of this hypothesis would suggest that this key assumption is violated, and require that the spatially variant effects revealed must be accounted for, both theoretically and methodologically, moving forward.

To assess the appropriateness of the spatial invariance assumption implicit in global models of neighborhood structural conditions and crime, I employ geographically weighted regression (Fotheringham, Brunsdon, and Charlton 2002). Typical global models that do not account for spatial relationships produce a single estimate for each variable, representing the average effect of the predictor on the outcome across the entire sample. GWR, however,

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6 Or any macro-level model, really – spatial invariance is a basic assumption of all non-spatial “global” models regardless of the relationship which is being examined.
produces a set of parameter estimates for each specific geographic unit in the sample. In GWR, the relationship is not assumed to be independent of location (i.e. is invariant across units), but instead allowed to vary across units. This difference can be expressed mathematically, where traditional OLS regression takes the form:

\[ y_i = \alpha + \beta x_i + e_i \]  
Equation (1)

Here, the constant (\(\alpha\)) and the coefficient (\(\beta\)) are the same regardless of location (i). Only the observed value of \(x\) varies over the set of \(i\) locations, in addition to the unobserved error \(e\).

GWR, on the other hand, takes the form:

\[ y_i = \alpha(u_i, v_i) + \beta(u_i, v_i)x_i + e_i \]  
Equation (2)

Equation (2) shows that both the constant and the coefficient can vary for each observation \((u_i, v_i)\), in addition to unit-specific variation in the observed values of \(x\) (and unobserved error). The value of the constant and all the coefficients are expressed as a function of the spatial location of a given unit, which is denoted here as geographic coordinates. When employing GWR, every observation must include some type of information (e.g. Cartesian coordinates) that allows its geographic position to be determined relative to all other observations in the sample. Each location in the sample then becomes the center of a local regression which employs a subsample of the units surrounding it. The result is a set of parameter estimates and model fit statistics localized to each NC in the full sample.

Like spatial econometric models, GWR models utilize a spatial weighting function where observations close to the local regression point are weighted more heavily than observations which are further away, in keeping with Tobler’s “first law of geography” (Tobler 1970). The
preferred weighting schema in GWR, and the one used here, is a spatially adaptive weighting function (Fotheringham, Brunsdon, and Charlton 2002) taking the form:

\[
W_{ij} = \left[1 - \left(\frac{d_{ij}}{g_i}\right)^2\right] \text{ if } d_{ij} < g_i \\
= 0 \text{ if otherwise}
\]

Here, \(g_i\) is the distance or “bandwidth” of the \(N\)th nearest neighbor from location \(i\) and \(d_{ij}\) is the geographic distance between units \(i\) and \(j\). The weight of a given observation varies with \(i\) by distance; observations closer to \(i\) are weighted more heavily than those further away. Equation (3) produces a continuous, near-Gaussian weighting function up to distance \(g\) and then weights any units beyond \(g\) as zero (Fotheringham, Brunsdon, and Charlton 2002; Light and Harris 2012).

In an adaptive function, the geographic extent or distance of the kernel determining which observations to include in a given local regression is shaped by the underlying density of potential data points. This means that in an area where there are many data points – for instance, a central business district where NCs are smaller and spatially denser – the function produces a kernel which is relatively small. In an area where there are fewer data points – say, on the city boundary or in industrial areas with larger NCs – the kernel extends further in order to capture more observations for use in the local regression. The adaptive schema is employed here to account for the spatial distribution and size differences in neighborhood clusters across NCs in Chicago, which tend to be smaller and denser closer to the city center. This way, I can ensure that the local regression sample size is relatively stable across the entire sample and that the standard errors are also more stable. A fixed-weighting schema employing a constant distance function to determine the kernel size would produce larger standard errors on the
boundaries of the city than at the center, due to fewer observations being included in the local regression sample. The optimal bandwidth selection was determined with a bi-squared weight, near-Gaussian function and an AICc minimization process, with convergence at a given local sample size a trade-off between minimizing model bias and maximizing the variance within each local regression.

The analysis proceeds in two parts. I first use traditional OLS regression to replicate previous work on the relationship between structural conditions and homicide, focusing primarily on concentrated disadvantage. This analytic strategy is aspatial and assumes the relationship is not place-specific. Prior research has shown a strong, positive relationship between the level of concentrated disadvantage and neighborhood homicide rates. I then investigate the possibility that the relationship varies across space, but before proceeding to a GWR analysis of the data, I consider whether this is necessary through a visual inspection of OLS regression residuals for substantial spatial clustering. If the relationships between structural conditions and neighborhood homicide rates are spatially invariant, the size and direction of the residuals produced by an OLS regression model should be randomly distributed across space. Clustering suggests that the OLS model is substantially better at predicting observed homicide rates in some locations than others and implies that the relationships are spatially variant. Finally, I apply GWR techniques to the same model, allowing the relationships to vary across space. A Monte Carlo test of spatial variation in the distribution of the parameter estimates indicates whether any observed heterogeneity in the relationships\(^7\) is statistically

\(^7\) It is critical to remember that I am testing for significant variation in the “local” relationship between variables across NCs, rather than a significant “global” relationship between two variables (as is the case in OLS regression) within the entire sample of NCs.
different from zero (Fotheringham, Brunsdon, and Charlton 2002; Graif and Sampson 2009). It is possible that variability in the relationships over space is the result of sampling variation or error, and the Monte Carlo test is used to assess if the variation is adequate to reject Hypothesis (1).

Results

The first step in this analysis is to replicate the results of previous research using OLS regression. NC homicide rates were regressed on the three factor measures of neighborhood conditions, with the results shown in Table 3.1. The Akaike Information Criterion and the adjusted $R^2$ are included for comparison with later GWR models. The results of the OLS regression model generally conform to previous findings. Concentrated disadvantage has a large, positive association with homicide rates ($b = .461, p < .001$), while the level of immigrant concentration has a non-significant relationship with homicide ($b = -.008$), though the relationship is in the expected negative direction. Strangely, residential stability has a significant effect on homicide but in an unexpected positive direction ($b = .085, p < .001$). While it is beyond the scope of this dissertation to explore this anomaly, it is consistent with the negotiated coexistence model of neighborhood effects (Browning 2009). Higher levels of residential stability imply denser and/or stronger social networks among NC residents, which may actually impede the operation of collective efficacy and lead to increased crime. It is also possible that residential stability, in itself, does not contribute to stronger social control or collective efficacy in presence of high disadvantage (Sampson, Raudenbush, and Earls 1997; Hipp 2010). Inversely, residential instability may be strongly related to recent immigration into
the neighborhood, which has been shown to have a beneficial effect on crime (Sampson 2008). It is probable that other contextual factors condition the relationship between neighborhood residential (in)stability and homicide rates (Martinez, Jr., Stowell, and Lee 2010; Velez 2009). From a subcultural perspective, residential stability coupled with high levels of disadvantage may contribute to delinquent, criminal, or violent subcultures which spread through the neighborhood and generate higher crime rates (Anderson 1999). Concentrated disadvantage has by far the largest standardized association with homicide in the model \( \beta = .808 \), net of the other predictors, with over six times the standardized relationship of residential stability \( \beta = .131 \). The overall model fits the data relatively well; the three factor measures of structural conditions explain about two-thirds of the variation in homicide rates across Chicago NCs (adjusted \( R^2 = .661 \)).

<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th>(SE)</th>
<th>( \beta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.795***</td>
<td>0.023</td>
<td></td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>0.461***</td>
<td>0.020</td>
<td>0.808</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.008</td>
<td>0.020</td>
<td>-0.016</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.085***</td>
<td>0.023</td>
<td>0.131</td>
</tr>
</tbody>
</table>

Adjusted \( R^2 \) 0.661
AIC 310.690

With the exception of the significant-but-positive relationship between residential stability and homicide rates, these results are generally in keeping with the findings of previous studies. Of particular relevance here is the very strong, positive relationship between concentrated disadvantage and homicide. The OLS regression model predicts that neighborhood clusters with higher levels of concentrated disadvantage are expected to have
much higher homicide rates, controlling for levels of immigrant concentration and residential stability. However, this model is aspatial and cannot account for the possibility that the true relationship between concentrated disadvantage and homicide varies across NCs, or is non-stationary. GWR allows me to explicitly test for spatial variation in the relationship, but it is useful to first check for spatial patterns in the OLS model to determine if proceeding to GWR is warranted.

Before applying geographically weighted regression techniques to this model, and of the disadvantage-homicide relationship specifically, I checked for systematic spatial variation in the OLS model fit. Residuals were calculated to reflect the difference between each NC’s observed homicide rate and the value predicted by the OLS model. These values were then mapped in ArcGIS and inspected visually for evidence of spatial clustering. Figure 3.1 displays the results of this mapping procedure below. While the overall model fits well and explains about 66% of the variation in homicide rates across NCs, an examination of the residuals across NCs suggests that there is substantial variation in model fit across Chicago. The OLS residuals range between -1.34 and 1.06 and though not large, there is clearly some level of spatial clustering in the residuals. For example, the OLS model overestimates the homicide rate in the northwestern corner of Chicago (where the residuals tend to be negative) and underestimates it in west-central Chicago (where the residuals tend to be positive). If the spatial invariance assumption were accurate, these residuals would be randomly distributed across NCs. Though small, there appears to be enough spatial clustering among the residuals to suggest this assumption does not hold.
Figure 3.1. OLS Residuals by Neighborhood Cluster, (ln) Homicide Rates on Structural Conditions

Given the visual evidence, previous qualitative observation of neighborhoods where levels of crime do not appear to conform with theoretical expectations regarding concentrated disadvantage (e.g. Pattillo 1998), and parallel findings in quantitative research on immigration at the tract level (Graif and Sampson 2009) and disadvantage at the county level (Light and Harris 2012), it appears that GWR analysis of concentrated disadvantage and homicide is warranted.
Geographically weighted regression allows me to not only explicitly test the spatial invariance assumption, but the residuals of the GWR model can be mapped and visually compared to those from the OLS model displayed in Figure 3.1. Unlike OLS regression, which estimates a global effect, GWR produces a set of local parameter estimates which can be mapped, indicating where the relationship between concentrated disadvantage and homicide is particularly strong, and possibly in opposite directions (likewise for immigrant concentration and residential stability). It should be noted before proceeding that GWR relies heavily on a well-specified global model. It cannot correct for model misspecification beyond accounting for potential spatially-variant relationship. Given the relatively good model fit produced in the OLS regression model, and the avoidance of multicollinearity of structural variables through the use of factor measures, I believe that this condition is met.

Using the statistical package GWR 3.0, a model was specified which was identical to that used in the OLS regression, with the exception of two additional variables. The \( X \)-coordinate and \( Y \)-coordinate, defined as Cartesian coordinates, were used to define the spatial organization of the neighborhood clusters across the sample. The first set of output produced is a replication of the global (OLS) regression parameters, which substantively match those produced earlier. The Akaike Information Criterion is also produced (included in Table 3.1 above), giving a measure of model fit which can be compared to the AIC in the GWR model. Using the spatially adaptive weighting function described earlier, the model converged at a local sample size of 50 neighborhood clusters. Given that the local sample size is close to one-seventh of the full sample, a smaller adaptive kernel would have been preferred – in essence, a more “local” estimation of the effects of structural conditions on homicide. However, this is
unavoidable given the unit of analysis used here, the limited number of NCs in the city of Chicago in the full sample, and the desire to maximize overall model fit while limiting model bias. A smaller average kernel size would exclude more distant NCs in a local regression model centered on a given NC, which are likely to be more dissimilar between distant observations. The result is a conservative estimation of the spatial distribution of the relationships across NCs. Statistically significant variation in the association between concentrated disadvantage and homicide rates, if found, will be smaller here than if the kernel size was limited to a smaller local sample.

The output of the GWR analysis, unlike the global OLS model, produces parameter estimates and model fit statistics for each observation in the sample, as well as model fit statistics for the overall GWR model. For the sake of simplicity, the results are organized as 5-number summaries of the estimates across all NCs. Table 3.2 displays the distribution of “local effects” for the three structural predictors across the full sample of NCs, including the minimum, maximum, and mean size of the relationship, the direction of significant relationships (positive, negative, or both), and if there is statistically significant variation in the association across NCs (assessed with the Monte Carlo test). It also includes the global estimate of the relationship produced by the earlier OLS regression model.
Table 3.2. GWR of Log Homicide Rate on Neighborhood Structural Conditions, 5-Number Parameter Summaries

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Lower Quartile</th>
<th>Median</th>
<th>Upper Quartile</th>
<th>Maximum</th>
<th>Sig. Local Effects</th>
<th>Monte Carlo Test</th>
<th>Global (OLS) Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.114</td>
<td>0.556</td>
<td>0.901</td>
<td>1.057</td>
<td>3.013</td>
<td>(+)</td>
<td>Non-stationary ***</td>
<td>0.795</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.499</td>
<td>0.271</td>
<td>0.380</td>
<td>0.496</td>
<td>0.681</td>
<td>(+)</td>
<td>Non-stationary ***</td>
<td>0.461</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.823</td>
<td>-0.106</td>
<td>-0.022</td>
<td>0.057</td>
<td>1.141</td>
<td>(-/+)</td>
<td>Non-stationary ***</td>
<td>-0.008</td>
</tr>
<tr>
<td>Residential stability</td>
<td>-0.451</td>
<td>-0.159</td>
<td>-0.052</td>
<td>0.058</td>
<td>0.453</td>
<td>(-/+)</td>
<td>Non-stationary ***</td>
<td>0.085</td>
</tr>
</tbody>
</table>

Adjusted R²: 0.804  
AIC: 189.600  
ANOVA F-value: 5.837 **

Local N = 50; Total N = 342  
* p < .05  ** p < .01  *** p < .001

Statistically significant local effects, p < .05
The primary finding of interest here is that relationship between concentrated disadvantage and neighborhood homicide rates vary significantly across Chicago. The local relationship ranges from a null to statistically significant positive association, with local b-coefficients extending from -.50 to .68. The Monte Carlo test for stationarity reveals that this variation is statistically significant (p < .001). This suggests that the spatial invariance assumption made by previous, aspatial studies of the concentrated disadvantage-homicide association does not hold. The same is true for the other two structural factors; the parameter estimates of both immigrant concentration and residential stability vary significantly across Chicago (p < .001). For both variables, the range of local effects spans both significantly negative and significantly positive relationships with homicide rates, which may explain why immigrant concentration had a non-significant association with homicide in the global OLS regression model above. The significant negative relationship between immigrant concentration and homicide in some areas may be “washing out” significant positive relationships in other areas. Similarly, the significant but positive association of residential stability and homicide in the global OLS model may be due to the influence of several “outlier” relationships which are unusually strong and positive.

Overall, the GWR local model fits the data somewhat better than the OLS regression model. The AIC value of the GWR model (AIC = 189.60) is substantially smaller than that of the global OLS model (AIC = 310.69). Additionally, even after accounting for the differences between models in the degrees of freedom, an ANOVA F-test indicates there is significant improvement in model fit (F = 5.84, p < .001). Finally, the GWR model accounts for about 17.5% more variation in homicide rates across NCs (adjusted $R^2 = .80$) than the OLS model (adjusted
Though this last difference is somewhat modest, the results of the Monte Carlo tests for spatial non-stationarity suggest that while not much more variance is accounted for, how that variance in homicide rates is explained is more accurately estimated using a spatial model that allows the relationships to vary across NCs.

One of the benefits of GWR is the wealth of output produced by the program. Not only does GWR provide summaries of the parameter estimates, but it also produces a full set of parameter estimates for each local regression. These include not only b-coefficients, t-tests, and p-values for each predictor variable, but also the local model fit and local model residuals, which can then be mapped. This allows me to visually examine a number of spatial patterns, such as the relationships between neighborhood structural conditions and homicide rates. First, an inspection of the GWR model’s explanatory power as a whole – using the local adjusted $R^2$ values – suggests that it varies substantially across NCs. The variance in homicide rates accounted for across the full sample ranges between roughly 27% and 89%, as shown in Figure 3.2. The variation in the explanatory power of this “typical” model of neighborhood-level associations evidenced by this map is a function of the distribution of local relationships between structural conditions and homicide rates across space (as seen above in Table 3.2). The color schema used in Figure 3.2 represents quintiles of the variance explained by the total model, with lighter grays denoting smaller and darker grays larger local adjusted $R^2$ values. Contrary to global conceptualizations of the ability of neighborhood structural conditions to predict homicide rates (or crime in general), the map suggests that global models mask substantial and systematic variation in the explanatory power of the models over geographical space. For example, the model clearly explains more variation in homicide rates in the southern
and north-western regions of Chicago (generally speaking), and less in northern and mid-central areas.

Figure 3.2. GWR Local R-Square by Neighborhood Cluster, (ln) Homicide Rates on Structural Conditions

Concerning the specific association between concentrated disadvantage and homicide rates, Figure 3.3 demonstrates a similar pattern. The relationship between concentrated disadvantage and homicide rates clearly exhibits a systematic spatial pattern across Chicago. While almost always statistically significant and positive, in some areas the relationship is substantially larger than in others. Using the same schema employed in Figure 3.2, these maps
display local parameter estimates of the t-values\textsuperscript{8} for concentrated disadvantage by quintile, with lighter gray denoting the smaller and dark gray the larger values. In roughly 16% of the NCs (55 of 342) the relationship between concentrated disadvantage and homicide rates is not statistically significant. The remaining 84% of NCs (i.e. the local regressions centered on these 287 units) exhibit a significant positive relationship as expected; however, the strength of this association fluctuates a great deal. There are distinct clusters of NCs within the city of Chicago where concentrated disadvantage has a much stronger association with homicide rates than in others. In almost a third of the neighborhoods (111 of 342) the t-value is 6 or higher.

\textsuperscript{8} Mapping t-values in a “surface map” is a typical method of visualizing the strength of a relationship (see Graif and Sampson 2009 for an example) as it incorporates both the size of the unstandardized b-coefficient and the standard error of that coefficient in the local regression. While using the t-value as a measure of the “strength” of the relationship is not a completely accurate interpretation (i.e. it is problematic for some to say that the relationship between X and Y is “more” or “less” statistically significant in a given local regression) it at least conveys the appropriate idea to the reader.
A final visual comparison of the residuals from the OLS and GWR models makes it possible to see the differences between the two techniques in terms of local model fit. As shown in Figure 3.1 above, the OLS regression residuals evidenced some degree of spatial patterning or clustering. An identical map of the GWR residuals shown in Figure 3.4 suggests that the distribution of the residuals is more random, though some minor spatial patterning remains. The residuals are less spatially autocorrelated in the GWR model of homicide than in the
traditional, aspatial OLS regression model, and the range of the residuals is substantially smaller in the GWR model than the OLS.

![Figure 3.4. GWR Residuals by Neighborhood Cluster, (In) Homicide Rates on Structural Conditions](image)

Taken together, the statistical and visual evidence produced by the geographically weighted regression models above suggests that cross-sectional estimates of the association between concentrated disadvantage and homicide rates may be sensitive to where that relationship is measured. If one were to only examine NCs (or tracts, or block groups) in the central business district of Chicago, the findings would be substantially different than a study of
NCs on the fringe of the city (and indeed, even between different areas on the edges of Chicago). It appears that conclusions drawn in previous aspatial studies of concentrated disadvantage and crime (and the assumption of spatial invariance on which they are based) ignore the spatialized nature of the relationship. In this sense such models are misspecified, and conclusions based on a single global estimate of the relationship within a sample are potentially inaccurate for a large segment of the sample.

**Discussion and Conclusions**

Clearly, Hypothesis (1) – *The relationship between concentrated disadvantage and homicide rates in neighborhood clusters will be spatially invariant across the sample of Chicago NCs* – may be rejected here. Though the relationship between this structural factor and homicide rates is almost always positive and statistically significant across the NCs in the sample, a global measure of the relationship estimated using aspatial OLS regression appears to be partially incorrect. The global coefficient produced by the more typical OLS regression model (b = .461) is a relatively accurate estimate of the association for part of the sample, but overestimates the magnitude of the effect in some NCs while underestimating it in others. This also appears to be the case for immigrant concentration and residential stability, where the global OLS estimate of the relationships can be much smaller or larger than the local GWR estimates.

The current set of analyses is congruent with the limited amount of extant research which also applies GWR techniques to studies of structural conditions and crime. Light and Harris, using a race-disaggregated sample of U.S. counties and 2000 Census data, also found significant spatial variation in the relationship between disadvantage and violent crime, though
using a slightly different measure of disadvantage and set of control variables (2012).

Particularly relevant to the current study, using 2000 Census data at the tract level, Graif and Sampson also found a significant level of spatial variability in the disadvantage-homicide rate relationship across the city of Chicago, though they primarily focused on spatial heterogeneity in the effects of immigration and language diversity (2009). Given that each of these studies, including the current one, used different units of analysis, two different composite measures of disadvantage, and two points in time, it appears that the conclusion drawn here is relatively robust to time frame, level of aggregation, and variable operationalization (also see Cahill and Mulligan 2007). As the evidence mounts, it is becoming clearer that future research on macrostructural conditions and crime must take account of the spatial organization of aggregate units and begin to question the appropriateness of the spatial invariance assumption.

Perhaps most importantly, existing theories of neighborhoods and crime should be reconsidered in light of the apparent spatial heterogeneity of the relationships they propose to explain. To date, much of the work on spatial dependencies between neighborhoods and spatially heterogeneous relationships in criminology has been descriptive in nature, alluding to but not directly testing processes like the “diffusion” of crime between spatial units, opportunities for violence, or interactions between neighborhoods and the larger spatial geography (Cahill and Mulligan 2007; Light and Harris 2012; Tita and Cohen 2004). One possible explanation for spatial variation in the concentrated disadvantage-homicide relationship found here is the role of “exposure” to disadvantaged conditions. Relative levels of disadvantage in neighboring areas at a single point in time have been discussed as a potential influence on the relationship within a given area (Light and Harris 2012; Peterson and Krivo 2009). In these
instances, exposure is considered in a cross-sectional manner, i.e. in terms of relative deprivation across neighboring communities. The remainder of this dissertation takes a similar approach with one critical departure. Rather than consider how neighboring areas – at a single point in time – condition the disadvantage-homicide relationship within a given neighborhood, I will explore how within-neighborhood (NC) histories of disadvantage over time may influence the relationship between concentrated disadvantage and homicide rates in cross-section, via time-varying effects of structural conditions on the key theoretical process of collective efficacy. Collective efficacy has been shown to mediate the structure-crime relationship (Morenoff, Sampson, and Raudenbush 2001; Sampson, Raudenbush, and Earls 1997). However, the first part of this theoretical model (the relationship between structural conditions and collective efficacy) may be sensitive to not only current neighborhood conditions (such as the level of concentrated disadvantage) but also historical neighborhood conditions as well (such as the stability of disadvantage over time). If this is the case, there may be neighborhood-specific relationships between structural conditions and crime. Neighborhoods with different histories of disadvantage, masked by the cross-sectional nature of most studies, could be expected to produce substantial and significant variation in the association between concentrated disadvantage and homicide (or crime generally) at a single point in time. One example of such an outcome was found in the preceding set of analyses. In the next chapter I explain how historical stability or change in structural conditions matters for the disadvantage-homicide relationship, in essence producing a “temporally-variant” relationship. I then discuss how this temporally-variant relationship can manifest as a spatially-variant relationship in a cross-sectional model, as was just demonstrated. I then explore how controlling for a neighborhood’s
prior disadvantage can explain the spatial variation in the cross-sectional association seen in this chapter.
CHAPTER 4. FROM LEVEL TO STABILITY: WHY AND HOW NEIGHBORHOOD HISTORIES OF CONCENTRATED DISADVANTAGE MATTER

Introduction

In this chapter, I attempt to explain how the history of a neighborhood – particularly its level of concentrated disadvantage over time – influences the relationship between disadvantage and crime at a given point in time. In Chapter 1, I described both historical and contemporary accounts of the neighborhood as a dynamic organism (Sampson 2012; Shaw and McKay 1969). For theoretical reasons we should expect that the stability or instability of a neighborhood’s structural conditions would play a substantial role in predicting crime-related outcomes like the homicide rate. The social processes linking the two do not immediately emerge fully-formed, but develop, wax and wane as a function of neighborhood change (or stability). It is possible that the effects of stability are separable from the effects of the level of a given structural condition, with the stability of that condition either intensifying or weakening the relationship between the level of that condition level and the outcome. Alternatively, it is also possible that the stability or instability of a condition plays no role in conditioning the cross-sectional relationship between level and outcome; this is essentially the “null” hypothesis against which the results of these analyses are compared.

The ecological perspective, however, rests on a conceptualization of neighborhoods as inherently dynamic. Prior empirical work has shown that the ecological structure of neighborhoods is often in flux rather than a state of equilibrium (Bursik 1986; Bursik and Webb 1982; Schuerman and Kobrin 1986). This equilibrium, or structural stability, plays an important role in the process of social disorganization and reorganization (Shaw and McKay 1969), and is
likely to influence the operation of collective efficacy in the neighborhood as well (Sampson, Raudenbush, and Earls 1997). As I previously outlined, neighborhoods which have experienced historically stable structural conditions are expected to have different levels of disorganization or collective efficacy, net of the level of a given condition, than neighborhoods which have experienced change (either increases or decreases), and thus different rates of homicide and other crimes.

The question of how structural stability and change matter is a particularly salient one for concentrated disadvantage. As I described in Chapter 1, this conceptualization of deprivation differs in important ways from univariate measures of poverty. Not only is the measure itself now based on multiple dimensions of deprivation (for both theoretical and statistical reasons), but how it affects the neighborhood also diverges from prior historical eras. Shaw and McKay described an ecological process through which poverty drove neighborhood instability (Shaw and McKay 1969). Within the time period they studied, social and residential mobility allowed individuals to move away from impoverished neighborhoods and generated neighborhoods with stable, high levels of social disorganization and thus crime and delinquency. Though the structural condition of poverty was stable, the internal composition of the neighborhood was not, and the process of disorganization rarely reached its ultimate stage of reorganization (though see Whyte 1943).

In the modern era, however, this relationship appears to have been reversed to a large degree. Wilson describes the emergence of concentrated disadvantage as a confluence of larger social and economic processes at work in the United States in the later decades of the 20th century (1996; 1997). Unlike the era of Shaw and McKay, however, the social and
residential mobility available to individuals and groups in such deprived neighborhoods was absent. Not only did high levels of concentrated disadvantage promote higher levels of crime and related social ills, but were commonly conceptualized as inhibiting neighborhood change. This is the critical point which will be explored here: while the level of disadvantage continues to predict between-neighborhood differences in homicide rates, the stability of neighborhood conditions would also predict differences in the strength of the disadvantage-homicide relationships among neighborhoods with similar levels of disadvantage. This is because neighborhoods suffering from high levels of disadvantage are likely to remain that way, isolating and trapping residents in structural conditions that represent a “tangle of pathologies” and are durable over time (Sampson 2009; Sampson 2012). This type of disadvantage does not lead to a lack of within-neighborhood equilibrium but instead may actually promote the continuity or stability that fosters neighborhood reorganization and the growth of collective efficacy. A similar mechanism has been observed in rural areas, where poverty promotes rather than deters residential stability, with concurrent reductions in crime (Osgood and Chambers 2000). In this case, social disorganization continues to have a positive association with area crime, but the distal relationship between poverty and disorganization is reversed.

This suggests that a similar mechanism may be at work in the relationship between concentrated disadvantage, collective efficacy, and homicide rates. In the face of continuous and stable disadvantage, neighborhoods may exhibit levels of collective efficacy that are higher than those predicted by the level of concentrated disadvantage alone. As a result, homicide rates in these neighborhoods would likewise be lower than predicted in cross-sectional models which do not control for historical stability or change. Inversely, neighborhoods with relatively
low levels of disadvantage may have higher than expected crime rates if current levels of disadvantage were preceded by a period of substantial change (e.g. gentrification). This reasoning is consistent with previous work which found that stability is related to declines in crime and delinquency over time (Bursik and Grasmick 1992), or that change (both increases and decreases in disadvantage) is linked to higher levels of violence and crime (Covington and Taylor 1989; Kreager, Lyons, and Hays 2011; Taylor and Covington 1988).

Since the processes linking structural conditions to crime are embedded in a neighborhood’s historical development, I argue that we must reconsider how “neighborhood effects” emerge and operate. If the relationship between concentrated disadvantage and crime is dependent on “when” in the neighborhood’s history we are looking (Bursik and Webb 1982), it can be characterized as temporally-variant. Lacking longitudinal data on a large sample of neighborhoods, it is not currently possible to assess this assertion directly (e.g. with a fixed-effects model of within-neighborhood change in disadvantage). However, it is possible to indirectly explore this possibility, using the spatially-variant association between concentrated disadvantage and neighborhood homicide rates found in Chapter 3 as a starting point.

This is possible due to the fact that a temporally-variant relationship such as I have described can manifest in cross-sectional data as spatially-variant. Reproducing in part the ideal typology of neighborhood level and change from Chapter 1, Figure 4.1 displays three possible neighborhood historical trajectories of stability and change. In cross-section at time $t$, all three neighborhoods have the same level of concentrated disadvantage; however, each has experienced a substantially different degree of stability in disadvantage over time. If, as I argue, stability and change condition the relationship between disadvantage and homicide rates, then
these three neighborhoods would exhibit quite different associations between that structural predictor and the outcome at time \( t \) and produce significant spatial variation in the relationship in cross-section, as was found in the previous chapter.

The association between concentrated disadvantage and homicide is not only a function of the level of disadvantage at time \( t \) but also the historical stability of disadvantage over time. When neighborhoods with similar levels of disadvantage at a given point in time have substantially different histories, the relationships between structural conditions and crime would differ; this line of reasoning combines the concept of spatial invariance with the theoretical importance of neighborhood structural stability to studies of neighborhood effects and neighborhood crime rates.
Data

In this chapter I continue to employ neighborhood clusters (NCs) as the unit of analysis, along with identical measures of structural conditions (concentrated disadvantage, immigrant concentration, and residential stability) in 1990 and neighborhood homicide rates in 2001-2005. However, it is here I introduce the measure of (in)stability of neighborhood concentrated disadvantage. Prior research has employed group-based trajectory analysis at the macro-level to explore and describe historical change within neighborhoods or similar units (Groff, Weisburd, and Yang 2010; Groff, Weisburd, and Morris 2009; Stults 2010). While this method, usually applied to groups of individuals rather than neighborhoods, is a promising avenue for future research, the realities of historical conditions of disadvantage in Chicago over the 1970-1990 time period make it difficult to apply here.

As described by Nagin (2005), the search for distinct group-based patterns of change over time is as much art as science, and relies heavily on variation within the sample being studied. Programs designed to analyze samples for distinct trajectory groups (e.g. the traj module designed for use in the STATA statistics package) are dependent upon the user to specify the number and shape of the trajectories (i.e. linear, quadratic, etc.). It is expected that the researcher will be guided both by theory and the empirical data itself. While the ideal-type model of level and change described earlier is conceptually sound, the patterns of change in Chicago that actually existed at this time did not lend themselves to a varied set of group-based trajectories upon examination. I initially explored several possible sets of trajectories for this dissertation, specifying a larger number of groups until the overall model fit of N trajectories to the data did not significantly increase with the addition of another group, and found that there
were seven distinct trajectory groups apparent in the data. However, upon further inspection most of the difference between these groups was the level of concentrated disadvantage over time, while the trajectories of change and stability were relatively similar.

As it appeared that a more parsimonious measure of change was possible, I instead constructed a simple change-score of concentrated disadvantage over time. Since the factor measure of concentrated disadvantage was based on the weights and distribution of the component univariate measures over the entire time period (see Chapter 2) and thus standardized across time points, this change score represents real changes within neighborhoods over the 1970-1990 period. I then explored a number of specifications of “change” over time based on possible directions of change (increases, decreases, or no change), the size of the change (e.g. large or minor increases), and the data itself. After examining a number of different possibilities, I found that the specification of change which was both the most theoretically parsimonious and the best representation of the actual data was a separation of the change score variable into quartiles. The quartiles of change over time represent four distinct groups: the first quartile are those NCs which experience relatively little change (either increases or decreases), the second quartile those which saw minor increases in disadvantage, the third moderate increases, and the fourth quartile those which saw major increases over 1970-1990.

Unfortunately, the actual distribution of change in Chicago over the 1970-1990 time period does not conform to the ideal-type model of level and change presented earlier, and makes it impossible to test several theoretical hypotheses about the role of neighborhood stability and change (for example, comparing gentrified neighborhoods with neighborhoods
that experienced recent increases in disadvantage but share a similar level of disadvantage in 1990. However, it is still possible to compare neighborhoods that share a common level of disadvantage in 1990 but differ in the degree they experienced change over the past 20 years (e.g. no change vs. minor increases, minor vs. major increases). Each NC was classified by which quartile of change it fell into and a dummy variable representing each of the four quartiles was calculated for each NC (1 = yes, 0 = no), characterizing the shift in the level of disadvantage within a given NC over time.

**Analytic Strategy**

Given the theoretical importance of neighborhood dynamics of change and stability to ecological explanations of crime, and the link between spatially-variant and temporally-variant relationships described above, in this chapter of the dissertation I test my second hypothesis:

**Hypothesis (2) –** Controlling for neighborhood structural stability (or the degree of structural change) will account for spatial variation in the cross-sectional association of concentrated disadvantage and neighborhood homicide rates.

Essentially, the spatially variant/heterogeneous relationship found in Chapter 3 will become non-significant (i.e. spatially invariant) once I control for within-neighborhood change in concentrated disadvantage. The **level** of disadvantage in 1990 is still expected to have a positive association with homicide; more disadvantaged NCs will have higher homicide rates than those with less disadvantage, net of the other variables, a finding common in the literature (Krivo and Peterson 1996; Kubrin and Weitzer 2003; Morenoff and Sampson 1997; Sampson, Raudenbush, and Earls 1997; van Wilsem, Wittebrood, and de Graaf 2006).
What remains unclear is how change in concentrated disadvantage will influence the cross-sectional relationship (beyond accounting for the spatial variation). Change at any level of disadvantage may be detrimental and lead to higher crime rates. After controlling for the level of disadvantage, NCs with more change will have higher rates of homicide than those with less (or none); I characterize this as “disruption,” as change disrupts the operation of whatever social process links structural conditions to crime (e.g. the positive relationship between low disadvantage and high collective efficacy). Alternatively, the effects of the level of disadvantage within a neighborhood may interact with the neighborhood’s structural (in)stability, in what I refer to as “accumulation.” In stable conditions, the unfavorable effects of concentrated disadvantage may build up over time (e.g. collective efficacy continues to diminish), so neighborhoods with stable high levels of disadvantage experience higher homicide rates than predicted by the level of disadvantage alone. Stability would, inversely, benefit neighborhoods with low levels of disadvantage, because the benefits of low disadvantage (e.g. a growth of collective efficacy) would similarly accrue over time and produce lower than expected homicide rates. In the former case, the positive relationship between disadvantage and crime would become stronger with more stability; in the latter, it is the negative relationship between advantage and crime that would strengthen.

Third, in the “lag” conceptualization of the role of stability, the effects of change could be dependent on the direction of the change. The community attachment, social ties, the ability of a neighborhood to establish mutual trust, and the ability to exercise social control can be seen as types of social capital (Granovetter 1973; Kasarda and Janowitz 1974; Morenoff, Sampson, and Raudenbush 2001; Oh 2005; Sampson 2012; Sampson, Raudenbush, and Earls
Neighborhoods with increasing disadvantage have ‘savings’ of social capital built up in a less-disadvantaged past, so the negative effects of disadvantage will only emerge once this savings is depleted. Such neighborhoods would have lower homicide rates than expected in cross-section compared to similarly disadvantaged neighborhoods, as the positive relationship between disadvantage and crime would be weaker than expected (at least until the ‘savings’ of social capital was depleted). Inversely, neighborhoods experiencing declines in disadvantage would require time to translate increases in resources into social capital; in this case, the negative relationship between advantage and crime would be weaker than expected (for a time), and homicide rates in these neighborhoods would be higher than expected relative to similarly disadvantaged neighborhoods.

The final possibility is that within-neighborhood stability of concentrated disadvantage – or structural conditions in general – would not substantially affect the relationship between the level of disadvantage and homicide in cross-section. The time necessary for concentrated disadvantage to impact the intervening social process (e.g. collective efficacy) may be relatively short, so that accounting for longer neighborhood histories of disadvantage would not be necessary. This seems unlikely, however, given how any ecological processes mediating the structure-crime relationship is inherently time-dependent – for example, how long it likely takes to build trust and establish shared expectations for informal social control in the collective efficacy model – and how slowly change occurs at this level of measurement. Of these four possible forms the relationship between historical stability, current levels of disadvantage, and homicide rates may take, it is not currently possible for me to test for the
“lag” model. As I outlined above, the reality of Chicago neighborhoods during the period in question contained very few NCs which saw declines in disadvantage; of these few, the declines were quite small. However, using GWR and OLS regression models, I can test for the presence of “disruption” or “accumulation,” treating the final possibility as the “null” model. I add the dummy measures of within-neighborhood change in disadvantage to the cross-sectional model of structural conditions and homicide constructed in Chapter 3 to observe if and how historical (in)stability accounts for spatial variation in the cross-sectional association between concentrated disadvantage and neighborhood homicide rates.

Results

The findings presented in Chapter 3 suggested that cross-sectional estimates of the disadvantage-homicide relationship are sensitive to where that relationship is being measured, with certain areas of Chicago exhibiting much stronger or weaker local associations than a global estimate would indicate. I hypothesize that this variation is due to within-neighborhood dynamics of structural stability and change, net of the current level of disadvantage (as well as the current level of immigrant concentration and residential stability). The time period under investigation, 1970-1990, is when the concentration of disadvantage described by Wilson accelerated and was at its peak (1996; 1997). It is possible that some of the NCs in this sample have long suffered from acute levels of disadvantage, while others have only recently seen increases to comparable levels, and the distribution of the change-score variable of concentrated disadvantage bears this out. Some neighborhoods have experienced high but stable levels of disadvantage over the 1970-1990 period, and some low and stable levels. Many
have seen disadvantage increase, and within this group there are three general types of increases: minor, moderate, and major.

As described earlier, I created dummy variables (1 = yes, 0 = no) to classify each NC as either relatively stable or experiencing minor, moderate, or major increases in disadvantage over time, based on the quartiles of the change-score distribution. I added these dummy variables to the prior GWR model, treating the first quartile (representing no or very minor change in either direction) as the omitted reference group. The resulting 5-number parameter summaries produced by the expanded GWR model indicate the inclusion of these variables in the model has a notable effect. For comparison, the original baseline GWR model is reproduced in Panel A of Table 4.1, while the results of the expanded model are presented in Panel B. 

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9 The expanded model presented in Panel B includes the dummy variables for quartiles of change, with the first quartile omitted as the comparison group. 5-number parameter summary data is not included for the dummy variables in this table, given the difficulties in interpreting spatial variation in a dummy variable (e.g. spatial variation in the difference between the effect of an NC belonging to the first quartile vs. the second). It is beyond the scope of this dissertation to explore spatial variation in the role of change (particularly how it is measured here) but offers a potentially fruitful avenue for future research.
Table 4.1. GWR of Log Homicide Rate on Neighborhood Structural Conditions and Change in Concentrated Disadvantage (1970-1990), 5-Number Parameter Summaries

<table>
<thead>
<tr>
<th>Panel A. Baseline Model</th>
<th>Minimum</th>
<th>Lower Quartile</th>
<th>Median</th>
<th>Upper Quartile</th>
<th>Maximum</th>
<th>Sig. Local Effects</th>
<th>Monte Carlo Test</th>
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<td>1.057</td>
<td>3.013</td>
<td>(+)</td>
<td>Non-stationary ***</td>
<td>0.795</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.499</td>
<td>0.271</td>
<td>0.380</td>
<td>0.496</td>
<td>0.681</td>
<td>(+)</td>
<td>Non-stationary ***</td>
<td>0.461</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.823</td>
<td>-0.106</td>
<td>-0.022</td>
<td>0.057</td>
<td>1.141</td>
<td>(-/+)</td>
<td>Non-stationary ***</td>
<td>-0.008</td>
</tr>
<tr>
<td>Residential stability</td>
<td>-0.451</td>
<td>-0.159</td>
<td>-0.052</td>
<td>0.058</td>
<td>0.453</td>
<td>(-/+)</td>
<td>Non-stationary ***</td>
<td>0.085</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.804</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>AIC</td>
<td>189.600</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>ANOVA F-value</td>
<td>5.837 **</td>
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</table>

<table>
<thead>
<tr>
<th>Panel B. Expanded Model</th>
<th>Minimum</th>
<th>Lower Quartile</th>
<th>Median</th>
<th>Upper Quartile</th>
<th>Maximum</th>
<th>Sig. Local Effects</th>
<th>Monte Carlo Test</th>
<th>Global (OLS) Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.2685</td>
<td>0.5016</td>
<td>0.5782</td>
<td>0.7287</td>
<td>1.2156</td>
<td>(+)</td>
<td>Non-stationary ***</td>
<td>0.521</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>0.0594</td>
<td>0.2310</td>
<td>0.3138</td>
<td>0.4166</td>
<td>0.5499</td>
<td>(+)</td>
<td>Stationary</td>
<td>0.289</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.2357</td>
<td>-0.0994</td>
<td>-0.0316</td>
<td>0.0188</td>
<td>0.1243</td>
<td>(-/+)</td>
<td>Non-stationary ***</td>
<td>-0.030</td>
</tr>
<tr>
<td>Residential stability</td>
<td>-0.2682</td>
<td>-0.0784</td>
<td>-0.0072</td>
<td>0.0214</td>
<td>0.1704</td>
<td>(-/+)</td>
<td>Non-stationary ***</td>
<td>0.050</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minor increase</td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate increase</td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Major increase</td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Model Fit and ANOVA

| Adjusted R²                   | 0.7743  |               |        |                |         |                    |                  |                      |
| AIC                           | 208.9518|               |        |                |         |                    |                  |                      |
| ANOVA F-value                 | 4.6734 *|               |        |                |         |                    |                  |                      |

Local N = 50 (baseline model), 126 (expanded model); Total N = 342

* p < .05  ** p < .01  *** p < .001

* Statistically significant local effects, p < .05
The range of the b-coefficient for concentrated disadvantage has shrunk considerably; in the baseline model it varied from -.499 through .681, while in the expanded model it now ranges between .059 and .550. The spatial variation in the association across local regressions – using the Monte Carlo test – is no longer statistically significant (at p < .05), and the relationship between concentrated disadvantage and neighborhood homicide rates can now be considered stationary. In this case, the assumption of spatial invariance inherent in OLS regression models now appears to hold, and the global OLS b-coefficient can be said to describe local relationships with (relative) accuracy. The ranges of the coefficients of immigrant concentration and residential stability have also shrunk; however, a statistically significant degree of spatial heterogeneity in the relationships across NCs (Monte Carlo p < .001) remains. It is not surprising that these latter two associations remain spatially variant, as the dummy variables added in the expanded model are unlikely to directly affect them.

A visual comparison of the baseline and expanded models is presented in Figure 4.2. Panel A is a replication of the t-surface map of the local concentrated disadvantage-homicide rate relationship presented in Chapter 3. Panel B displays the same map based on the expanded model. The association between disadvantage and homicide is clearly more consistent across NCs now that within-neighborhood changes are accounted for. The t-surface map of the expanded model still reveals several areas where the level of concentrated disadvantage is not significantly related to the homicide rate in 2001-2005, but these now comprise less than 5% of the total sample (15 of 342 NCs) rather than the 16% found in the baseline model. In a similar fashion, the number of localities where the relationship is exceptionally strong and the t-value is 6 or larger is just over 8% (30 of 342), compared to almost a third in the baseline model.
Having established that historical changes (or stability) in concentrated disadvantage account for cross-sectional spatial variation in the disadvantage-homicide relationship across NCs, a closer examination of these dynamics is warranted. Now that the spatial invariance assumption is supported for the model – at least in the case of concentrated disadvantage – a return to OLS regression modeling is suitable for the purpose. The results of the expanded OLS model presented in Table 4.2 are very similar to the baseline model examined earlier. Overall, the model explains roughly 70% of the variation in homicide rates across NCs; this is statistically significant but substantively small improvement compared to the 66% of the baseline model (F
However, there is a sizable reduction in the strength of the global relationship between disadvantage and homicide \((b = .289, p < .001)\). While this relationship remains the strongest of the structural predictors \((\beta = .509)\), it is noticeably weaker than before the addition of the dummy change variables \((b = .461, p < .001, \beta = .808)\).

**Table 4.2. OLS Regression of Log Homicide Rate on Neighborhood Structural Conditions and Change in Disadvantage**

<table>
<thead>
<tr>
<th></th>
<th>(b)</th>
<th>(SE)</th>
<th>(\beta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.521 ***</td>
<td>0.045</td>
<td>0.509</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>0.289 ***</td>
<td>0.034</td>
<td>0.808</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.030</td>
<td>0.020</td>
<td>-0.056</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.050 *</td>
<td>0.022</td>
<td>0.077</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minor increase</td>
<td>0.293 ***</td>
<td>0.060</td>
<td>0.196</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>0.499 ***</td>
<td>0.074</td>
<td>0.335</td>
</tr>
<tr>
<td>Major increase</td>
<td>0.601 ***</td>
<td>0.101</td>
<td>0.399</td>
</tr>
</tbody>
</table>

Adjusted \(R^2\) 0.698

AIC 270.095

\(N = 342\)

* \(p < .05\)  ** \(p < .01\)  *** \(p < .001\)

The degree of historical change in neighborhood concentrated disadvantage clearly matters for the prediction of cross-sectional homicide rates. Compared to the omitted first quartile – which includes NCs experiencing very little or no change in the level of disadvantage between 1970 and 1990 – neighborhoods with more change are expected to have significantly higher homicide rates. The association between the (in)stability of disadvantage within the neighborhood and homicide appears to follow a roughly linear pattern, with each successive quartile showing an additional increase in the expected homicide rate net of the level of disadvantage in 1990. Inclusion in the second quartile (minor increases in the level of disadvantage in 1990) increases the estimated homicide rate by .29 \((p < .001)\), inclusion in the
third (moderate increases) by .50 (p < .001), and the fourth (major increases) by .60 (p < .001),
relative to NCs which experience little or no change.

Supplemental analyses (see the Appendix, Table A.1) using each quartile as the omitted
comparison group indicate that the differences between all the groups were statistically
significant, with the exception of the third and fourth quartiles (or moderate and major
increases). This indicates that in addition to the expected positive cross-sectional association
between the level of concentrated disadvantage in an NC and its homicide rate, that rate is also
substantially influenced by change, or how (un)stable that level has been within the NC over
time. Net of the level of disadvantage in 1990, NCs with more historical change in disadvantage
are predicted to have higher homicide rates. This is in keeping with the “disruption”
conceptualization proffered earlier of how within-neighborhood change matters, and
supports Hypothesis (2) by suggesting that neighborhood structural dynamics play an important
role in how concentrated disadvantage impacts homicide (and other crime) within the
neighborhood at a given point in time.

Interestingly, another set of analyses testing the interaction of the level and change in
concentrated disadvantage found additional support for Hypothesis (2), but for different
reasons. While it is difficult to interpret the coefficients of the constituent measures when
interaction terms are included in an OLS model, Table 4.3 displays the results of a model which
includes interactions terms for the level of concentrated disadvantage in 1990 and which
quartile of change a given NC falls into. This variable was constructed simply by multiplying the

---

10 As mentioned several times, given the realities of changes in disadvantage over the 1970-1990 time period in
Chicago, it is impossible to compare NCs that experienced similar degrees of change but in the opposite direction
decreasing disadvantage to see if within-neighborhood improvement is as destabilizing as deterioration.
However, I feel that there is sufficient variation in the degree of increasing disadvantage to tentatively support a
“disruption” interpretation of these findings.
NC’s level of concentrated disadvantage in 1990 by the dummy variables for quartiles of change. The result is a parallel set of “dummy” interaction variables (i.e. an NC has a value of 0 for the three quartiles to which it does not belong).

Table 4.3. OLS Regression of Log Homicide Rate on Neighborhood Structural Conditions, Change in Disadvantage, and Disadvantage Level*Change Interaction

<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th>(SE)</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.807</td>
<td>***</td>
<td>0.108</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>0.678</td>
<td>***</td>
<td>0.138</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.027</td>
<td>0.019</td>
<td>-0.049</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.076</td>
<td>**</td>
<td>0.022</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>Minor increase</td>
<td>0.069</td>
<td></td>
<td>0.114</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>0.119</td>
<td></td>
<td>0.125</td>
</tr>
<tr>
<td>Major increase</td>
<td>0.578</td>
<td>***</td>
<td>0.140</td>
</tr>
<tr>
<td>Disadvantage Level*Change</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disadvantage*No change (omitted)</td>
<td>-</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>Disadvantage*Minor increase</td>
<td>-0.097</td>
<td>0.159</td>
<td>-0.034</td>
</tr>
<tr>
<td>Disadvantage*Moderate increase</td>
<td>-0.268</td>
<td>0.148</td>
<td>-0.183</td>
</tr>
<tr>
<td>Disadvantage*Major increase</td>
<td>-0.537</td>
<td>***</td>
<td>0.142</td>
</tr>
</tbody>
</table>

| Adjusted R² | 0.726 |
| AIC         | 238.694 |

N = 342  * p < .05  ** p < .01  *** p < .001

Omitting the disadvantage*quartile (1) group for comparison, it appears that the positive association between the level of disadvantage in 1990 and neighborhood homicide becomes weaker in the presence of higher degrees of change. Compared to NCs with no change (the omitted comparison group), the positive relationship between concentrated disadvantage and homicide is slightly smaller for NCs with minor increases (the second quartile interaction term), though this difference is not statistically significant (b = -.097, p = .542). The relationship is yet weaker for NCs which experienced moderate increases, and marginally significant (b = -.268, p <
Finally, the association is significantly smaller for NCs that saw major increases compared to stable NCs (b = -0.537, p < .001). This set of findings supports the “accumulation” conceptualization of within-neighborhood stability. High levels of disadvantage in 1990 are more detrimental when the neighborhood is relatively stable (in terms of disadvantage, at least). Across all neighborhoods, those with higher levels of concentrated disadvantage are still expected to have higher homicide rates than neighborhoods with lower disadvantage (b = 0.678, p < .001). The positive relationship between disadvantage and homicide, however, is stronger in structurally stable neighborhoods, and net of the level of disadvantage in 1990, neighborhood homicide rates will be higher in more stable neighborhoods. Given that there were no comparable neighborhoods over this time period that saw declines in disadvantage, it is not possible to know if similar “accumulation” occurs in the least disadvantage neighborhoods – for example, stable affluent areas have significantly lower homicide rates than recently affluent ones, net of low levels of disadvantage in 1990. However, this model is consistent with such an interpretation.  

Discussion and Conclusions

In this chapter, the results of models controlling for within-neighborhood change in concentrated disadvantage, net of the level of disadvantage in 1990, clearly support Hypothesis (2) – Controlling for neighborhood structural stability (or the degree of structural change) will

This finding could also support the “lag” model of within-neighborhood change, given that neighborhoods which saw levels of disadvantage increase would have lower than expected homicide rates, and could be drawing on prior lower levels of disadvantage (and higher levels of collective efficacy) to delay increases in homicide/crime. However, lacking data on neighborhoods which saw decreases to comparable levels of disadvantage – no NCs in Chicago experienced more than very minor decreases in disadvantage between 1970-1990 – it is not possible to predict if these areas have higher than expected homicide rates and thus fully support a “lag” interpretation.
account for spatial variation in the cross-sectional association of concentrated disadvantage and neighborhood homicide rates. I expected that the spatially-variant relationship between disadvantage and homicide rates found in Chapter 3 would be attributable in some part to the stability of conditions within the neighborhood, and my findings in this chapter bear that out. Within-neighborhood dynamics clearly influence the cross-sectional relationship; once the degree of neighborhood change was accounted for, the effect of concentrated disadvantage in 1990 on homicide rates became spatially invariant/stationary. This suggests that – to some degree – models of neighborhood effects must account for not only between-neighborhood differences in the level of disadvantage, but also the within-neighborhood dynamics of change in that condition.

While there was no statistical difference in the rates of homicide between neighborhoods experiencing major and moderate increases in concentrated disadvantage, there were significant differences in all other two-way comparisons. This adds an important dimension to theorizing on the role of neighborhood structural conditions in producing or reducing crime. Neighborhoods with dissimilar histories of disadvantage, though they have equivalent levels of disadvantage in cross-section, may evidence substantial variation in how much crime occurs within them. Though the current study limits its examination to homicide rates, it seems possible – if not likely – that within-neighborhood change has a similar role in the explanation of other violent and property crimes.

I laid out four possible ways that structural change within the neighborhood might be related to homicide rates, including a “null” model where change did not matter. The findings here are congruent with both the “disruption” and “accumulation” models of change and
homicide. Net of the 1990 level of disadvantage, neighborhoods which experienced greater increases in disadvantage over the 1970-1990 period were predicted to have higher homicide rates. This relationship followed a fairly regular pattern: each increase in the degree of change, measured by quartiles, saw an accompanying increase in predicted homicide. There was also partial support for the “accumulation” model, which implied an interaction between the level of disadvantage in 1990 and the degree of within-neighborhood stability over time. The positive association between concentrated disadvantage and neighborhood homicide rates was strengthened in the face of neighborhood structural stability. The more change occurred within a neighborhood, the weaker this relationship became, though only the difference between the stable group of neighborhoods and the group with the largest increases was statistically significant. This implies that stability is detrimental for neighborhood homicide rates when coupled with high levels of disadvantage; inversely, stability is particularly beneficial when disadvantage is low.

I should note here that these models of change (and the interpretations based on the results) are built on an idealized conceptual framework of change which was only partly realistic for Chicago in this time frame. Neighborhoods could range between relatively high and low levels of disadvantage in 1990, and this was the case here (due in large part to the standardized factor measure of concentrated disadvantage, which is created to have a normal distribution of negative and positive values centered on a mean of zero). However, while the level of disadvantage in 1990 was distributed evenly across NCs, the direction and degree of historical change was not. Ideally, the level of disadvantage in 1990 could be preceded by increases, decreases, or no change over time, but this was not the actual case for my sample of
NCs. Most neighborhoods in this sample experienced relatively consistent or increasing levels of disadvantage over the 1970-1990 period; less than 5% of NCs had seen disadvantage decline over time (and these declines were very small). There were not enough neighborhoods which “matched” on the degree of change but in opposite directions to allow for multiple direct comparisons – for example, to fully test the “lag” model across neighborhoods with a given level of disadvantage in 1990 but had reached that level via historical increases, decreases, or relative stability. One possible direction for future research would be to examine a sample of neighborhoods during a time period which captures the full range of possible neighborhood dynamics. Given the lack of an extensive literature on within-neighborhood structural dynamics and crime, this dissertation is largely exploratory, and I have chosen to focus on a setting and time period that has been extensively studied (Graif and Sampson 2009; Morenoff, Sampson, and Raudenbush 2001; Park, Burgess, and McKenzie 1967; Sampson 2012; Sampson, Raudenbush, and Earls 1997; Shaw and McKay 1969; Wilson 1996) so my results could be compared to a well-established literature on the disadvantage-crime relationship.

Any conclusions drawn about the theoretical mechanisms linking the dynamics of neighborhood concentrated disadvantage to homicide rates at this point remain speculative. My purpose in Chapter 4 was simply to explore if and how change (or stability) in concentrated disadvantage within the neighborhood contributed to homicide rates in cross-section, above and beyond the accepted role of the level of concentrated disadvantage in explaining between-neighborhood differences in crime. I did find, however, that greater change in disadvantage was linked to higher rates of homicide, net of the level of disadvantage in 1990. This is consistent with social disorganization theories of neighborhood crime (Osgood and Chambers
2000; Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997; Shaw and McKay 1969). In neighborhoods with shifting disadvantage (and potentially including other structural conditions), it is expected that building social ties, generating community attachment, establishing mutual trust, and exercising informal social control would be more difficult, regardless of the level of disadvantage at a given point in time. Inversely, neighborhoods which have experienced relatively stable levels of disadvantage (whether high or low) would have a greater capacity to inhibit crime and exhibit “organization” (Whyte 1943). Qualitative work in this area has found that even criminals become embedded in primarily non-criminal social networks over time, becoming not only subject to informal social control but possible agents of social control themselves (Pattillo-McCoy 1999; Pattillo 1998).

This all suggests that while disadvantage has largely concentrated in particular neighborhoods, creating “traps” and high levels of social isolation for residents (Massey and Denton 1993; Sampson 2009; Wilson 1996; Wilson 1997), there may be a very slender silver lining to this problem. Acute levels of disadvantage in these neighborhoods drive crime rates upward, but it is possible that the stability engendered by the concentration process itself may act as a countervailing force and limit the amount of crime that occurs within the neighborhood. This is not to suggest that concentrated disadvantage is a benefit – the harmful effects of the level of disadvantage far outweigh any benefits of structural stability.

The goal of this chapter was to assess the role of neighborhood stability, in terms of concentrated disadvantage, and test if stability influenced crime rates independently of the level of disadvantage as well as if stability conditioned the cross-sectional relationship. Lacking

\[12 \text{ And I stress very slender.}\]
any measure of a mediating social process linking structural conditions to crime, I cannot yet say if change indirectly influences homicide rates through a relationship with a process like collective efficacy, and if so, how. I turn to this question in the next chapter. The influence of both the level and historical stability of concentrated disadvantage is hypothesized to work via collective efficacy. Beginning with a test of the spatial invariance assumption mirroring the models in Chapter 3, I explore the implications of structural stability and the level of disadvantage for collective efficacy, then move to the construction of a “full” model of neighborhood dynamics, structural conditions, and the social process of collective efficacy that is theorized to link them to neighborhood crime rates.
CHAPTER 5. COLLECTIVE EFFICACY AND WITHIN-NEIGHBORHOOD CHANGE: THE IMPACT OF STABILITY ON THE LINK BETWEEN CONCENTRATED DISADVANTAGE AND HOMICIDE

Introduction

To this point, I have demonstrated that there are two important gaps in the literature on concentrated disadvantage and neighborhood homicide rates (and crime generally) which should be explored in future research. First, it appears that the cross-sectional relationship between disadvantage and homicide significantly varies across neighborhoods (using NCs as the unit of analysis). This finding clearly violates the assumption of spatial invariance, a key component for the interpretation of “global” models of structural conditions and crime, and begs the question of why the relationship should be stronger or weaker in some places than others.

One potential explanation for this variation in the relationship is the role of neighborhood dynamics, or within-neighborhood stability over time. Theoretically, neighborhood structural stability should have a positive effect on neighborhood organization, net of its level of disadvantage (or some other condition), producing lower-than-expected crime rates. The analyses in the previous chapter support this argument; once within-neighborhood changes in concentrated disadvantage were accounted for, the cross-sectional association between disadvantage and homicide became spatially invariant. The results of the expanded model suggested that, net of the level in 1990, change in concentrated disadvantage was disruptive to the neighborhood. It also appeared that stability conditioned the relationship between the level of disadvantage and homicide, with the detrimental effects of high disadvantage – or the benefits of low disadvantage – accumulating when structural conditions
within the neighborhood were more stable during the 1970-1990 period. Within-neighborhood dynamics play an important role in the relationship between structural conditions and crime (at least homicide), and this second gap in contemporary work should also be addressed.

The disruptive effects of within-neighborhood change and the cumulative effects of disadvantage via neighborhood stability found here are consistent with previous work on neighborhood “equilibrium” (Bursik 1986; Bursik and Webb 1982), gentrification (Covington and Taylor 1989; Kreager, Lyons, and Hays 2011; Taylor and Covington 1988; van Wilsem, Wittenbrood, and de Graaf 2006), rural poverty (Osgood and Chambers 2000), and the concentration of disadvantage (Krivo and Peterson 1996; Morenoff, Sampson, and Raudenbush 2001; Wilson 1996; though see Hipp and Yates 2011). However, neighborhood structural instability, like structural conditions at a given point in time, is not directly related to neighborhood crime rates. Instead, they are linked via some social process that mediates the association. For Shaw and McKay and others, this process was social disorganization (Bursik 1986; Osgood and Chambers 2000; Park 1967; Sampson and Groves 1989; Shaw and McKay 1969; Veysey and Messner 1999). From this perspective, within-neighborhood structural instability undermines the ability of the neighborhood to reorganize (though possibly along a qualitatively different standard of social norms and expectations; see Whyte 1943), likely through the building of social ties and community attachment that depends on temporal stability in neighborhood structural conditions (Kasarda and Janowitz 1974).

The importance of within-neighborhood structural stability remains in recent evolutions of the social disorganization perspective. One of these – collective efficacy – has become one of the dominant theoretical perspectives on neighborhood conditions and crime (as well as a host
of other outcomes) in the last several decades (Browning 2002; Bruinsma, Pauwels, Weerman, and Bernasco 2013; Morenoff, Sampson, and Raudenbush 2001; Sampson 2003; Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997). While rarely made explicit, neighborhood structural stability is theoretically important to the creation and operation of collective efficacy (though see Sampson 2012), and is one probable mechanism through which temporal (in)stability in the neighborhood exerts an influence on homicide rates. Conceptually, collective efficacy is a combination of two types of social capital in the neighborhood: social cohesion and mutual trust amongst residents, and a willingness (and ability) to exercise informal social control in the neighborhood (Sampson, Raudenbush, and Earls 1997). Empirical tests of collective efficacy’s role as a mediator of structural conditions and crime generally find support for this model (Morenoff, Sampson, and Raudenbush 2001; Sampson 2012; Sampson, Raudenbush, and Earls 1997), though there is some evidence that the benefits of collective efficacy can be diluted in neighborhoods with strong social networks (where criminals draw upon rules of "reciprocated exchange" with pro-social individuals to avoid informal or formal sanctioning; see Browning 2009; Browning, Feinberg, and Dietz 2004) and that collective efficacy does not operate in the same fashion in non-U.S. neighborhoods (Bruinsma, Pauwels, Weerman, and Bernasco 2013).

Some of the earliest work on collective efficacy discusses the “destabilizing potential” of neighborhood change (Sampson, Raudenbush, and Earls 1997, p. 919), and points out that within-neighborhood stability contributes to the construction of social ties and efforts to maintain social control. However, the influence of within-neighborhood stability on collective efficacy – and thus crime – has largely been ignored in recent work. The structural stability (or
instability) of neighborhood conditions over time represents a potentially critical dimension of the link between neighborhood conditions and crime. The levels of a particular condition remain important in explaining between-neighborhood differences in collective efficacy and crime. It is the stability of neighborhood disadvantage, however, that would explain differences across neighborhoods which share a particular level of disadvantage. Reorganization or collective efficacy may exist in the face of disadvantage given neighborhood structural stability over time, resulting in lower crime rates than would be predicted by the level of disadvantage alone. Inversely, neighborhoods with relatively low levels of disadvantage (or high levels of affluence) may have lower levels of collective efficacy than expected, leading to higher crime rates.

Building upon the theoretical arguments and the results of the preceding analyses, it is now possible to construct a more complex model of the relationship between concentrated disadvantage and homicide rates (and crime rates in general) that accounts for within-neighborhood dynamics. To this point, I have demonstrated that the association between disadvantage and homicide is spatially variant in cross-section. Within-neighborhood change in disadvantage appears to have both a direct effect on homicide rates, net of the level of disadvantage, as well as interact with the level of disadvantage. As a simple path diagram, this model would look like this:
Change within the neighborhood would not, however, have a direct association with crime rates. As outlined above, the relationship would actually be mediated through the social process of collective efficacy (or a similar social process). Given the apparently disruptive effects of structural instability, and the cumulative effects of stability, on homicide rates, in the prior model, it is logical to suppose that similar associations occur between the level and stability of concentrated disadvantage and collective efficacy, producing the relationships found earlier. In this case, the model looks almost identical to Figure 5.1, but the outcome is now the neighborhood's level of collective efficacy (measured in 1995):
The level of disadvantage is expected to explain between-NC differences in collective efficacy, while the stability of disadvantage, net of disadvantage in 1990, is expected to either 1) have a direct influence on collective efficacy in the form of disruption, 2) interact with the level of disadvantage in the form of accumulation, 3) evidence both relationships, or 4) have no effect on collective efficacy.

With the exception of the last possibility (i.e. a null relationship between neighborhood change in disadvantage and collective efficacy), each of these three possible forms of the relationship between change and collective efficacy suggests that, as in the models with the 2001-2005 neighborhood homicide rate as the outcome, a cross-sectional model of disadvantage in 1990 and collective efficacy will find a spatially-variant association when the model does not control for historical (in)stability of neighborhood disadvantage. If this relationship is also spatially-variant, and can be accounted for by within-neighborhood change,
then it is logical to hypothesize that change will not have a significant direct relationship with homicide rates in a “full” model which includes collective efficacy as a mediator of the disadvantage-homicide relationship. This is because the influence of historical change will be captured in the measure of collective efficacy:

![Diagram](image)

**Figure 5.3. The Full Model of Disadvantage Level & Changes, Collective Efficacy, and Neighborhood Homicide Rates**

It will no longer be necessary to control for within-neighborhood change to satisfy the assumption of a spatially-variant relationship between the level of concentrated disadvantage and neighborhood homicide rates, since accounting for collective efficacy will serve the same purpose.

In summary, this final empirical chapter of the dissertation is oriented around the construction of a “full” model of neighborhood structural conditions and crime. This model
attempts to simultaneously account for within-neighborhood dynamics of change and stability, the association between the level of disadvantage and homicide in cross-section, and collective efficacy. Collective efficacy is believed to mediate not only the relationship between the level of concentrated disadvantage at a given point in time and neighborhood homicide rates, but also the association between within-neighborhood structural stability and homicide rates. The remainder of this chapter is dedicated to a number of analyses which explore these various possibilities.

Data & Analytic Strategy

The same units of analysis – Chicago NCs – and measures of structural conditions are employed in this chapter. These include the factor measures of concentrated disadvantage, immigrant concentration, and residential stability in 1990, as well as the dummy measures of within-neighborhood changes in disadvantage between 1970 and 1990 (the first quartile, representing no or very little change, is again used as the omitted reference group). The only new variable to be used in these models is a measure of collective efficacy, which is constructed according to prior work in this area (Browning 2009; Browning, Feinberg, and Dietz 2004; Morenoff, Sampson, and Raudenbush 2001; Sampson 2012; Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997).

The Project on Human Development in Chicago Neighborhoods Community Survey (PHDCN-CS; Earls, Brooks-Gunn, Raudenbush, and Sampson 2007) includes NC-level univariate measures of neighborhood social cohesion and informal social control, which are themselves based on sets of questions answered by individual respondents to the survey, in 1995.
Consistent with prior research, the univariate NC-level measures of cohesion and control are strongly and significantly correlated \((r = .801, p < .001)\). These two univariate measures were combined into a summary measure of collective efficacy in 1995. This measure taps into both the degree of mutual trust and cohesion among neighborhood residents and their willingness to exert informal social control (Sampson, Raudenbush, and Earls 1997).

The empirical analyses in this chapter are divided into two general parts, again employing a combination of OLS and geographically-weighted regression. The first set is essentially a replication of the analyses in Chapters 3 and 4, but rather than predict homicide rates, the outcome of interest is the level of neighborhood collective efficacy. Prior analyses support the conclusion that within-neighborhood changes in concentrated disadvantage matter for the prediction of homicide rates. If, as I expect, the effects of change operate through neighborhood collective efficacy (rather than exert a direct or interactive influence), then similar analyses using collective efficacy as the dependent variable should produce similar results. This leads to parallel hypotheses:

**Hypothesis (3)** – The relationship between concentrated disadvantage and collective efficacy in neighborhood clusters will be spatially invariant across the sample of Chicago NCs.

**Hypothesis (4)** – Controlling for neighborhood structural stability (or the degree of structural change) will account for spatial variation in the cross-sectional association of concentrated disadvantage and neighborhood collective efficacy.

Like in previous chapters, these analyses are essentially a test of the spatial invariance assumption in cross-sectional models – but between disadvantage and collective efficacy rather
than homicide – and models that attempt explore if any spatial variation/heterogeneity in the relationship is attributable to within-neighborhood changes in concentrated disadvantage. This first set of analyses is necessary because if within-neighborhood change does operate through the production and operation of collective efficacy, rather than have a direct relationship with homicide rates, then it must have a relationship to collective efficacy that is similar to its association with homicide found earlier.

The second set of analyses depicts a “full” model of within-neighborhood change, cross-sectional levels of disadvantage and collective efficacy, and homicide rates. If neighborhood changes in disadvantage actually affect collective efficacy, and thus crime, rather than directly affecting neighborhood homicide rates, then controlling for collective efficacy will account for prior historical conditions (whether stable or not). In this manner, the cross-sectional relationship between the level of concentrated disadvantage in 1990 and homicide rates in 2001-2005 will become spatially invariant without including the dummy variables for neighborhood change in the model, because collective efficacy will act as a proxy for structural (in)stability (e.g. the variation in the spatial relationship attributed earlier to within-neighborhood change is now attributable to the association of change and the level of collective efficacy in a given NC). While there are – again – several possible ways that within-neighborhood changes in disadvantage will be related to collective efficacy (if it is at all), the results of the previous models suggest that change will be both disruptive (a direct effect on collective efficacy) and cumulative (an interaction effect between change and the level of disadvantage in 1990).
Results

The Spatial Invariance Assumption

I first test the assumption of spatial invariance for the concentrated disadvantage-collective efficacy relationship intrinsic to aspatial models. Using the same spatially adaptive weighting function employed earlier, the GWR model converged at a local sample size of 99 neighborhood clusters. The increase in the local sample size is attributable to less variation in collective efficacy across units; the weighting function attempts to maximize variation in the local sample while limiting bias introduced by including distant NCs in the local sample (which are more likely to be dissimilar). As before, a smaller adaptive kernel size would be preferable, but the results of the GWR model may be considered a conservative estimate of spatial variation in the relationship since the variation in the association will be smaller than if the kernel size was more limited.

Table 5.1 displays the 5-number parameter summaries of the estimated relationships between structural conditions (in 1990) and collective efficacy (in 1995) across local regressions. The table also includes the results of Monte Carlo tests for stationarity (i.e. spatial invariance) and global estimates of the coefficients from an OLS model for comparison.

---

While I began by replicating the findings of existing research in Chapter 3, then explored the necessity of applying GWR to the model, these steps are not necessary here. For theoretical reasons I am already assuming the disadvantage-collective efficacy relationship is spatially variant (as I believe it accounts for the effects of neighborhood change on homicide).
Table 5.1. GWR of Collective Efficacy on Neighborhood Structural Conditions, 5-Number Parameter Summaries

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Lower Quartile</th>
<th>Median</th>
<th>Upper Quartile</th>
<th>Maximum</th>
<th>Sig. Local Effects&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Monte Carlo Test</th>
<th>Global (OLS) Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.133</td>
<td>0.106</td>
<td>0.244</td>
<td>0.416</td>
<td>0.779</td>
<td>(+)</td>
<td>Non-stationary ***</td>
<td>0.246</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-1.213</td>
<td>-0.754</td>
<td>-0.586</td>
<td>-0.493</td>
<td>-0.331</td>
<td>(-)</td>
<td>Non-stationary ***</td>
<td>-0.602</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.576</td>
<td>-0.260</td>
<td>-0.187</td>
<td>-0.096</td>
<td>0.077</td>
<td>(-)</td>
<td>Non-stationary ***</td>
<td>-0.174</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.006</td>
<td>0.171</td>
<td>0.296</td>
<td>0.431</td>
<td>0.565</td>
<td>(+)</td>
<td>Non-stationary **</td>
<td>0.289</td>
</tr>
</tbody>
</table>

Adjusted R² 0.642
AIC 653.008
ANOVA F-value 3.825 ***

Local N = 99; Total N = 342

* p < .05  ** p < .01  *** p < .001

<sup>a</sup> Statistically significant local effects, p < .05
As before, it is clear that the association between the level of neighborhood concentrated disadvantage and its level of collective efficacy is not invariant across NCs. The relationship is almost always significant (in only four cases out of 342 was the local estimate non-significant), and in the expected negative direction (more disadvantage predicts less collective efficacy), but the strength of the relationship varies a great deal. Compared to the global estimate of the relationship (b = -.602, p < .001), the local relationships can be both considerably stronger (roughly 100% stronger; minimum b = -1.213, p < .001) and weaker (about 45%; maximum b = -.331, p < .001) across NCs. The Monte Carlo test indicates that this variation is statistically significant (p < .001). The same is true for the control variables; local estimates of both relationships vary significantly across Chicago (p < .01). Immigrant concentration evidences both null and statistically significant negative associations with collective efficacy, while the relationship between residential stability and collective efficacy ranges between non-significant and significantly positive.

Overall, the GWR model (AIC = 653.008) appears to fit the data better than the comparable OLS model (AIC = 687.947), though this difference is relatively small. Accounting for differences in the degrees of freedom, the ANOVA F-test indicates this improvement in model fit is statistically significant (F = 3.8247, p < .001). The GWR model accounts for over 11% more variation in collective efficacy across models (adjusted $R^2 = .642$) than does the OLS model (adjusted $R^2 = .570$). Visual inspection of the statistical results supports two conclusions. First, the explanatory power of the overall model clearly varies across Chicago. As indicated in Figure 5.4, the variation in collective efficacy accounted for by neighborhood structural conditions
ranges between 28% and 80%, with lighter gray indicating the smallest quintile of local adjusted $R^2$ values and darker gray the largest quintile.

![GWR Local R-Square by Neighborhood Cluster, Collective Efficacy on Structural Conditions](image)

**Figure 5.4. GWR Local R-Square by Neighborhood Cluster, Collective Efficacy on Structural Conditions**

This clearly implies global models of neighborhood structural conditions and collective efficacy are to some degree misspecified, given they ignore substantial and systematic variation in how well such models “explain” collective efficacy rates across spatial units.

Secondly, while a global estimate of the relationship between concentrated disadvantage and neighborhood collective efficacy is relatively accurate for many NCs, there
are clearly areas where the association is substantially different. The t-surface map presented in Figure 5.5 presents the t-values of local parameter estimates of the disadvantage-collective efficacy relationship, with lighter gray denoting smaller coefficients and darker gray the larger.

![Figure 5.5 GWR t-Surface of Local Parameter Estimates of Concentrated Disadvantage, Collective Efficacy on Structural Conditions](image)

The association was non-significant in less than 2% of NCs (4 out of 342), and was negative and significant for the rest as theoretically predicted. However, there is clearly a great deal of variation in the strength of the relationship, with significant t-values ranging anywhere from roughly -2 to -10. All told, the statistical and visual evidence of the “baseline” GWR model
indicates that the cross-sectional relationship between concentrated disadvantage and collective efficacy is *not* spatially invariant, and Hypothesis (3) is not supported. Estimates of the relationships are clearly sensitive to *where* one is looking.

*Concentrated Disadvantage Changes and Spatial Invariance*

Having established that, like the disadvantage-homicide association, the relationship between concentrated disadvantage and neighborhood collective efficacy is spatially variant, the next step is to explore the possibility that within-neighborhood changes in disadvantage can account for this variation. Theoretically, NCs which are structurally stable over time may manifest higher levels of collective efficacy than expected, net of the level of disadvantage in 1990. Inversely, neighborhoods with more structural change would have lower levels of collective efficacy than other neighborhoods with comparable but stable levels of disadvantage (even if that level is relatively low). As in Chapter 4 – but with collective efficacy as the outcome of interest – the dummy variables representing within-NC changes in concentrated disadvantage (minor, moderate, or major increases) were added to the “baseline” model above. The dummy variable for the first quartile of the change distribution, representing no or very little change in either direction, is the omitted reference group. Panel A of Table 5.2 reproduces the original baseline GWR model for comparison, with the results of the expanded model presented in Panel B.  

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14 As in Chapter 4, Table 4.1, the expanded model excludes the 5-number parameter summaries for the dummy change variables, given the difficulties in interpreting spatial variation in the effects of categorical dummy variables and the limited scope of this dissertation.
Table 5.2. GWR of Collective Efficacy on Neighborhood Structural Conditions and Change in Concentrated Disadvantage (1970-1990), 5-Number Parameter Summaries

<table>
<thead>
<tr>
<th>Panel A. Baseline Model</th>
<th>Minimum</th>
<th>Lower Quartile</th>
<th>Median</th>
<th>Upper Quartile</th>
<th>Maximum</th>
<th>Sig. Local Effects</th>
<th>Monte Carlo Test</th>
<th>Global (OLS) Parameter</th>
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<td>0.779</td>
<td>(+)</td>
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<td>(-)</td>
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<td>(-)</td>
<td>Non-stationary ***</td>
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<tr>
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<td>0.171</td>
<td>0.296</td>
<td>0.431</td>
<td>0.565</td>
<td>(+)</td>
<td>Non-stationary **</td>
<td>0.289</td>
</tr>
</tbody>
</table>

Adjusted $R^2$ 0.642
AIC 653.008
ANOVA F-value 3.825 ***

Panel B. Expanded Model

| Constant                | 0.1994  | 0.3988         | 0.5486 | 0.7094         | 0.9751  | (+)               | Non-stationary * | 0.629                  |
| Concentrated disadvantage| -0.696  | -0.448         | -0.353 | -0.292         | -0.175  | (-)               | Stationary       | -0.312                 |
| Immigrant concentration | -0.3397 | -0.2146        | -0.1551| -0.1016        | -0.0311 | (-)               | Non-stationary   | -0.163                 |
| Residential stability   | 0.1736  | 0.2599         | 0.2984 | 0.4422         | 0.5259  | (+)               | Non-stationary * | 0.344                  |

Change in Disadvantage
- No change (omitted)
- Minor increase (+) Stationary -0.329
- Moderate increase (+) Stationary -0.661
- Major increase (+) Stationary -1.022

Model Fit and ANOVA

| Adjusted $R^2$ | 0.6376 |
| AIC            | 659.0453 |
| ANOVA F-value  | 2.3236 ** |

Local N = 99 (baseline model), 156 (expanded model); Total N = 342

* p < .05   ** p < .01   *** p < .001

a Statistically significant local effects, p < .05
Given the findings in Chapter 4, it is perhaps unsurprising that including measures of within-neighborhood changes in disadvantage have a substantial impact on the model. The overall range of the disadvantage b-coefficient has become smaller, now varying between a minimum of -.696 and a maximum of -.175, compared to a range of -1.213 to -.331 in the baseline model. While this actually represents an increase in the maximum b-coefficient—a smaller negative value, so a shift to the right in terms of the overall distribution of the local relationship—the corresponding shift on the left hand side towards smaller negative values is more substantial, resulting in a more compressed overall distribution or range of local associations. The Monte Carlo test indicates that spatial variation in the relationship between disadvantage and collective efficacy is no longer statistically significant across NCs (at p < .05). After controlling for within-neighborhood changes in disadvantage, the cross-sectional relationship between the level of disadvantage in 1990 and collective efficacy can be considered stationary or spatially invariant. As the assumption of spatial invariance appears to hold once the model accounts for changes in disadvantage over time, the global OLS b-coefficient for the level of disadvantage (b = -.312, p < .001) is now likely to be a much more accurate estimation of its association with collective efficacy across all NCs in the sample.

What is somewhat surprising in the expanded model, however, is the effect of including the change dummy measures on the spatial variation in the relationship between immigrant concentration and collective efficacy. In the GWR models in Chapter 4, where I was predicting neighborhood homicide rates, the inclusion of change measures of disadvantage did not appreciably alter the spatial variation in either of the other two structure-homicide relationships (immigrant concentration and residential stability). At the time this was not
unexpected; there was no reason to believe that controlling for changes in disadvantage over time would affect spatial variation in the other associations. Here, controlling for changes in disadvantage does not substantially reduce spatial heterogeneity in the relationship between the level of residential instability and collective efficacy (paralleling the previous results, it is still statistically significant; Monte Carlo p < .05), but it does affect spatial variation in the relationship between the level of immigrant concentration and collective efficacy, which is no longer significant (at the p < .05 level). It is beyond the scope of this dissertation to explore the other two structural conditions in any depth – including the role of change – but this result is notable and future research should examine it further. One possible explanation is that changes in concentrated disadvantage are somehow cyclically linked to the level of immigrant concentration at a given point in time, and thus exert some influence over the immigrant concentration-collective efficacy relationship. Sampson has laid out a compelling argument for a nonrecursive model of neighborhood effects (2012), and this may be evidence of such a feedback loop or cyclical process.

A visual comparison of the baseline and expanded models of structural conditions and neighborhood collective efficacy is presented in Figure 5.6. Panel A is a replication of the t-surface map of the local concentrated disadvantage-collective efficacy relationship presented above, and Panel B displays the same map for the expanded model. The association between the level of disadvantage in 1990 and neighborhood collective efficacy is clearly more consistent across NCs now that within-neighborhood changes in disadvantage are accounted for. The t-surface map of the expanded model still reveals clusters of NCs where the level of
concentrated disadvantage is more strongly related (in the southwest) or more weakly related (in the northwest) to collective efficacy, but the variation is no longer significant.

One notable difference is in the number of NCs where the relationship is not statistically significant. In the baseline model, only 4 NCs out of the full sample of 342 (less than 2%) did not estimate a significant local relationship, but in the expanded model that number has climbed to 25 out of 342 NCs (just over 7% of the sample). This is possibly a statistical artifact of the expanded GWR model, introduced through an increase in the size of the local regression kernel from 99 to 156 NCs. Adding the dummy variables to the model required a substantially larger

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**Figure 5.6 GWR t-Surface of Local Parameter Estimates of Concentrated Disadvantage, Collective Efficacy on Structural Conditions and Change in Disadvantage**

Panel A. Baseline Model (change variables omitted)  
Panel B. Expanded Model (change variables included)
local sample size to maximize variation across local regressions and increase statistical power (see Fotheringham, Brunsdon, and Charlton 2002), but this means that relatively distant NCs were included in each local regression. As I pointed out earlier, distant NCs are likely to be quite dissimilar to the focal NC; the findings described here can be considered conservative estimates of the true relationship between disadvantage and collective efficacy.

Why Change Matters for Collective Efficacy

Having established that within-neighborhood change (or lack thereof) in concentrated disadvantage accounts for cross-sectional spatial variation in the disadvantage-collective efficacy relationship across NCs, I return to OLS regression models (since the spatial invariance assumption is now supported) to explore the effects of change, the level of disadvantage, and collective efficacy. The expanded OLS model is presented in Table 5.3, Panel B, and the results are fairly similar to the baseline model shown in Panel A. Overall, the expanded model explains almost 61% of the variation in collective efficacy across NCs; this is a statistically significant but substantively small improvement compared to the 57% of the baseline model (F = 11.32, p < .001). However, the strength of the global relationship between disadvantage and collective efficacy is substantially smaller in the expanded model (b = -.312, p < .001) than in the baseline model (b = -.602, p < .001). While the relationship remains the strongest of the structural predictors (β = -.353), it is almost 50% smaller than in the baseline model (β = -.681).
The degree of historical change in neighborhood concentrated disadvantage clearly matters for the prediction of cross-sectional levels of collective efficacy. Compared to the first quartile – which includes NCs experiencing very little or no change in the level of disadvantage between 1970 and 1990 – neighborhoods with more change are expected to have significantly lower collective efficacy in 1995, net of the level of disadvantage in 1990. The association between the (in)stability of disadvantage within the neighborhood and collective efficacy once again appears to follow a roughly linear pattern. In succession, each quartile indicates an accompanying drop in collective efficacy: minor increases (compared to no change) lowers

<table>
<thead>
<tr>
<th>Panel A. Baseline Model</th>
<th>b</th>
<th>(SE)</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.246</td>
<td>***</td>
<td>0.034</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.602</td>
<td>***</td>
<td>0.035</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.174</td>
<td>***</td>
<td>0.040</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.289</td>
<td>***</td>
<td>0.040</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.570</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>685.768</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Panel B. Expanded Model</th>
<th>b</th>
<th>(SE)</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.629</td>
<td>***</td>
<td>0.080</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.312</td>
<td>***</td>
<td>0.060</td>
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<tr>
<td>Immigrant concentration</td>
<td>-0.163</td>
<td>***</td>
<td>0.036</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.344</td>
<td>***</td>
<td>0.040</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minor increase</td>
<td>-0.329</td>
<td>**</td>
<td>0.106</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>-0.661</td>
<td>***</td>
<td>0.130</td>
</tr>
<tr>
<td>Major increase</td>
<td>-1.022</td>
<td>***</td>
<td>0.179</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.606</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>658.746</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N = 342  
* p < .05  ** p < .01  *** p < .001

Table 5.3. OLS Regression of Collective Efficacy on Neighborhood Structural Conditions and Change in Disadvantage
collective efficacy by .329 (p < .01), moderate increases lower collective efficacy by .661 (p < .001), and major increases lower it by -1.022 (p < .001). Supplemental analyses (see the Appendix, Table A.2) using each quartile as the omitted reference group find that all of the group-to-group differences were statistically significant.

This finding clearly demonstrates that in addition to the expected negative cross-sectional association between the level of concentrated disadvantage in an NC and its level of collective efficacy, collective efficacy is also substantially influenced by change, or how (un)stable the level of disadvantage has been within the NC over time, Controlling for concentrated disadvantage in 1990, NCs with more historical change in disadvantage are predicted to have significantly lower levels of collective efficacy. This is in keeping with the “disruption” conceptualization outline earlier and supports Hypothesis (4) by suggesting that neighborhood structural dynamics play an important role in how concentrated disadvantage impacts collective efficacy within the neighborhood at a given point in time.

Unlike the earlier set of analyses predicting neighborhood homicide rates, however, further explorations of the effects of change did not support an “accumulation” model (see the Appendix, Table A.3). While the direct effects of the change dummy variables are statistically significant, interaction terms of the level of disadvantage and within-neighborhood change (concentrated disadvantage*change dummy variable) did not appear to be significantly related to collective efficacy. The association between disadvantage and collective efficacy is not conditioned by how much change a neighborhood has undergone; alternatively, the effects of changes in disadvantage are not moderated by the level of disadvantage in the neighborhood in 1990. Changes in disadvantage over time appear to inhibit the ability of the neighborhood to
exercise collective efficacy, net of the level of disadvantage. Stability, however, does not appear to benefit neighborhoods with low levels of disadvantage by weakening the negative relationship between disadvantage and collective efficacy, nor is stability detrimental to highly disadvantaged neighborhood through strengthening that association.

The Full Model

Through the series of analyses presented throughout the last three chapters, it has become clear that within-neighborhood change matters, for both the prediction of neighborhood homicide rates (in Chapter 4) and now for the prediction of collective efficacy (Chapter 5). What remains is the construction of a model that represents the simultaneous influence of the level of disadvantage and change in disadvantage on homicide rates, as mediated by the level of collective efficacy in the neighborhood. As was just demonstrated, changes in concentrated disadvantage are significantly related to the level of neighborhood collective efficacy. Given such a result, it is logical to expect that collective efficacy in 1995 will mediate the relationship between neighborhood changes in disadvantage between 1970 and 1990 and neighborhood homicide rates in 2001-2005. Previous research has shown that collective efficacy mediates the relationship between the level of disadvantage and crime (Browning, Feinberg, and Dietz 2004; Morenoff, Sampson, and Raudenbush 2001; Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997), and it is a natural extension of the theory to explain the role of change.

If this argument is true, it means that controlling for neighborhood collective efficacy will not only reduce the strength of the relationship between neighborhood structural stability
and homicide rates (as one would expect a mediating variable to do), but also eliminate spatial variation in the cross-sectional association between the level of neighborhood concentrated disadvantage and homicide rates. If the influence of within-neighborhood change is “channeled” through collective efficacy, then accounting for efficacy in the model will act as a proxy for change and account for this spatial variation in the same way controlling for within-neighborhood change did in earlier models, without including the dummy variables of change in the model. My final hypothesis is based on this line of reasoning:

**Hypothesis (5):** Controlling for collective efficacy (but NOT within-neighborhood changes in disadvantage), the cross-sectional relationship between the level of disadvantage in the neighborhood and neighborhood homicide rates will be spatially invariant.

This can be interpreted as another test of the spatial invariance assumption, but specifically tailored to a collective efficacy theory of neighborhood conditions and crime. As before, I use GWR to test this assumption and hypothesis.

The results of this GWR model, which includes measures of structural conditions in 1990, collective efficacy in 1995, and the average homicide rate for 2001-2005, are enlightening. The 5-number parameter summaries of this model, as well as the results of the Monte Carlo test for stationarity and global OLS estimates of the relationships (for comparison) are displayed in Table 5.4. It is immediately apparent that there is a great deal of spatial variation in the cross-sectional association between the level of neighborhood concentrated disadvantage and neighborhood homicide rates, even after accounting for collective efficacy. The relationship ranges between negative – but non-significant – at the minimum (b = -.512) to a significant and positive maximum (b = .747). The Monte Carlo test indicates that this spatial

variation in the relationship is statistically significant ($p < .001$), which contradicts Hypothesis (5). It appears that collective efficacy has mediated the cross-sectional relationship between the level of disadvantage and neighborhood homicide rates to some degree – the size of the global OLS coefficient is smaller here ($b = .366$, $p < .001$) than in the earlier model which did not control for collective efficacy (Chapter 3, Table 3.1; $b = .461$, $p < .001$). However, it did not account for spatial variation in the relationship as I expected it would [Hypothesis (5)].

\[15\]

\[15\] Nor did it account for spatial variation in the relationships between immigrant concentration/residential stability and homicide. Though these are treated as controls in this dissertation, and I did not make any specific predictions about how collective efficacy would account for variation in these relationships, I would have expected that collective efficacy mediated the influence of these sources of structural change in a similar fashion.
Table 5.4. GWR of Log Homicide Rate on Neighborhood Structural Conditions and Collective Efficacy, 5-Number Parameter Summaries

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Lower Quartile</th>
<th>Median</th>
<th>Upper Quartile</th>
<th>Maximum</th>
<th>Sig. Local Effects&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Monte Carlo Test</th>
<th>Global (OLS) Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.137</td>
<td>0.607</td>
<td>0.918</td>
<td>1.064</td>
<td>2.873</td>
<td>(+) Non-stationary ***</td>
<td>0.834</td>
<td></td>
</tr>
<tr>
<td>Collective efficacy</td>
<td>-0.509</td>
<td>-0.161</td>
<td>-0.077</td>
<td>0.014</td>
<td>0.237</td>
<td>(-) Stationary</td>
<td>-0.157</td>
<td></td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.512</td>
<td>0.213</td>
<td>0.340</td>
<td>0.475</td>
<td>0.747</td>
<td>(+) Non-stationary ***</td>
<td>0.366</td>
<td></td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.840</td>
<td>-0.121</td>
<td>-0.041</td>
<td>0.042</td>
<td>1.068</td>
<td>(-/+ Non-stationary ***</td>
<td>-0.035</td>
<td></td>
</tr>
<tr>
<td>Residential stability</td>
<td>-0.411</td>
<td>-0.141</td>
<td>-0.041</td>
<td>0.070</td>
<td>0.510</td>
<td>(-/+ Non-stationary **</td>
<td>0.131</td>
<td></td>
</tr>
</tbody>
</table>

Adjusted R<sup>2</sup> 0.820  
AIC 189.628  
ANOVA F-value 4.865 ***

Local N = 50; Total N = 342

<sup>a</sup> Statistically significant local effects, p < .05

* p < .05  ** p < .01  *** p < .001
The spatial invariance assumption holds for the collective efficacy-homicide relationship, which ranges from significant and negative (as theoretically expected; minimum $b = -0.509$, $p < 0.001$) to non-significant and positive (maximum $b = 0.237$). The Monte Carlo test indicates that the variation across NCs is not statistically significant ($p = 0.27$), and the global estimate of the coefficient ($b = -0.157$, $p < 0.001$) is likely an accurate representation of the relationship for the entire sample. Overall, the GWR model ($AIC = 189.628$) fits the data substantially better than the OLS model ($AIC = 286.309$). The OLS model accounted for the majority of the variation in the homicide rate across NCs (adjusted $R^2 = 0.681$), but the GWR model explained roughly 17% more (adjusted $R^2 = 0.820$). The ANOVA F-test indicates this improvement is statistically significant ($F = 4.865$, $p < 0.001$).

Having tested the spatial invariance assumption in a model that controls for neighborhood collective efficacy, the question remains: what accounts for variation in the cross-sectional relationship between the level of concentrated disadvantage in the neighborhood and its subsequent homicide rate if not collective efficacy? It was logical to assume that because change appeared to be disruptive for collective efficacy, such disruptions would be accounted for with the inclusion of a measure of collective efficacy in the model. As that appears to be false, I re-inserted the dummy measures of change into the model to assess if within-neighborhood change, net of collective efficacy, can still explain spatial variation in the disadvantage-homicide relationship.

Contrary to Hypotheses (5) – that collective efficacy would completely account for the influence of within-neighborhood structural changes in disadvantage – this appears to be the
case. The results of the expanded “full” GWR model\textsuperscript{16} are displayed in Panel B of Table 5.5 (Panel A replicates the results of the baseline full model seen above for comparison). The 5-number parameter summary of the distribution of the disadvantage-homicide relationship across local regressions reveals that controlling for the degree of change in concentrated disadvantage within the neighborhood from 1970 to 1990 substantially reduces the range of the association, net of the levels of collective efficacy, immigrant concentration, and residential stability. The range has shrunk at both ends of the distribution, with a minimum b-coefficient of .028 (compared to -.512 in the baseline model) and a maximum b-coefficient of .563 (compared to .747 earlier). The variation across NCs is no longer statistically significant, as assessed with the Monte Carlo test (at a p < .05 threshold). The global estimate of the relationship between the level of disadvantage and homicide rates (b = .255, p < .001) now satisfies the spatial invariance assumption and can be considered a relatively accurate estimate of the relationship across the entire sample.

\textsuperscript{16} It is expanded in that this model includes the dummy measures for quartiles of change in disadvantage; it is “full” in the sense that it also includes a measure of the theoretical mediating process of collective efficacy.
Table 5.5. GWR of Log Homicide Rate on Neighborhood Structural Conditions, Change in Concentrated Disadvantage (1970-1990), and Collective Efficacy, 5-Number Parameter Summaries

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Lower Quartile</th>
<th>Median</th>
<th>Upper Quartile</th>
<th>Maximum</th>
<th>Sig. Local Effects</th>
<th>Monte Carlo Test</th>
<th>Global (OLS) Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Baseline Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.137</td>
<td>0.607</td>
<td>0.918</td>
<td>1.064</td>
<td>2.873</td>
<td>(+)</td>
<td>Non-stationary</td>
<td>0.834</td>
</tr>
<tr>
<td>Collective efficacy</td>
<td>-0.509</td>
<td>-0.161</td>
<td>-0.077</td>
<td>0.014</td>
<td>0.237</td>
<td>(-)</td>
<td>Stationary</td>
<td>-0.157</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.512</td>
<td>0.213</td>
<td>0.340</td>
<td>0.475</td>
<td>0.747</td>
<td>(+)</td>
<td>Non-stationary</td>
<td>0.366</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.840</td>
<td>-0.121</td>
<td>-0.041</td>
<td>0.042</td>
<td>1.068</td>
<td>(-/++)</td>
<td>Non-stationary</td>
<td>-0.035</td>
</tr>
<tr>
<td>Residential stability</td>
<td>-0.411</td>
<td>-0.141</td>
<td>-0.041</td>
<td>0.070</td>
<td>0.510</td>
<td>(-/++)</td>
<td>Non-stationary</td>
<td>0.131</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.820</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>189.628</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ANOVA F-value</td>
<td>4.865</td>
<td>***</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td><strong>Panel B. Expanded Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.341</td>
<td>0.539</td>
<td>0.626</td>
<td>0.812</td>
<td>1.258</td>
<td>(+)</td>
<td>Non-stationary</td>
<td>0.590</td>
</tr>
<tr>
<td>Collective efficacy</td>
<td>-0.329</td>
<td>-0.186</td>
<td>-0.085</td>
<td>-0.055</td>
<td>0.030</td>
<td>(-)</td>
<td>Stationary</td>
<td>-0.109</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>0.028</td>
<td>0.203</td>
<td>0.272</td>
<td>0.359</td>
<td>0.563</td>
<td>(+)</td>
<td>Stationary</td>
<td>0.255</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.242</td>
<td>-0.114</td>
<td>-0.049</td>
<td>0.008</td>
<td>0.094</td>
<td>(-)</td>
<td>Non-stationary</td>
<td>-0.047</td>
</tr>
<tr>
<td>Residential stability</td>
<td>-0.139</td>
<td>-0.034</td>
<td>0.017</td>
<td>0.050</td>
<td>0.191</td>
<td>(-/++)</td>
<td>Non-stationary</td>
<td>0.088</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minor increase</td>
<td></td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate increase</td>
<td></td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Major increase</td>
<td></td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.784</td>
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<td>AIC</td>
<td>202.624</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>ANOVA F-value</td>
<td>4.266</td>
<td>***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Local N = 50 (baseline model), 126 (expanded model); Total N = 342

* p < .05  ** p < .01  *** p < .001

Statistically significant local effects, p < .05
The inclusion of the dummy measures of within-neighborhood change also had a notable effect on the distribution of the collective efficacy-homicide rate relationship across NCs. Though the spatial variation in this relationship was not statistically significant in the baseline model, the distribution of the relationship across NCs was relatively wide. Controlling for within-neighborhood changes in disadvantage had the effect of narrowing this distribution at both ends, from a minimum value of -.509 to -.329 in the expanded model and a maximum value of .237 in the baseline model to .030 in the expanded model. In both models the relationship was only statistically significant in a negative direction, though there are a number of NCs/local regressions where the relationship is non-significant in either direction.

Turning now to the specific effects of within-neighborhood change, which remain even after accounting for neighborhood collective efficacy, I explored the relationship between change and homicide rates using OLS regression as I did in Chapter 4 (now that the spatial invariance assumption is met for the disadvantage-homicide relationship). Both “disruption” and “accumulation” interpretations of the relationship between changes in disadvantage and neighborhood homicide rates were supported in Chapter 4. Though the expanded model in Chapter 4 was “incomplete” and did not control for collective efficacy, the results produced are similar. Panel A of Table 5.6 displays the results of the expanded model (paralleling the expanded model in Chapter 4), which now includes not only the dummy measures of within-neighborhood change, but the measure of collective efficacy as well. For the models described in Panel B, I added the interaction terms for the level of disadvantage and the degree of neighborhood change.
Table 5.6. OLS Regression of Log Homicide Rate on Neighborhood Structural Conditions, Change in Disadvantage, Collective Efficacy, and Disadvantage Level*Change Interaction

<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th>(SE)</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. No Interaction Terms</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.590</td>
<td>**</td>
<td>0.048</td>
</tr>
<tr>
<td>Collective efficacy</td>
<td>-0.109</td>
<td>**</td>
<td>0.030</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>0.255</td>
<td>***</td>
<td>0.035</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.047</td>
<td>**</td>
<td>0.020</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.088</td>
<td>***</td>
<td>0.024</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minor increase</td>
<td>0.257</td>
<td>***</td>
<td>0.060</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>0.426</td>
<td>***</td>
<td>0.075</td>
</tr>
<tr>
<td>Major increase</td>
<td>0.490</td>
<td>***</td>
<td>0.104</td>
</tr>
<tr>
<td><strong>Adjusted R²</strong></td>
<td>0.709</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>AIC</strong></td>
<td>256.693</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| **Panel B. Interaction Terms** |       |       |       |
| Constant               | 0.851 | ***  | 0.108 |
| Collective efficacy    | -0.086 | **   | 0.029 |
| Concentrated disadvantage | 0.638 | ***  | 0.137 |
| Immigrant concentration | -0.042 | *    | 0.020 |
| Residential stability  | 0.104 | ***  | 0.024 |
| Change in Disadvantage |       |       |       |
| No change (omitted)    |   -   |   -   |   -   |
| Minor increase         | 0.048 |       | 0.113 |
| Moderate increase      | 0.085 |       | 0.124 |
| Major increase         | 0.478 | ***  | 0.143 |
| **Disadvantage Level*Change** |       |       |       |
| Disadvantage*No change (omitted) |   -   |   -   |   -   |
| Disadvantage*Minor increase | -0.100 | 0.157 | -0.035 |
| Disadvantage*Moderate increase | -0.271 | 0.147 | -0.185 |
| Disadvantage*Major increase | -0.511 | ***  | 0.141 |
| **Adjusted R²**        | 0.732 |       |       |
| **AIC**                | 232.048 |      |       |

N = 342

* p < .05    ** p < .01    *** p < .001
I discovered earlier that compared to relative stability in neighborhood disadvantage, successive degrees of increasing disadvantage over time – minor, moderate, and major – had a roughly linear relationship with homicide rates. More change was significantly related to higher homicide rates, net of an NC’s level of disadvantage in 1990, for all group-to-group comparisons except the moderate-major pair. The same pattern emerges in the expanded full model (Panel A). Net of the level of concentrated disadvantage AND collective efficacy (as well as immigrant concentration and residential stability), groups with more change are predicted to have higher rates of homicide than groups with less. Compared to NCs which were relatively stable over time, NCs with minor increases (b = .257, p < .001), moderate increases (b = .426, p < .001), and major increases (b = .490, p < .001) are all expected to have significantly higher homicide rates.

As before, analyses using each group as the omitted reference category show that the differences between groups are all significant (p < .05) with the exception of the moderate- and major-increase groups. This finding supports a “disruption” interpretation of change and neighborhood homicide, now net of collective efficacy. The relationship between the level of concentrated disadvantage and homicide is still statistically significant (b = .255, p < .001), as is the collective efficacy relationship (b = -.109, p < .001). Taken together, these latter two results (as I briefly mentioned above) are supportive of the collective efficacy model and in keeping with prior research. Collective efficacy appears to mediate a substantial portion of the disadvantage-homicide relationship found in the “incomplete” model (b = .366, p < .001), but a significant direct relationship remains even after controlling for collective efficacy.

There is also limited support for the “accumulation” model of change and homicide rates, now net of collective efficacy. The model in Panel B adds interactions terms of the level
of disadvantage and the dummy variables representing neighborhood changes in concentrated disadvantage, omitting the first group [disadvantage*quartile (1)] as the reference category. It again appears that the relationship between the level of neighborhood disadvantage in 1990 and homicide rates in 2001-2005 is conditioned by within-neighborhood change. This relationship is weaker for NCs which have experienced change, relatively to NCs which have been relatively stable. However, this difference is not significant for NCs which saw minor increases ($b = -.100, p = .526$) and only marginally significant for NCs in the moderate change category ($b = -.271, p < .1$).

The relationship is significantly smaller for NCs that experienced major increases than in stable NCs ($b = -.511, p < .001$). The positive direct relationship between concentrated disadvantage and homicide rates ($b = .638, p < .001$), net of collective efficacy, is substantially and significantly weaker in the neighborhoods which have undergone the greatest changes over time. This is consistent with an “accumulation” interpretation of the association, though only in part. High levels of disadvantage are particularly harmful (in terms of higher rates of homicide) when the neighborhood is structurally stable; inversely, low levels of advantage are especially beneficial. The level of disadvantage in 1990 is still significantly predictive of between-neighborhood differences in homicide, but the relationship is stronger in the most stable neighborhoods.

It is also possible that a similar cumulative effect occurs with collective efficacy and homicide rates. A final model was generated to explore this possibility, this time including an interaction term for collective efficacy and the degree of change in concentrated disadvantage (collective efficacy*quartile). The first group was once again treated as the omitted reference
category. The results of this model, shown in Table 5.7, were consistent with the prior findings.

The level of collective efficacy is still predictive of significant between-neighborhood differences in homicide (b = -0.219, p < .001); net of concentrated disadvantage and within-neighborhood change, NCs with more collective efficacy will have significantly lower rates of homicide.

However, this negative relationship fluctuates when accompanied by within-neighborhood change, though not in the regular manner evidenced by the disadvantage*change interaction model.

Table 5.7. OLS Regression of Log Homicide Rate on Neighborhood Structural Conditions, Change in Disadvantage, Collective Efficacy, and Collective Efficacy*Change Interaction

<table>
<thead>
<tr>
<th>term</th>
<th>b</th>
<th>(SE)</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.695</td>
<td>***</td>
<td>0.062</td>
</tr>
<tr>
<td>Collective efficacy</td>
<td>-0.219</td>
<td>***</td>
<td>-0.338</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>0.267</td>
<td>***</td>
<td>0.469</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.048</td>
<td></td>
<td>-0.088</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.099</td>
<td>***</td>
<td>0.152</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minor increase</td>
<td>0.158</td>
<td>*</td>
<td>0.106</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>0.308</td>
<td>***</td>
<td>0.208</td>
</tr>
<tr>
<td>Major increase</td>
<td>0.454</td>
<td>***</td>
<td>0.303</td>
</tr>
<tr>
<td>Collective Efficacy*Change</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Efficacy*No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Efficacy*Minor increase</td>
<td>0.115</td>
<td>0.064</td>
<td>0.078</td>
</tr>
<tr>
<td>Efficacy*Moderate increase</td>
<td>0.105</td>
<td>0.066</td>
<td>0.066</td>
</tr>
<tr>
<td>Efficacy*Major increase</td>
<td>0.228</td>
<td>**</td>
<td>0.173</td>
</tr>
</tbody>
</table>

Adjusted $R^2$ 0.716
AIC 252.395

N = 342  * p < .05  ** p < .01  *** p < .001

The difference in the association across stable NCs and those experiencing minor increases in disadvantage is moderately significant (b = .115, p < .1) and non-significant
between stable NCs and those with moderate increases (b = .105, p = .113). The relationship is significantly weaker in NCs that have seen major increases in disadvantage (b = .228, p < .05) compared to stable NCs; in fact, the direct negative relationship between collective efficacy and homicide rates is completely eliminated in this group of neighborhoods, as the coefficient of the interaction term is larger (in an absolute sense) than the coefficient for the direct relationship. Like the concentrated disadvantage-homicide relationship, stability appears to be particularly beneficial for neighborhoods with high collective efficacy through strengthening the association between higher collective efficacy and lower homicide. Inversely, stability is especially detrimental for neighborhoods with low collective efficacy by strengthening the relationship between low efficacy and high homicide rates.17

Discussion and Conclusions

Having laid the foundation in Chapters 3 and 4, in the current chapter I have attempted to construct a relatively complete model of the relationships between within-neighborhood dynamics of change, the level of structural conditions at a given point in time, and the social process of collective efficacy through which they are theoretically expected to influence neighborhood homicide rates. Using a combination of OLS and geographically-weighted regression, I found that like the cross-sectional relationship between the level of neighborhood concentrated disadvantage and homicide rates, the association between disadvantage and collective efficacy also substantially and significantly varied across spatial units. This result

17 I also estimated a model which included interaction terms for both (disadvantage level*disadvantage change) and (collective efficacy*disadvantage change). The standard errors of the estimates were greatly inflated, unsurprising given the multicollinearity among the predictor variables included in the model, which suggests the estimates produced by such a model are unreliable. An ANOVA comparison of model fit indicated there was no significant improvement compared to either of the previous models that included only a single interaction term.
failed to support Hypothesis (3) – *The relationship between concentrated disadvantage and collective efficacy in neighborhood clusters will be spatially invariant across the sample of Chicago NCs* – and contradicts the spatial invariance assumption implicit in aspatial models.

The initial conclusion of a spatially-variant relationship has important implications for future theoretical and empirical work. First, simply from an empirical standpoint, aspatial models that do not account for spatial variation in the relationships between structural conditions and collective efficacy are likely to be misspecified. The spatial organization of neighborhoods clearly matters for the estimation of relationships between structural conditions and outcomes like homicide rates. Prior work has produced evidence of significant spatial effects (both spatial lag and spatial error) within typical macro-structural models of crime (Baller, Anselin, Messner, Deane, and Hawkins 2001; Griffiths and Chavez 2004; Light and Harris 2012; Messner, Anselin, Baller, Hawkins, Deane, and Tolnay 1999; Tita and Cohen 2004).

Most importantly for this dissertation, recent work that directly tests the spatial invariance assumption generally finds it unsupported (Cahill and Mulligan 2007; Graif and Sampson 2009; Light and Harris 2012). My findings add to the growing evidence that aspatial models do not produce accurate estimates of structural-crime relationships for a large proportion of macro-level units. The “global” coefficients produced by typical OLS models (and by extension, logistic and similar aspatial methods) are “average” estimates of statistical associations across neighborhoods (or counties, census tracts, etc.). While the global coefficient is likely to be a relatively accurate estimate of a given association for many units in the sample, it is just as likely to be inaccurate for many localities. This model misspecification is potentially a substantial source of statistical error and given recent advances in statistical methods and
computing technology (e.g. GWR 3.0 or GWR modeling capabilities in ArcGIS), researchers in this area should do what they can to eliminate this inaccuracy (Anselin 1994; Fotheringham, Brunsdon, and Charlton 2002; Matthews, Yang, Hayslett, and Ruback 2010).

Secondly, as I proposed earlier in Chapter 4, theories of neighborhood effects (particularly those that focus on disadvantage and crime) should be able to account for significantly different relationships between key predictors and outcomes across spatial units. The spatial invariance assumption is a key component of most structural theories of crime – and the statistical models used to test them – but a growing body of work finds this assumption is likely erroneous (Cahill and Mulligan 2007; Deller and Deller 2012; Graif and Sampson 2009; Light and Harris 2012). The same implication applies specifically to theories of collective efficacy, as one of the most widely-researched perspectives on social mechanisms linking structural conditions to crime. The relationship between concentrated disadvantage and collective efficacy is generally assumed to work in a substantively similar fashion across neighborhoods, and through this mediating relationship, influence neighborhood crime rates. However, the findings in this chapter do not support this assumption. While there is clearly a direct relationship between disadvantage and neighborhood collective efficacy, it is not universally negative and significant association as theorized (Morenoff, Sampson, and Raudenbush 2001; Sampson, Raudenbush, and Earls 1997) but varies between a null relationship and an exceptionally strong negative relationship. Future theorizing on the structural antecedents of collective efficacy – particularly concentrated disadvantage – should work to explain why these associations vary across neighborhoods.
Building upon my earlier analyses, I proffered one theoretical explanation for the spatial variation in the cross-sectional association of concentrated disadvantage and collective efficacy: within-neighborhood structural stability and change. I argued that while differences in the level of disadvantage at a given time point would predict differences in collective efficacy across neighborhoods as expected (Browning 2002; Morenoff, Sampson, and Raudenbush 2001; Sampson 2012; Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997), within-neighborhood structural stability in disadvantage over time would also matter. Change was likely to be a disruptive influence on the ability of a neighborhood to build and exercise collective efficacy, regardless of the level of disadvantage or advantage. Within-neighborhood stability was a crucial component of the earliest theories on social disorganization and the social processes assumed to link structural conditions with negative outcomes like juvenile delinquency and crime (Shaw and McKay 1969; Whyte 1943). Contemporary research has likewise suggested that superficially positive changes in neighborhood disadvantage can be detrimental to the functioning of the neighborhood (Kreager, Lyons, and Hays 2011; Taylor and Covington 1988; Thompson, Bucerius, and Luguya forthcoming; van Wilsem, Wittebrood, and de Graaf 2006), and that both increases and decreases in disadvantage can be harmful (Bursik 1986).

As far as I am aware, however, there have been no direct tests of the role of within-neighborhood structural stability on the social processes theorized to mediate the structure-crime relationship. As one of the most widely-researched perspectives on neighborhood effects and crime, collective efficacy is a prime candidate for such a test. Theoretically, change would not be directly linked to higher crime rates (as modeled in Chapter 4), but operate through the
mediating social process of collective efficacy. In this way, changes in concentrated disadvantage would disrupt the ability of the neighborhood to establish social cohesion and mutual trust and exercise informal social control, and thus produce higher-than-predicted homicide rates net of the level of disadvantage. My results supported Hypothesis (4) -

*Controlling for neighborhood structural stability (or the degree of structural change) will account for spatial variation in the cross-sectional association of concentrated disadvantage and neighborhood collective efficacy.* The spatial variation in the association evident in the baseline model became non-significant once I accounted for within-neighborhood changes in disadvantage between 1970 and 1990. By analyzing the first “stage” of this theoretical model, I found that neighborhood instability had a direct negative relationship with collective efficacy; higher levels of change predicted lower levels of collective efficacy after controlling for the level of disadvantage in the neighborhood.

However, while changes in disadvantage had a direct negative association with collective efficacy (i.e. disruption), the role of (in)stability was *not* conditioned by the level of disadvantage of the neighborhood. The negative relationship between disadvantage and collective efficacy – or inversely, the positive relationship between advantage and collective efficacy – was not significantly stronger in stable neighborhoods. This suggests that the detrimental effects of disadvantage – or the benefits of affluence – on collective efficacy do not “accumulate” when the level of concentrated disadvantage is relatively stable. Taken together, these last two results suggest that within-neighborhood structural change has a significantly disruptive effect on neighborhood collective efficacy, independent of its structural conditions in
cross-section, and that structurally stable conditions do not contribute to the accumulation of collective efficacy (or a lack of it).

Once I found that change mattered for the prediction of collective efficacy, it was theoretically appropriate and logical to posit Hypothesis (5) – *Controlling for collective efficacy (but NOT within-neighborhood changes in disadvantage), the cross-sectional relationship between the level of disadvantage in the neighborhood and neighborhood homicide rates will be spatially invariant.* If within-neighborhood changes in disadvantage were related to neighborhood homicide rates through the change-collective efficacy relationship, then controlling for collective efficacy would eliminate spatial variation in the disadvantage-homicide relationship found in Chapter 3. The results, however, did not support the hypothesis. Including a measure of collective efficacy in the “full” model did not remove substantial and significant levels of spatial variation in the association between the neighborhood level of concentrated disadvantage and subsequent homicide rate. While the direct relationship between disadvantage and homicide was mediated to a degree by collective efficacy, the distribution of the relationship across the full sample of NCs was relatively wide, indicating the relationship was not stationary across neighborhoods.

Instead, within-neighborhood changes in disadvantage continued to play an important part in the cross-sectional relationship. Even after accounting for the level of neighborhood collective efficacy, it was only after the measures of change were included in the expanded full model that the cross-sectional disadvantage-homicide relationship became spatially invariant. Not only did change continue to explain spatial variation in the cross-sectional association, but it remained important for the same two reasons postulated in Chapter 4: disruption and
accumulation.\textsuperscript{18} Net of the level of concentrated disadvantage, immigrant concentration, and residential stability in 1990, and collective efficacy in 1995, structurally stable neighborhoods were predicted to have significantly lower homicide rates than neighborhoods undergoing change (and in a relatively linear fashion). Furthermore, the positive cross-sectional relationship between disadvantage and homicide was significantly weaker in neighborhoods experiencing the most change between 1970 and 1990, relatively to neighborhoods which had experience no change, suggesting that the harmful effects of disadvantage (or benefits of advantage) accumulate when structural conditions are stable. A similar interaction was found between collective efficacy and change; the negative relationship between collective efficacy and homicide rates was significantly weaker in neighborhoods which had changed the most, relative to stable neighborhoods.

Ultimately, both the level and stability of concentrated disadvantage appear to matter for neighborhood homicide rates, though not entirely for the reason I expected them to. It is well-established that the level of disadvantage is significantly related to differences in crime across neighborhoods, and tests of the full theoretical model have found that the relationship is mediated in part by collective efficacy (Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997). However, while within-neighborhood (in)stability has a significant relationship with collective efficacy, it does not appear as if collective efficacy fully mediates the relationship between neighborhood change and crime rates. My findings clearly suggest that future theoretical and empirical work on neighborhood structural conditions and crime

\textsuperscript{18} These terms are possibly inappropriate now, as they theoretically refer to the lower levels of collective efficacy produced by change at any level of disadvantage (disruption) and increases in the strength of the negative relationship between disadvantage and collective efficacy under stable structural conditions (accumulation).
incorporate (or rather, re-incorporate) concepts and measures of within-neighborhood change into models of these relationships. Why this relationship matters – for collective efficacy, crime outcomes, or both – remains an open question. The results of these analyses are suggestive, but I must conclude that the full expanded model described here cannot entirely explain the relationships between historical change, the level of concentrated disadvantage, collective efficacy, and homicide rates at the neighborhood level. After summarizing the general findings of the dissertation and drawing some conclusions relevant to studies of neighborhood effects and crime, as well as outlining some shortcomings of the current research, I will offer some speculations and suggestions for future research in Chapter 6.
CHAPTER 6. WITHIN-NEIGHBORHOOD DYNAMICS, DISADVANTAGE, COLLECTIVE EFFICACY, AND HOMICIDE: IN SUMMARY

Introduction

The quote by McKenzie which opened this dissertation referred to the spatial and temporal dynamism of neighborhoods, a conceptual orientation that grounded the empirical analyses and theoretical discussions that followed. While the earliest scholars of the Chicago School largely focused on the then-current growth of American cities and the spread of urbanism (Park 1967; Park, Burgess, and McKenzie 1967; Thomas and Znaniecki 1996; Wirth 1938), their findings laid the foundation for an enormous body of work on macro-level relationships between structural conditions, social processes, and a host of outcomes including crime and juvenile delinquency (Bursik and Grasmick 1993a; Bursik and Grasmick 1993b; Cloward and Ohlin 1960; Cohen 1955; Lowenkamp, Cullen, and Pratt 2003; Messner and Tardiff 1985; Miller 1958; Osgood and Chambers 2000; Park 1967; Sampson 2012; Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997; Shaw and McKay 1969; Veysey and Messner 1999; Wright, Caspi, Moffitt, Miech, and Silva 1999).

Following several decades of neglect, what is now generally referred to as “neighborhood effects” research re-emerged as an important area of academic inquiry in the last quarter of the 20th century. In contemporary research, collective efficacy – an intellectual heir to the social disorganization theories of Shaw and McKay (1969) – has become one of the dominant perspectives of neighborhood structural conditions and crime, spurred by the work of Robert Sampson and his colleagues (Graif and Sampson 2009; Morenoff, Sampson, and Raudenbush 2001; Sampson 1991; Sampson 2000; Sampson 2002a; Sampson 2002b; Sampson...
While earlier empirical work suffered from “black box” problems, where the social process(es) linking structural conditions to crime outcomes at the neighborhood level were largely inferred, and was vulnerable to criticisms of tautological logic in the linkage of “disorganization” and crime (or social disorder), advances in measurement, data collection, and statistical modeling have gone far in addressing these shortcomings. One area which has suffered, however, is the attention given to the intrinsically dynamic nature of neighborhoods.

As I discussed in Chapter 1, one of the key insights of the original Chicago School was to view the growth of the city as the outcome of a number of social processes – which are inherently temporal – occurring at multiple levels simultaneously, like industrialization and immigration. Neighborhoods are embedded in a complex system of economic and social forces, which both produced neighborhood structural conditions and were a product of them. This system could produce both structural changes and structural stability; for example, while this system produced neighborhoods with stable high levels of poverty, the impoverished condition of these same neighborhoods led them to experience a great deal of instability in the form of residential turnover (Shaw and McKay 1969). In my opinion, contemporary work in this area has largely ignored this intrinsic dynamism, and the importance of within-neighborhood change for crime and related outcomes. There are a number of possible reasons for such neglect, both practical and conceptual: a lack of quality longitudinal data at the macro-level, the influence of research trends focused on the measurement of “deprivation,” the search for parsimonious models to explain between-neighborhood differences in cross-section, and perhaps most
importantly, a lack of theorizing on the role of within-neighborhood change in addition to the role of the level of structural conditions.

It is not my goal here to broadly criticize prior work. Rather, I hope through the analyses presented here to suggest that within-neighborhood change plays a critical role in outcomes of interest to researchers (like neighborhood homicide), and that future work – both theoretical and empirical – would profit from addressing this understudied dimension of neighborhood effects. Neighborhoods and the structural conditions within them do not exist in a temporal vacuum; that is, conditions like the level of concentrated disadvantage do not simply appear in the neighborhood and go on to impact social processes like collective efficacy and through them crime. Neighborhood structural conditions are part of the history of the neighborhood, and as such can be framed in developmental or life-course terms. Originally applied to the explanation of individual-level behavior and outcomes (Giordano, Cernkovich, and Holland 2003; Laub, Nagin, and Sampson 1998; Moffitt and Caspi 2001; Sampson and Laub 1993; Sampson and Laub 2005; Uggen 2000; Warr 1998), it has been recently suggested that a similar perspective could be fruitfully applied to macro-level units (Sampson 2012; Sampson 2013). The ‘present’ of a neighborhood could be – and likely is – as dependent on its ‘past’ as it is for individuals. Here, I have treated neighborhood “history” as a macro-analogue to individual “biography.”

Starting with work on neighborhood structural conditions (specifically concentrated disadvantage) and crime, the social process of collective efficacy which links them, spatial relationships across macro-level units, and recent theorizing on the “life course of place” (Sampson 2013, p. 12), in the preceding chapters I constructed a model of neighborhood
structural conditions and homicide that incorporates both geographical and temporal effects. This produces a relatively more complex model of “neighborhood effects” – specifically of concentrated disadvantage – on crime which I believe is more accurate, theoretically and empirically, than current models, as it addresses the inherent dynamism of neighborhoods. While these analyses suffer from several shortcomings (which will be addressed below), I believe none are sufficient to negate my key findings, which I will now briefly discuss. They can be summarized quite simply: change matters.

**Concentrated Disadvantage, Homicide, and Spatial Invariance**

Using data on structural conditions from the Neighborhood Change Database (Geolytics), which standardized the geographical boundaries of the neighborhood cluster (NC) units of analyses across three decennial censuses (1970, ’80, and ’90), and geocoded data on homicides in Chicago between 2001-2005, I began my analyses by testing a key assumption of non-spatial models of neighborhood conditions and crime. The spatial invariance assumption is critical to the construction and interpretation of aspatial models, because it implies that the relationships between structural conditions and the outcome of interest are substantively identical across neighborhoods (or similar macro-level units). “Global” modeling strategies like OLS regression estimate a single coefficient representing the association between a given structural predictor and the dependent variable. This coefficient can be viewed as the average relationship across the entire sample; however, like the mean value of a single variable, the estimate of the average relationship can be influenced by “outliers” as well as obscure substantial and statistically significant levels of variation around the average relationship.
Recent work which has directly tested the spatial invariance assumption across samples of counties (Light and Harris 2012) and census tracts (Graif and Sampson 2009) finds that the relationships between structural conditions like disadvantage or immigrant concentration and crime outcomes are not invariant across units. Instead, the associations are substantially and significantly larger in some places and weaker in others. Employing factor measures of structural conditions in the neighborhood in 1990, my parallel test of spatial invariance in the concentrated disadvantage-homicide relationship at the neighborhood (cluster) level produced similar findings. Employing geographically-weighted regression (GWR) models and controlling for levels of neighborhood immigrant concentration and residential stability, “local” estimates of the association between the level of concentrated disadvantage in 1990 and the average neighborhood homicide rate between 2001 and 2005 varied substantially. A Monte Carlo test of the spatial variation in the relationship revealed it was statistically significant (“non-stationary”), suggesting the spatial invariance assumption does not hold for typical aspatial models of structural conditions and crime (or at least homicide).

Where the local relationship between disadvantage and homicide was statistically significant, it was always in the expected positive direction. However, a number of neighborhoods evidenced an extremely strong positive association, while in others the relationship was not significant at all. Similar results were obtained for the cross-sectional relationships of immigrant concentration and residential stability with homicide rates. These latter two results are beyond the scope of this dissertation to explore, but offer a potential topic for future research. The finding of significant spatial variation in these relationships is not only important empirically in terms of accurate model specification, but also for the theories
that attempt to explain the links between structural conditions and crime. Why does the relationship vary between neighborhoods?

**Accounting for Within-Neighborhood Changes in Disadvantage**

One possible explanation for the spatially-variant relationship was historical changes in concentrated disadvantage within neighborhoods. As I posited earlier, within-neighborhood structural (in)stability is a potentially important dimensions for explanations of neighborhood conditions and crime outcomes. This is not a new suggestion (Bursik 1986; Bursik and Grasmick 1992; Shaw and McKay 1969), and it has been argued that even highly disadvantaged areas can be less disorganized than one might predict based on the level of disadvantage alone. Structural stability, in the face of high disadvantage, may promote neighborhood reorganization, though qualitatively different than a middle-class normative standard (Whyte 1943). Social disorganization was originally theorized to be only one part of a larger process of neighborhood disruption and change eventually leading back to social (re)organization, once neighborhoods stabilized (Shaw and McKay 1969). However, this insight has been largely forgotten or ignored in the literature in favor of models which focus on between-neighborhood differences in crime in cross-section (though see Sampson 2012).

Based on this argument, I constructed measures of within-neighborhood changes in disadvantage between 1970 and 1990. Because the factor measure of concentrated disadvantage was standardized across all three time points, it was possible to measure the amount of real change in disadvantage over time (rather than the measure capture artificial change produced by shifts in the standard distribution across census years; see Chapter 2). I
examined the distribution of change over time and found that neighborhood clusters in Chicago were characterized by either relative stability or several degrees of increases in concentrated disadvantage. Unfortunately, the realities of change in Chicago diverged from an ideal-type model of change (which included decreases in disadvantage). This is a potential flaw in the current work, as it is impossible to compare neighborhoods which were similarly disadvantaged in 1990 but had reached that level of disadvantage through substantially different historical pathways. Future research should attempt to rectify this issue and employ an analytic sample which can capture the full range of within-neighborhood change over time. However, given the exploratory nature of this dissertation, I chose to focus on a city and time period that has been extensively studied (Griffiths and Chavez 2004; Morenoff and Sampson 1997; Papachristos, Smith, Scherer, and Fugiero 2011; Pattillo 1998; Sampson 2012; Sampson and Raudenbush 2004; Shaw and McKay 1969; Wilson 1996; Wilson and Taub 2006). There was enough variation across neighborhoods to warrant further study, and in the interest of constructing a parsimonious measure, I chose to construct four dummy variables to represent the degree of change in disadvantage within a neighborhood: none/stable, minor increases, moderate increases, and major increases.

In Chapter 4, the dummy measures of increases in disadvantage were added to the baseline GWR model constructed in Chapter 3. In support of my argument, accounting for within-neighborhood change eliminated significant variation in the cross-sectional relationship between the level of disadvantage and neighborhood homicide rates. Using OLS regression models – now that the spatial invariance assumption was supported – the expanded model of structural conditions and homicide rates indicated that compared to relatively stable
neighborhoods, change within the neighborhood predicted significantly higher homicide rates, net of the level of concentrated disadvantage, and in a linear fashion. This suggested that change had a “disruptive” influence on neighborhoods; regardless of the level of disadvantage in 1990, historically unstable neighborhoods experienced more homicide.

Nor did change appear to only exert a directly disruptive effect. A model which added an interaction term for the level and change in disadvantage intimated that the positive cross-sectional relationship between the level of disadvantage and subsequent homicide rates was conditioned by the degree of change experienced previously. Compared to structurally stable neighborhoods, this positive association was significantly weaker in neighborhoods which had experienced a major increase in disadvantage between 1970 and 1990. This is suggestive of an “accumulation” process, where the detrimental effects of disadvantage grow stronger when disadvantage is stable; inversely, the benefits of advantage/affluence would also accumulate. While this conclusion is tentative, given the lack of a full range of possible level-change combinations in my data, future work should attempt to replicate this finding with a sample of neighborhoods that can capture the full set of ideal-type patterns.

Changes in Disadvantage, Collective Efficacy, and Neighborhood Homicide

The influence of within-neighborhood structural changes is not exerted directly on neighborhood homicide and crime, however. As argued by Sampson and others (Browning 2009; Browning, Feinberg, and Dietz 2004; Morenoff, Sampson, and Raudenbush 2001; Sampson, Raudenbush, and Earls 1997), the relationship between structural conditions and homicide (as well as other outcomes) is mediated through the social process of collective
efficacy. Collective efficacy is currently one of the dominant theoretical perspectives in the neighborhood effects literature. As a social process, it combines the informal social control of the classic social disorganization perspective (Kornhauser 1978; Shaw and McKay 1969) with more recent findings on the role of social ties in producing community attachment, social cohesion and mutual trust, and the channeling of social capital within the neighborhood (Bursik and Grasmick 1993b; Granovetter 1973; Kasarda and Janowitz 1974; Sampson 1988; Sampson, Raudenbush, and Earls 1997). Having established that within-neighborhood change plays a role in neighborhood homicide rates, I expected that this role was a function of the relationship between change and collective efficacy. Like the relationship between the level of disadvantage and crime, the association of structural change and homicide would be mediated by collective efficacy.

I began Chapter 5 by confirming with GWR models that the relationship between concentrated disadvantage in 1990 and neighborhood collective efficacy in 1995 was spatially variant across NCs. If collective efficacy was to mediate the change-homicide relationship, the relationship between the level of disadvantage and collective efficacy in the neighborhood had to follow the same pattern found in the earlier analyses. The negative association between disadvantage and collective efficacy was substantially and significantly weaker (or stronger) in some neighborhoods than others, and in several NCs the local estimate of the association was not significant at all, net of immigrant concentration and residential stability. Mirroring the analyses in Chapter 4, I moved to an expanded model of the relationship which included the dummy measures of within-neighborhood changes in disadvantage. As before, the spatial variation in the cross-sectional relationship between disadvantage and collective efficacy was
reduced to non-significance, suggesting that within-neighborhood change explained differences in the local estimates of the relationship.

Further analysis revealed that compared to structurally stable neighborhoods, increases in disadvantage over time predicted significantly lower levels of collective efficacy, net of the level of disadvantage in 1990. This is again suggestive of “disruption”; regardless of a neighborhood’s level of disadvantage at a particular point in time, structural instability lowers collective efficacy, and does so in a fairly linear fashion (given the regular increases in the absolute size of the coefficient across dummy categories of change). While the same caveat applies to this set of analyses as before – the measure of change captures only increases in disadvantage or relative stability – the findings are theoretically consistent and logical. Unlike the prior analyses, however, an “accumulation” model of neighborhood change and collective efficacy was not supported. The association between disadvantage in 1990 and collective efficacy in 1995 was not conditioned by the degree of within-neighborhood change from 1970 to 1990; none of the interaction terms for disadvantage*change were statistically significant when added to the expanded model. Having established that the theoretically-necessary relationship(s) between change and collective efficacy were present, I moved on to the construction of a “full” model of neighborhood conditions and homicide.

The Full Model

The analyses in Chapters 3 and 4 of concentrated disadvantage and homicide, and the parallel models in Chapter 5 of disadvantage and collective efficacy, suggest that the relationship between the level of disadvantage and homicide or collective efficacy operates in a
substantively and significantly different way across neighborhoods. Further, it appears that within-neighborhood changes in disadvantage can explain this spatial variation, with change having a disruptive effect on the neighborhood (and contributing to an accumulation of unfavorable outcomes, though only for the homicide rate). Based on these findings, I tested a full model of neighborhood structural conditions, collective efficacy, and homicide rates. I hypothesized that the effects of within-neighborhood change would be completely mediated by collective efficacy, and as such, controlling for collective efficacy would explain spatial variation in the relationship between concentrated disadvantage in 1990 and neighborhood homicide in 2001-2005, *without* including a measure of change in the statistical model.

This, however, was not the case. Contrary to expectations, collective efficacy did not account for spatial variation in the cross-sectional disadvantage-homicide relationship. Geographically-weighted regression of the baseline full model showed that the relationship still significantly varied across NCs, even after accounting for collective efficacy. Given that my hypothesis was refuted, I added the dummy measures of change back to the model to explore if it once again mattered. Change continued to have an independent association with homicide rates after controlling for the levels of structural conditions and collective efficacy in the neighborhood. Neighborhoods which had experienced a higher degree of change were predicted to have significantly higher rates of homicide than neighborhoods that had seen less, or no, change in disadvantage between 1970 and 1990. This again supports the possibility that structural changes in the neighborhood are both disruptive and contribute to an accumulation of benefits/harm, but as these relationship emerge even after controlling for collective efficacy,
it is unclear what change is actually disruptive for (or prevents from accumulating), in terms of an alternative social process to collective efficacy.

One possible explanation of this finding is offered by recent work on the “negotiated coexistence” model by Browning and his colleagues (Browning 2009; Browning, Feinberg, and Dietz 2004). In the negotiated coexistence model, collective efficacy and local social ties/networks exercise independent mediating effects between neighborhood structural conditions and crime. While collective efficacy is negative related to crime, as expected, social ties in the neighborhood appear to counteract this association. In other words, while high levels of collective efficacy are beneficial for neighborhood crime rates, these benefits are diminished in the presence of strong social networks. This is consistent with qualitative work which has argued for the embeddedness of criminal individuals within neighborhoods (as sons/daughters, fathers/mothers, friends, neighbors, etc.) and shown how the informal social control capacity of the neighborhood (e.g. collective efficacy) over these individuals can be limited (Pattillo-Mc Coy 1999; Pattillo 1998).

Accounting for an alternative social process that, like collective efficacy, is time-dependent and affected by within-neighborhood change, offers a potentially fruitful direction for future research in this vein. The building of social ties/networks and the social capital that accompanies strong ties (in the form of "reciprocated exchange"; see Browning 2009) or weak ones (particularly ties that cross neighborhoods or organizational levels; see Bursik and Grasmick 1993b) is one potential mechanisms through which change can operate. Similarly, the establishment, transmission, and operation of subcultural norms that are conducive to criminal behavior and violence are inherently dependent on neighborhood structural stability in some
form. Long-term disadvantage may lead to the creation of delinquent, violent, or “cynical” subcultures (Anderson 1999; Cohen 1955; Matza and Sykes 1961; Miller 1958; Sampson and Bartusch 1998; Tittle 1989; Topalli 2005; Wolfgang and Ferracuti 1967). It is logical to suppose that stable neighborhood disadvantage allows such a subculture to become established and ongoing, while the level of disadvantage predicts whether or not it emerges at all. This possibility was actually addressed by Shaw and McKay in their original statement of social disorganization theory (1969), though later research focused almost entirely on the social control aspects of their theory, beginning with Kornhauser (1978).

A final explanation for this last finding is that the models I have constructed and tested—and the conclusions based on the results—are misspecified. Given the relative complexity of the model, and drawing on current debates in the neighborhood effects literature, there are several sources of statistical error that may be influencing my results. First, the correlation between my dummy measures of within-neighborhood change and the level of disadvantage in 1990, while not particularly large, is significant. Given the nature of changes across Chicago neighborhoods during the time period under investigation, it is more likely that a highly-disadvantaged NC in 1990 experienced an increase in disadvantage over time. Post-estimation tests performed after my OLS analyses of the expanded models indicated that the mean collinearity between the predictors was acceptable (VIF = 2.77), though the values for the “major increase” quartile group (VIF = 5.14) and the level of disadvantage in 1990 (VIF = 4.02) approached a problematic level of collinearity. This is likely due to the relatively strong correlation between membership in the “major increase” group and disadvantage in 1990 (r = .71); this is not surprising, given that NCs experiencing major increases in disadvantage from
1970 to 1990 are naturally more likely to have high levels of disadvantage in 1990. It is possible that a different specification of change would avoid this issue to a greater degree. As these models were largely exploratory, and the actual distribution of change in my data was relatively limited, I chose to employ a comparatively simple and parsimonious measure of within-neighborhood change. Future research should explore alternative measures of change, in addition to using a sample which captures the full range of ideal types of levels and changes in disadvantage (e.g. neighborhoods in other cities, during other time periods, or both).

Relatedly, these models do not account for the possibility the relationships between structural conditions, collective efficacy, and homicide rates are nonrecursive, or cyclical. It is theoretically plausible that while disadvantaged conditions initially lead to lower levels of collective efficacy and thus higher crime rates, that increased crime in turn destabilizes the neighborhood, decreases collective efficacy further, and in turn produces even higher rates of crime. Research on the residential mobility of whites in the face of racial/ethnic change in the neighborhood, the mobility of middle-class residents out of disadvantage areas (or into gentrifying ones), and the cyclical relationship between disadvantage, disorder, and crime support this perspective (Sampson 2012; Sharkey 2012; South and Crowder 1997; Wilson 1996; Wilson 1997; Wilson and Taub 2006; Xie and McDowall 2008). For the reasons given above, however, I chose to limit the scope of the dissertation to establishing a basic model of structural changes, conditions, collective efficacy, and crime. Given the apparently temporal nature of the disadvantage-crime relationship (as well as the disadvantage-collective efficacy relationship), this model seems particularly well-suited for exploration in a nonrecursive model.
It is for similar reasons that I have not employed multi-level models in this dissertation. There are certainly individual-level relationships which are not accounted for here, as well as cross-level interactions, and a truly complete neighborhood effects model would account for multi-level influences (Sampson 1991; Sampson 1993; van Wilsem, Wittebrood, and de Graaf 2006). My findings offer a starting point for later work, and suggest a number of testable hypotheses I hope will be incorporated into future research. However, my reliance on neighborhood-level measures of social control and social cohesion to construct a measure of collective efficacy has likely impacted the estimated relationships between structural conditions, collective efficacy, and crime. The full PHDCN-CS includes both an individual-level and neighborhood-level component, and prior research has often constructed a measure of collective efficacy using a multi-level modeling strategy (see Sampson, Raudenbush, and Earls 1997). This approach adjusts for error in the measurement of an underlying latent variable(s) – here, the measures of social control and social cohesion that together constitute collective efficacy. Not only does a hierarchical modeling strategy incorporate measurement error across an individual’s responses to a set of items that tap into an underlying latent construct like social control, it can account for between-individual differences (like sex, age, or SES) that influence the estimation of a neighborhood’s “true” level of social control or cohesion (p. 921). Prior research has shown that using a “manifest” measure of an inherently latent mechanism, which do not account for measurement error, are likely to exaggerate the importance of structural conditions on the crime outcome relative to the importance of social mechanisms theorized to mediate the relationship (Raudenbush and Sampson 1999a). Measurement error in neighborhood-level collective efficacy is an important potential source of the weak mediating
relationship between structural conditions and homicide rates (in both the OLS and GWR models) found here, and should be accounted for in future research.

A second source of statistical error is the modeling strategy (or strategies) used here. Geographically-weighted regression was used to test the spatial invariance assumption, and then again to see if change, collective efficacy, or both could account for such variation in the relationships of interest. However, once a model had been found which satisfied the assumption, I employed familiar OLS regression techniques to produce a global estimate of the relationships between my structural predictors, collective efficacy, and homicide. I did not control for spatial effects in these latter models, such as spatial lag and spatial error, which previous researchers have found (Light and Harris 2012; Morenoff, Sampson, and Raudenbush 2001; Sampson, Morenoff, and Earls 1999; Tita and Radil 2010; Zeoli, Pizarro, Grady, and Melde 2012). My goal here was to establish a basic framework of neighborhood structural conditions and crime that incorporated dimensions of both level and change, in addition to the mediating social mechanism of collective efficacy. Adding more complexity to this framework in the form of spatial lag or spatial error models is one avenue for subsequent research to follow, but lies outside the scope of this dissertation.

It is also possible that the relationship between the level of concentrated disadvantage (and the change in disadvantage) and the outcome is sensitive to the type of crime under examination. Homicide rates are commonly used in this area of research as they are likely to be the most reliably reported and measured type of crime (Gove, Hughes, and Geerken 1985). However, focusing on homicide rates may produce conservative estimates of the relationships for several reasons. Prior research has divided homicide into a number of sub-types; for
example, by motivation or victim-offender relationship (Kovandzic, Vieraitis, and Yeisley 1998). Recently, Kubrin found that different neighborhood factors are associated with different sub-types of homicide (2003); her measure of disadvantage was significantly related to all types of homicide but the size of this association varied across sub-types. It is possible that the “heat of the moment” nature of many homicides makes it less susceptible to the exercise of collective efficacy within the neighborhood. Neighborhoods which typically exercise strong informal social control over crime in the area may have a much more difficult time preventing crimes which erupt this quickly, especially when they tend to occur between non-strangers and in private (Kubrin 2003). The extremely violent nature of homicide also makes it less likely that neighborhoods which are low in collective efficacy would attempt to prevent this crime to the same degree that higher-efficacy neighborhoods would. In this way, homicide is likely to be relatively weakly related to structural conditions and collective efficacy, and such models would produce conservative estimates of the associations (though see Kubrin 2003 for alternative theoretical links between structural conditions and homicide).

Finally, there is a potential source of model mis-specification which is both theoretically and methodologically important. Within the current neighborhood effects literature, there is an ongoing debate over what constitutes a “neighborhood” (Cummins, Curtis, Diez-Roux, and Macintyre 2007; Groff, Weisburd, and Yang 2010; Hipp 2007; Land, McCall, and Cohen 1990; Lee, Reardon, Firebaugh, Farrell, Matthews, and O'Sullivan 2008; Raudenbush and Sampson 1999b; Short 1998). Theoretically, neighborhoods are important because they are assumed to offer their residents – and individuals who work, play, shop, or otherwise spend time in them – some social value (e.g. self-identification with the neighborhood, a place to raise children,
healthy environmental conditions, or attractive aesthetics). Here, neighborhoods are the unit at which informal social control is created and exercised to limit crime. However, the “proper” operationalization of the neighborhood unit is an open question, with various scholars using neighborhood clusters (as I have here), census tracts, block groups, “community areas,” cities, counties, or street segments, among others. While structural theories should be able to explain and predict relationships between structural conditions and crime outcomes at all levels of measurement to be truly general theories of crime, the processes linking the two are widely believed to operate at some yet-unknown (or at least, yet-agreed upon) unit of “neighborhood” or “community.” Some researchers have even suggested a measure of neighborhood which is not place-oriented, i.e. politically defined, but based on where individuals spend their time (see Hipp and Boessen 2013).

Methodologically, prior work has shown that estimates of relationships between structural conditions and a given outcome are sensitive to the level of measurement used. In geographically-oriented research on space, place, and structural relationships, this is generally referred to as the modifiable areal unit problem (or MAUP; see Fotheringham and Wong 1991; Groff, Weisburd, and Yang 2010; Openshaw 1984; Weisburd, Groff, and Yang 2013). I have chosen to employ neighborhood clusters as my unit of analysis because the PHDCN-CS offers one of the only datasets that includes a measure of the intervening social process theorized to mediate the structure-crime relationship. Using this data allowed me to include the measure of collective efficacy in my models, making for a more theoretically “complete” specification. However, as the PHDCN-CS aggregated the data to the neighborhood cluster and limited to the city of Chicago, it was necessary to use the same analytic unit here. A positive byproduct of this
Hobson’s choice is that my findings can be compared to a substantial body of prior research on Chicago NCs (Browning 2002; Browning 2009; Browning, Feinberg, and Dietz 2004; Morenoff, Sampson, and Raudenbush 2001; Papachristos, Smith, Scherer, and Fugiero 2011; Sampson 2012). It is left to future research to explore if my findings are replicable at different levels of measurement and/or for places outside Chicago.

**In Conclusion**

In large part, my results are consistent with the extensive contemporary literature on neighborhood disadvantage, collective efficacy, and crime. In all these analyses, the level of concentrated disadvantage in the neighborhood was predicted to have a detrimental effect on both its homicide rate and its level of collective efficacy. However, contrary to the assumptions of prior, aspatial models, these relationships were substantially and significantly dependent on which neighborhood (or set of neighborhoods) was being examined. The conclusion of spatial variation in these associations is not without precedent (Graif and Sampson 2009; Light and Harris 2012), but the analyses in this dissertation are the first (of which I am aware) that can empirically account for such variation.

Additionally, by linking the apparently spatialized nature of the disadvantage-homicide relationship with the temporal dynamics of neighborhoods, I have incorporated two important dimensions of neighborhood effects and crime literature. Others have found that neighborhoods, like individuals, evidence historical trajectories of development (akin to a person’s life-course or “biography”). The majority of these studies, however, are largely descriptive or exploratory applications of group-based trajectory models to macro-level units
(Groff, Weisburd, and Yang 2010; Groff, Weisburd, and Morris 2009; Stults 2010). This dissertation, by joining a temporal perspective with extant theorizing on neighborhood disorganization and collective efficacy, represents an important contribution to future work in this area. Though not without its flaws, I hope I have demonstrated how important neighborhood structural stability and change are to our theoretical and empirical models. The concentration of disadvantage described by Wilson (Sampson 2012; Wilson 1996; Wilson 1997; Wilson 1998) shows no signs of reversing, and both neighborhood decline and neighborhood improvement can be problematic for existing residents (Covington and Taylor 1989; Kreager, Lyons, and Hays 2011; McDonald 1986; Papachristos, Smith, Scherer, and Fugiero 2011; Sampson 2009; Skogan 1992; Taylor and Covington 1988; van Wilsem, Wittebrood, and de Graaf 2006; Wilson and Taub 2006) for a complexity of reasons. It is imperative that future work look not only to explain cross-sectional differences in conditions and outcomes between neighborhoods, but look within neighborhoods as well, and attempt to understand more clearly the importance of the neighborhood itself – as a *dynamic* organism – in the social ecological spirit of the original Chicago School.
REFERENCES


Thompson, Sara K., Sandra M. Bucerius, and Mark Luguya. forthcoming. "Unintended Consequences of Neighbourhood Restructuring: Uncertainty, Disrupted Social Networks and Increased Fear of Violent Victimization among Young Adults." *British Journal of Criminology*.


APPENDIX. SUPPLEMENTAL ANALYSES

This appendix contains the results of several supplemental analyses referenced in the text. As part of the test of the “disruption” hypothesis, I performed between-quartile comparisons of the relationship (net of 1990 neighborhood structural conditions) between changes in disadvantage and neighborhood homicide rates (Tables A.1 and A.2). In all but one instance, each category of within-neighborhood change exerted a significantly different effect on the outcome – the log homicide rate in Table A.1 and collective efficacy in Table A.2 – than the other categories. In a test of the “accumulation” hypothesis, the interaction of the level of disadvantage with change in disadvantage was explored, finding there was no significant interaction effect on neighborhood collective efficacy (Table A.3).
Table A.1. OLS Regression of Log Homicide Rate on Neighborhood Structural Conditions and Change in Disadvantage, Between-Quartile Comparisons

<table>
<thead>
<tr>
<th>Change in Disadvantage</th>
<th>b</th>
<th>(SE)</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minor increase</td>
<td>0.293</td>
<td>0.060</td>
<td>0.196</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>0.499</td>
<td>0.074</td>
<td>0.335</td>
</tr>
<tr>
<td>Major increase</td>
<td>0.601</td>
<td>0.101</td>
<td>0.399</td>
</tr>
<tr>
<td>No change</td>
<td>-0.293</td>
<td>0.060</td>
<td>-0.197</td>
</tr>
<tr>
<td>Minor increase (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>0.205</td>
<td>0.065</td>
<td>0.139</td>
</tr>
<tr>
<td>Major increase</td>
<td>0.308</td>
<td>0.090</td>
<td>0.206</td>
</tr>
<tr>
<td>No change</td>
<td>-0.499</td>
<td>0.074</td>
<td>-0.335</td>
</tr>
<tr>
<td>Minor increase (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>-0.205</td>
<td>0.065</td>
<td>-0.138</td>
</tr>
<tr>
<td>Major increase</td>
<td>0.103</td>
<td>0.066</td>
<td>0.069</td>
</tr>
<tr>
<td>No change</td>
<td>-0.601</td>
<td>0.101</td>
<td>-0.405</td>
</tr>
<tr>
<td>Minor increase</td>
<td>-0.308</td>
<td>0.090</td>
<td>-0.207</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>-0.103</td>
<td>0.066</td>
<td>-0.069</td>
</tr>
<tr>
<td>Major increase (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Adjusted $R^2$ 0.698
AIC 270.095

N = 342  
* p < .05  ** p < .01  *** p < .001
Table A.2. OLS Regression of Collective Efficacy on Neighborhood Structural Conditions and Change in Disadvantage, Between-Quartile Comparisons

<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th>(SE)</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.629</td>
<td>***</td>
<td>0.080</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.312</td>
<td>***</td>
<td>0.060</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.163</td>
<td>***</td>
<td>0.036</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.344</td>
<td>***</td>
<td>0.040</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minor increase</td>
<td>-0.329</td>
<td>**</td>
<td>0.106</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>-0.661</td>
<td>***</td>
<td>0.130</td>
</tr>
<tr>
<td>Major increase</td>
<td>-1.022</td>
<td>***</td>
<td>0.179</td>
</tr>
<tr>
<td>No change</td>
<td>0.329</td>
<td>**</td>
<td>0.106</td>
</tr>
<tr>
<td>Minor increase (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>-0.333</td>
<td>**</td>
<td>0.115</td>
</tr>
<tr>
<td>Major increase</td>
<td>-0.693</td>
<td>***</td>
<td>0.160</td>
</tr>
<tr>
<td>No change</td>
<td>0.661</td>
<td>***</td>
<td>0.661</td>
</tr>
<tr>
<td>Minor increase (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>-0.361</td>
<td>**</td>
<td>0.116</td>
</tr>
<tr>
<td>Major increase</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>No change</td>
<td>1.022</td>
<td>***</td>
<td>0.179</td>
</tr>
<tr>
<td>Minor increase</td>
<td>0.693</td>
<td>***</td>
<td>0.160</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>0.361</td>
<td>**</td>
<td>0.116</td>
</tr>
<tr>
<td>Major increase (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.606</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>658.746</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N = 342

* p < .05    ** p < .01    *** p < .001
Table A.3. OLS Regression of Collective Efficacy on Neighborhood Structural Conditions, Change in Disadvantage, and Disadvantage Level*Change Interaction

<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th>(SE)</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.515</td>
<td>**</td>
<td>0.199</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.470</td>
<td>0.254</td>
<td>-0.532</td>
</tr>
<tr>
<td>Immigrant concentration</td>
<td>-0.172</td>
<td>***</td>
<td>-0.203</td>
</tr>
<tr>
<td>Residential stability</td>
<td>0.328</td>
<td>***</td>
<td>0.324</td>
</tr>
<tr>
<td>Change in Disadvantage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minor increase</td>
<td>-0.247</td>
<td>0.210</td>
<td>-0.107</td>
</tr>
<tr>
<td>Moderate increase</td>
<td>-0.406</td>
<td>0.230</td>
<td>-0.177</td>
</tr>
<tr>
<td>Major increase</td>
<td>-1.165</td>
<td>***</td>
<td>-0.502</td>
</tr>
<tr>
<td>Disadvantage Level*Change</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disadvantage*No change (omitted)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Disadvantage*Minor increase</td>
<td>-0.031</td>
<td>0.293</td>
<td>-0.007</td>
</tr>
<tr>
<td>Disadvantage*Moderate increase</td>
<td>-0.034</td>
<td>0.273</td>
<td>-0.015</td>
</tr>
<tr>
<td>Disadvantage*Major increase</td>
<td>0.299</td>
<td>0.262</td>
<td>0.267</td>
</tr>
</tbody>
</table>

Adjusted R² = 0.613
AIC = 656.363

N = 342
*p < .05  ** p < .01  *** p < .001
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Becker, Jacob H. “Concentrated Disadvantage, Collective Efficacy, and Homicide over the Neighborhood Life Course.” In preparation.

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