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Abstract

Social scientists have long observed strong correlations between social structure and violent crime rates at the neighborhood level. Yet little is known about the relationship between changes in social structure and violent crime trends. Furthermore, the spatial distribution of crime trends has received little attention in the literature. The dissertation explores the trajectories and spatial dynamics of neighborhood homicide rates and social structure in St. Louis, Missouri between 1980 and 2000.

Multilevel growth curve models are used to describe the nature of, and variation in, census tract homicide trajectories as functions of structural characteristics and changes in those features. Exploratory spatial data analysis is used to measure and describe the spatial distribution and autocorrelation of homicide trends and social structure. Finally, spatial regression models are used to determine if the distribution of social structure explains the spatial autocorrelation of homicide trends across neighborhoods.

The findings show that St. Louis neighborhoods experienced significantly different homicide trajectories. Communities with higher levels of economic disadvantage experience the most pronounced fluctuations in violence. However, changes in structural characteristics provide only weak explanation of the variations in homicide trends between neighborhoods. The results indicate that homicide trends may have reciprocal influences on structural changes and that structure-crime processes operate differentially across regions of St. Louis. Furthermore, homicide trends and structural changes both exhibit positive spatial autocorrelation. Finally, between 1987 and 2000, the level and changes in structural conditions reduces residual clustering in homicide trends to zero.

The results indicate a need to further explore changes in neighborhood contexts and trends in non-structural correlates of violence. Furthermore, future research should examine the interdependence of spatial regimes in the development of dynamic urban systems. Finally, criminologists should examine more closely the influence of crime on neighborhood conditions.

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Acknowledgements

"*What a long, strange trip it's been.*" – Robert C. Hunter (1970)

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Chapter 1: Structural Change and Neighborhood Crime Trends

"We are living in such a period of individualization and social disorganization. Everything is in a state of agitation—everything seems to be undergoing a change. Society is, apparently, not much more than a congeries and constellation of social atoms."
– Robert E. Park from *The City* (1925: 107)

Introduction

The modern city, as a unit of social analysis, is a varied and diversified place. As Park noted eighty years ago, the conditions of city life have changed dramatically, and continue to do so today. Analyses of local communities within cities have long sought to explain the sources of differentiation in their observed conditions. A variety of theoretical perspectives have developed during this period including social disorganization, routine activities, and cultural perspectives. While each of these perspectives attempts to explain the genesis of crime through differing mechanisms, two commonalities persist. Each conceives of the community context as a vital precursor to the variation in crime rates, and each presents a dynamic process as the core mechanism.

Much of the research surrounding these theories has focused on refinement, extension, or integration of the proposed mechanisms. Additionally, most of this research has attempted to explain differences in crime rates across communities using cross-sectional research designs. Yet, little is known regarding whether or not the dynamic relationships suggested by these perspectives are associated with longitudinal profiles of crime and delinquency within local communities. This study seeks to begin filling this gap in the literature by examining the dynamics relating neighborhood social structure to crime rates over time. The primary research question asks whether there is a relationship between structural changes and neighborhood crime trends.

The primary research question is divided into two separate, yet interrelated parts designed to provide a broad understanding of community dynamics over time. Each of these parts will address a substantive issue within the context of the primary question. The first, and most important, issue regards the specification of a longitudinal model of neighborhood crime as a function of the changing social structure within, as well as between, the communities. Second, the dissertation will examine the influence of spatial positioning within the city on covariates for each of the neighborhoods. The dissertation will examine these questions using data for neighborhoods in St. Louis, Missouri. The study period begins in 1980 and extends through 2000.

Through the analysis, this study hopes to add to our understanding of crime by providing answers to two critical questions. First, do the same static explanatory indicators of neighborhood crime rates also provide explanatory power in studying the dynamic nature of social structure and crime over time? Secondly, how are changes in neighborhood structure and crime distributed in space across the urban landscape?

Theoretical Considerations

A variety of theoretical perspectives have been developed that link social structure to crime rates. The hypotheses derived from these theories can generally be categorized into three broad classes of process: opportunity, motivation, and social control. Based on these distinctions, the primary difference between theories is found in the mediating mechanisms that generate crime. The major theories of interest include social disorganization, routine activities, strain, relative deprivation, and cultural processes.

As discussed above, in relating social structure to neighborhood crime rates, each of these perspectives posits different processes to account for spatial variations. The following discussion will highlight the complexity of these mechanisms. However, one of the greatest difficulties faced in testing such processes is the collection of valid and reliable measures for key concepts (Bursik and Grasmick, 1993). Generally, detailed and widespread survey data would need to be collected from the residents of each community. Additionally, since the interest of this study lies in community profiles over time, longitudinal survey data are necessary. The logistics and funding for such an undertaking have generally been beyond the reach of most researchers.[1] Therefore, the vast majority of studies regarding community structure and crime have been unable to directly measure the processes assumed to explain observed relationships. This dissertation suffers from the same limitation, and therefore does not represent a comprehensive test of any specific theory. Rather, guided by the existing theories, the dissertation seeks to explore the longitudinal profiles of neighborhood crime and structural change. Where relationships are observed, theoretical implications will be discussed, but future research will be necessary to fully describe the underlying processes at work.

Social Disorganization

During the early 1900s, American social scientists observed massive influxes of immigrants to the United States. As urban areas grew and developed, the local communities of major cities could be differentiated along several social dimensions that

[1] For an exception, refer to the Project on Human Development in Chicago Neighborhoods.

included occupation, economic status, racial/ethnic composition, and commercial/residential development (Burgess, 1925). In Chicago, Shaw and McKay (1942) examined these differences in relation to juvenile delinquency patterns, producing several important findings.[2] First, the Chicago data indicated that there was an inverse relationship between the distance from the central business district and juvenile delinquency rates. Secondly, over the course of a thirty year period, the relative location of high delinquency areas in the city remained stable. Finally, Shaw and McKay (1942) found that high delinquency persisted regardless of the racial or ethnic composition of the population. These findings became the basis of social disorganization theory.

Based on these observations, Shaw and McKay (1942) argued that the level of juvenile delinquency in a neighborhood was not a function of the types of people living in a community. Rather, they viewed delinquency rates as a function of characteristics inherent to the social aggregate, or community. The neighborhoods with the highest levels of delinquency were characterized by low socioeconomic status, large proportions of new immigrants resulting in racial and ethnic heterogeneity, and high levels of residential turnover. Such communities were persistently located just outside the central business district of Chicago.[3] The characteristics of these neighborhoods were largely a function of their location near city factories. Living quarters were inexpensive and located near economic opportunities, affording new immigrants a point of first-settlement until they could assimilate more fully into the economic and cultural fabric of the city. As

[2] Shaw and McKay specifically examined juvenile delinquency rates as opposed to adult criminal actions. The same conceptual processes have received wide support in explaining adult criminal actions as well. While there are notable differences in the quantity and nature of juvenile and adult offending patterns, the remainder of this study will use the terms delinquency and crime interchangeably.

[3] This area is known as the “zone in transition” (Burgess, 1925). The housing stock in this area is relatively dilapidated in comparison to other residential areas. Through the invasion-succession process, this zone is likely to transition from residential property to light industrial and commercial property. Facing this inevitability, property owners are less likely to invest in maintaining property that will shortly be sold.

individuals and families adjusted to urban life and accumulated financial independence, they would move out of the neighborhood and into more desirable housing located further away from the central business district.

Shaw and McKay (1942) argued that the community context was related to the level of juvenile delinquency through the ability of residents to regulate individual behavior in the neighborhood. Population heterogeneity impeded the development of cooperative social relations among the residents of the neighborhood through both language and cultural barriers. High levels of population turnover, resulting from a desire to move from the community as soon as possible, meant that residents would not invest in the general prosperity and well-being of the community. In addition to heterogeneity and mobility, the socio-economic composition of the community was a persistent predictor of high crime areas. As discussed above, immigrant populations generally held low-paying jobs upon first arrival to the city. This in turn dictated what living accommodations could be afforded until residents became more assimilated to the occupational structure of the city and could move to better conditions (Bursik and Grasmick, 1993). These three factors worked together to reduce the capacity of the neighborhood to foster social control among residents and visitors. Without such control, the likelihood of delinquent activity increased.

A few of the communities in Chicago exhibited high levels of delinquency in spite of the fact that they did not exhibit the typical characteristics of high delinquency areas. In the effort to overcome this inconsistency in the theory, Shaw and McKay (1942) argued once a neighborhood developed a high level of delinquency, a culture of delinquency was created. This culture was then transmitted to others over time, and the community would exhibit high levels of delinquency regardless of the structural context. However, this hypothesis was interpreted by many as a conceptual inconsistency on the verge of tautology[4] (Bursik, 1988). Kornhauser (1978) later suggested that this aspect of the theory is based on the assumption that people are socialized into delinquency and crime. This assumption conflicts with the core dynamic of social disorganization that posits social control as a preventive mechanism for delinquency. Primarily for this reason, cultural transmission is not included as a conceptual argument in contemporary social disorganization models.[5]

The social disorganization model enjoyed prominence in criminology for a number of years. However, criticisms of the theory and disciplinary shifts toward individual-level explanations of criminal behavior caused a decline in its use (Bursik, 1988). During the 1980s, the perspective resurfaced through a series of clarifications and extensions. Specifically, attention was given to understanding the determinants of neighborhood social control. The nature of social organization within a community was recast in terms of systemic social control (Sampson, 1988; Sampson and Groves, 1989; Bursik and Grasmick, 1993). Using Hunter's (1985) concept of systemic social control, three levels of control are specified along a continuum of interpersonal affect and relationship networks: private, parochial, and public. The private social order is comprised of personal ties between friends, intimates, and relatives. The parochial order encompasses the relationship networks that interlock individuals through local

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[4] The Shaw and McKay model argues more forcefully that crime is an outcome of attenuated social control. To identify disorganized communities on the basis of their crime rates, rather than the precursors of delinquency, results in circular logic.

[5] Heitgerd and Bursik (1987) provide evidence that socially organized communities may still exhibit high levels of crime and delinquency due to factors exogenous to the neighborhood itself. This evidence will be discussed later.

institutions such as “local stores, schools, churches, and voluntary associations of various kinds” (Hunter, 1985: 233). The public social order reflects community connections to the broader institutions of the state or metropolitan area, such as police protection and city council representation. These are the relationship networks shared between all communities and encompass all external resources available.

In the systemic reformulation, neighborhood social structure is related to crime rates through its influence on community relationship networks. Specifically, neighborhoods with extensive racial and ethnic heterogeneity, high rates of population mobility, and economic disadvantage are less able to form the relationship ties necessary for effective primary social control (Bursik and Grasmick, 1993: 34). Without sufficient time spent within a given community it is difficult for residents to develop lasting bonds as friends or intimates. Residential diversity also reduces the effectiveness of parochial controls by “limiting the breadth of such networks” (Bursik and Grasmick, 1993: 35). With regard to the public order of control, attenuation of the primary and parochial levels of control creates a fragmented system of cohesion within the community. Under these circumstances it is difficult, if not impossible, for local community groups to develop the political capital necessary to secure external resources for the neighborhood (Bursik and Grasmick, 1993: 38).

Strain

Strain theory as first described by Merton (1938) depicts high crime rates as being a function of the disassociation between culturally defined goals of success and the institutional structures that prevent or provide access to those goals. The perspective views the overemphasis of material success in America as having an anomic consequence among individuals.[6] While most people adhere to the culturally defined goal of achieving material success, some of these people will not have access to the legitimate means by which to achieve these goals. For these individuals, a sense of anger and frustration sets in, and they are motivated to engage in behavior they would not otherwise. When faced with this situation, Merton describes a set of behaviors that may be adopted and engaged in, with deviant behavior as a possibility.

Although it is couched as a single theoretical perspective, Merton in fact makes two logically independent arguments: one regarding social organization, the other regarding deviant motivation (Messner, 1988). According to the social organization argument, the level of crime within a society will be associated with the degree of disjuncture present between cultural goals and legitimate means. Thus, a relative deprivation argument is made regarding the social status of collectivities and their ability to succeed. As it applies to the study of neighborhoods, one expects to find an inverse relationship between economically deprived areas and crime rates. Furthermore, the social organization argument does not depend on the validity of the deviant motivation argument (Messner, 1988). It may not be the case that cultural-structural disassociations produce deviant motivations. As an alternative that is consistent with control theories, the disjuncture between goals and means may simply reduce social control, thereby freeing individuals to commit crime in the pursuit of success. For this dissertation, the social organization arguments are of prime concern. The validity of Merton's deviant motivation component is beyond the current scope.

[6] Merton does not define *anomie* in his original work (1938). However, Durkheim (1897[1951]) provides the theoretical discussion of *anomie* as a sense of a weakened normative order or social regulation.

In an extension and reformulation of Merton's strain theory, Messner and Rosenfeld (1997) argue that it is not simply the disassociation between cultural goals and structural access to legitimate means that produce high crime rates. An additional component to be considered is the institutional balance of power in society. Specifically, in the United States, the concept of the "American Dream" promotes the cultural goal of economic success. The emphasis placed on economic goals is strong enough that other social institutions competing for normative equality become weakened. Institutions such as the family, education, and the political system are dominated by economic pressures and are no longer able to provide the social controls necessary to prevent crime. Applying this perspective to the study of neighborhood structure and crime, one expects that areas with the weakest indicators of other social institutions will exhibit higher crime rates than areas where these institutions are stronger.

Relative Deprivation

The relative deprivation perspective argues that the degree of economic inequality existing in a society will be positively associated with the crime rate (Blau and Blau, 1982). This hypothesis is born from the notion that resources are differentially distributed throughout society. When the unequal distribution of resources is great, one expects an urban underclass to coalesce and act in order to redistribute resources more evenly. However, where the distribution of resources is correlated with ascribed positions such as race, there is a higher likelihood that economic inequality will result in violent crime.

In examining the state of the literature relating poverty to crime, Blau and Blau (1982) note that many macro level theories argue for a positive relationship between the two. Poverty is expected to coalesce in specific groups in society and produce areas with significant proportions of disadvantaged residents. Under these conditions, poverty is expected to contribute to an anomic or disorganized state of affairs. In high poverty areas, a subculture argument is often invoked that relates high poverty to norms of "toughness, smartness, excitement, and fatalism" (Blau and Blau, 1982: 116). Youth in high poverty areas are therefore expected to have increased contact with the law, and thus produce higher crime rates.

While many perspectives suggest a positive relationship between absolute levels of poverty and crime, Blau and Blau interpret such theories as having income inequality effects as well. For example, Marxian theories of crime focus on the exploitation of the poor by the rich. Under these circumstances, simply improving the economic conditions of the poor is not expected to reduce crime. Rather, it is the redistribution of wealth and production to a more uniform status that is expected to reduce crime. Similarly, as discussed above, strain theory is concerned explicitly with the unequal distribution of the legitimate means to economic success (Merton, 1938; Messner and Rosenfeld, 1994).[7]

The argument for the importance for economic inequality ultimately rests on the observation that the distribution of economic resources is correlated with ascriptive group membership status. "The hypothesis inferred is that socioeconomic inequalities that are associated with ascribed positions, thereby consolidating and reinforcing ethnic and class differences, engendering pervasive conflict in a democracy," (Blau and Blau, 1982: 119).[8] Furthermore, the authors argue that economic inequalities act to undermine social

[7] In a later formulation of strain theory, Cloward and Ohlin (1960) argue that delinquency also depends on the distribution of access to illegitimate means of success.
[8] Importantly, Blau and Blau argue that "[g]reater economic inequalities generally foster conflict and violence, but ascriptive inequalities do so particularly," (1982: 119). Thus, economic inequality itself is expected to be positively associated with crime rates. However, the magnitude of the relationship will vary based on the nature of the inequality examined.

integration among community residents, “creating multiple parallel social differences which widen the separations between ethnic groups and between social classes,” (pp.119). Inequality is thus linked to the level of anomie and social disorganization in the community.

Blau and Blau test their model using data using 1970 data for the largest 125 SMSAs in the Unites States. They find that economic inequality is positively associated with nearly all violent crime outcomes (e.g. murder, rape, and aggravated assault). In each case, when poverty is included in the model, it has no significant association with the outcome. While poverty was significantly associated with robbery rates, the association was relatively weak, and the magnitude of the standardized coefficient was substantially smaller than the inequality estimate.

Routine Activities

During the 1960s and 1970s, violent crime rates in the US rose precipitously, particularly in urban areas. During the same period, many of the macro-level indicators of social and economic conditions were trending in directions that should have reduced crime rates (Cohen and Felson, 1979). This presented a paradox for ecological theories such as social disorganization because the observed relationships were trending in directions inconsistent with current conceptualizations of social control. However, as Cohen and Felson (1979: 589) noted, ecological theories did not, “consider…the fundamental human ecological character of illegal acts as *events* which occur at specific locations in *space* and *time*…” (emphasis in original). Thus, the routine activities theory was developed as a perspective that could account for spatial, as well as temporal patterns of crime, based on concepts derived from the urban ecology literature.[9]

Cohen and Felson (1979: 590) argue that there are three minimal components to any predatory crime: "an *offender* with both criminal inclinations and the ability to carry out those inclinations, a person or object providing a *suitable target* for the offender, and *absence of guardians* capable of preventing violations" (emphasis in original). The convergence in time and space of these elements is expected to result in a criminal event.[10] The probability of a convergence is a function of the routine activities, or day-to-day events, in the community. Ultimately, it is the social structure of the neighborhood that governs the temporal variations in routine activities. Additionally, variations in structure across communities govern the spatial variation in routine activities.

Drawing from Hawley's (1950) theory of human ecology, the routine activities of an area can be assessed along three structural dimensions.[11] The periodicity, frequency, and co-occurrence of events are referred to as rhythm, tempo, and timing (Cohen and Felson, 1979: 590). Just as urban ecologists noted that local communities vary in their socioeconomic status and racial composition, it is important to note that there are variations in activities as well. As an example, consider the daily population flow between suburban residential communities and the central business district in a city. A

[9] As originally conceptualized, the routine activities perspective was intended to explain crime *rates*. However, a number of published papers have used the perspective to explain the victimization of *individuals* in different contexts (i.e. home, work, school) and across status traits (i.e. age, gender, race, etc.) (see Hindelang et al., 1978). Given the purpose of the dissertation, the individual-level literature will not be discussed in detail. Rather, discussion will focus on the application of routine activities theory to the explanation of crime rates.

[10] It is important to note that the elements of a crime here are not independent and additive. Instead, since the presence of all three conditions is required for a crime to occur, this conceptualization is multiplicative in nature (Bursik and Grasmick, 1993).

[11] Social structure, as commonly used, refers to characteristics used to differentiate group variations in aggregate populations. Here, the term takes on a subtly different reference to examining temporal variation. While both uses of the term structure are related, the primary focus of routine activities theory lies in the examination of temporal variation.

significant proportion of the population may be found in the business district between 8:00 AM and 5:00 PM. This same population is likely to be found in suburban communities between 6:00 PM and 7:00 AM.[12] The rhythm of population movement is daily on weekdays, but not on weekends. The frequency of such movement for any given community is the number of people who work in the central business district. To understand the timing of this event, it must be examined in relation to other activities. Elementary and high schools are in session at the same time that the majority of workers need to be at work. Therefore the timing of travel to and from school and work is a near perfect co-occurrence.

It is important to note that Cohen and Felson "take criminal inclination as a given and examine the manner in which the spatio-temporal organization of social activities helps people to translate their criminal inclinations into action" (1979: 589). In this way, routine activities theory is similar to social disorganization theory in that it is assumed that a certain proportion of the population holds a propensity to criminal action. Yet, no action will be taken without the opportunity to do so.

Structural Influences on Culture

To this point, the dissertation has examined macro-level structural theories of crime. Yet, an often overlooked aspect of many of these theories is their orientation toward cultural aspects of society. For example, Shaw and McKay (1942) are best known for their arguments pertaining to the structural sources of social disorganization. Yet, in order to explain evidence of high delinquency areas that had all of the indicators of socially organized communities, they rely on the concept of cultural transmission. Once a

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[12] One hour is estimated to allow for commuting between work and home as an example only. Actual travel times vary based on a variety of conditions.

neighborhood develops a high rate of delinquency, the intergenerational transmission of values promoting delinquency perpetuates delinquency rates despite improved economic conditions and the stabilization of residential mobility patterns. For Shaw and McKay, this portion of their model was criticized for being tautological and containing incompatible assumptions regarding the consensus of values and norms (Bursik, 1988; Kornhauser, 1978). Recently, however, macro level social science has returned to the concept of culture. Specifically, a few papers have examined the manner in which social structure may have an influence on cultural values and norms.

Perhaps the most vivid explanation of structural influence on culture is presented by Elijah Anderson (1999). Anderson describes two sets of value orientations, "decent" and "street," that exist in poor urban communities. "Decent" families adhere to mainstream, middle-class values. However, in these communities, the intense joblessness, poverty, and alienation from mainstream institutions, such as the police, produces an oppositional "street" culture. It is the street culture that dominates public spaces in these neighborhoods. From this culture, a "code of the street" has developed which is "a set of informal rules governing interpersonal public behavior, particularly violence," (Anderson, 1999: 33). The core concept associated with the code is personal respect, and the interpersonal negotiation of that respect. A person with sufficient respect can expect to be relatively safe in public. However, if respect is not maintained, interpersonal violence becomes a likely possibility.

Anderson provides a description of street subculture that pervades public spaces in poor urban neighborhoods. Yet, understanding of the "code" and its tenets for producing violence does not explain how the "street" culture developed such a prominent role in these communities. Warner (2003) provides such an explanation through the concept of cultural attenuation, or cultural disorganization. This perspective is based on the notion that the strength of cultural values varies across communities (Kornhauser, 1978). The variation in cultural strength is related to structural factors that generally create social disorganization (e.g., economic disadvantage and population instability). Such structural conditions make it difficult for residents to realize commonly held values while simultaneously inhibiting the formation and maintenance of relational networks. The result is that residents become uncertain as to the common nature of mainstream values, and are less likely to maintain and enforce such values. When mainstream values are not visibly enforced, the perception of a consensus among residents is diminished and the ability of the community to maintain social control is weakened (see also Sampson et al., 1997).

The concept of cultural attenuation provides an explanation as to why the "street" culture develops dominance in the public arena of poor and unstable neighborhoods. Where structural factors influence cultural strength, social control in public spaces is more likely to be weakened. Under these conditions, the maintenance of personal safety becomes a matter of negotiation on an interpersonal level rather than through collective means or institutional arrangements. This explanation also provides the structural basis for the observation that many "decent" people in poor urban neighborhoods will exhibit some adherence to the "code" while in public (Anderson, 1999). Further support for this argument is provided by the observation that the out-migration of affluent and middle-class families has left underclass minority neighborhoods socially isolated from mainstream resources and role models (Wilson, 1987, 1996).

Structural Pathways to Crime: A Summary

The dissertation will explore the relationship between neighborhood social structure and homicide over time. Examination of the relevant theoretical perspectives suggests that the mechanisms linking structure to violence are varied. Social disorganization theory describes the mediating mechanism in terms of systemic social control networks among intimates, acquaintances, and institutions. Strain and relative deprivation theories argue that economic inequalities produce increased criminal motivations among disenfranchised portions of society. Routine activities theory argues that the daily activities of a community influence the opportunity structure for crime. Finally, theorists are beginning to re-examine cultural strength as a mechanism through which structural features of neighborhoods influence crime rates.

Full tests of these theories are compounded by several problems. First, the data pertaining to social networks, daily activities, motivational attitudes, and perceptions of cultural strength can only be collected through detailed survey instruments. Secondly, to examine these relationships over time, survey collection must be carried out at multiple time points. As noted above, the logistical resources and funding for such an endeavor are generally not available. For the current study, annual homicide data are used to examine neighborhood profiles of violent crime, while decennial census data provide a description of neighborhood characteristics and how they change over time. At present, there is no known source that would provide longitudinal data, for St. Louis, pertaining to the mediating mechanisms discussed above. Therefore the dissertation, like many other studies, must assume a mediating mechanism in any observed relationships. The interpretations of such associations will be debatable and are left for future research to clarify.

Chapter 2: Structure and Crime: Empirical Assessments Across Time and Space

Chapter one describes the theoretical paradigms most often used to explain variations in community crime rates. While the intervening mechanisms of social disorganization, strain, and routine activities differ, each proposes hypotheses that link social structure to violence. These processes include the evolution of generalized frustration from the structural lack of opportunities for economic success, the weakening of the capacity of local social networks to regulate behavior, the inability of the community to provide capable guardianship over targets of crime, and the attenuation of the cultural strength of mainstream values. This chapter will now provide an overview of the relevant empirical literature. The literature review will discuss the findings related to specific domains of social structure, such as disadvantage, ethnic heterogeneity, and population mobility. The chapter will then discuss the study of neighborhood change over time, as well as studies of the spatial dependence of crime. Throughout the chapter, relevant hypotheses are derived using existing theory and the extant research.

Disadvantage

Perhaps the single most enduring feature of high crime communities has been high levels of social and economic deprivation (Figueira-McDonough, 1991; Brooks – Gunn et al., 1997; Pratt and Cullen, 2005). The association between low socioeconomic status and high crime rates in neighborhoods is particularly salient in central cities and urban areas (Lauritsen, 2001). A variety of indicators have been used to describe the economic conditions of neighborhoods, such as the poverty rate, income inequality, unemployment, the percentage of female-headed families with children under 18 years of age, and median income. The findings from research using single measures of economic conditions have been varied, and have been attributed to methodological issues (Messner and Rosenfeld, 1999). However, more recent research has combined multiple economic indicators to produce a single measure of economic disadvantage, or resource deprivation, with more consistent results (Land et al., 1990).

Measures of economic deprivation are commonly related to the income, earnings potential, or distribution of income within a community. The *poverty rate* is used as a measure of absolute economic deprivation, and represents the percentage of the population with incomes below the official poverty threshold. Where poverty rates are high, it is expected that residents have greater difficulty maintaining subsistence living standards (Messner and Rosenfeld, 1999). Whereas the poverty rate measures absolute deprivation, *income inequality* is a measure of relative deprivation. The widely used Gini coefficient describes the concentration of income across earnings categories (Blau, 1977). Where inequality is high, a disproportionately small population controls a large proportion of income. In keeping with Merton's (1938) concept of anomie, economic inequality is expected to engender frustration and anger among populations without comparable economic resources.

Blau and Blau (1982) find that inequality is positively associated with all violent crime types when poverty rates are controlled. Additionally, poverty rates do not explain crime rates when income inequality is included in the model.[13] Examining racially disaggregated homicide rates across 125 SMSAs, Peterson and Krivo (1993) find that

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[13] Poverty rates are significantly associated with robbery rates. However, the magnitude of the coefficient is smaller than that for inequality. Additionally, the sign on the poverty coefficient is negative, a likely result of collinearity.

neither income inequality nor poverty rates are significantly associated with black homicide rates.

At the neighborhood level, Messner and Tardiff (1986) examine economic inequality, poverty, and homicide rates in Manhattan neighborhoods. They find that poverty, but not economic inequality, is positively related to homicide rates. Similarly, Krivo and Peterson (1996) find that poverty rates are positively associated with violent crime rates in communities in Columbus, Ohio.[14] Finally, poverty has been shown to have a positive relationship with violent crime rates in suburbs as well (Liska et al., 1998). The differences in these findings suggest that absolute deprivation is more salient than inequality in producing violent crime rates at the neighborhood level.

In addition to income measures of deprivation, employment measures of economic conditions have been commonly used. The *unemployment rate* represents the percentage of the civilian labor force over the age of 15 that is not employed. At the national level, Cohen and Felson (1979) note that victimization rates for robbery and assault are unusually high for those who are unemployed. Opportunity theories, such as routine activities, argue that work and leisure activities away from the home are associated with higher crime rates. Therefore, Cohen and Felson argue that the higher rates of victimization among the unemployed may be spurious due to the spatial proximity of motivated offenders and the unemployed. Land et al. (1990) echo this hypothesis, and show that unemployment has a consistent negative association with homicide rates at the SMSA and city level between 1960 and 1980.

[14] Krivo and Peterson (1996) do not examine the relationship between economic inequality and crime rates at the neighborhood level.

At the neighborhood level, Schmid (1960a, 1960b) finds positive correlations between the male unemployment rate and robbery and assault. In their study of Chicago neighborhoods, Heitgerd and Bursik (1987) find that unemployment has a positive relationship with delinquency rates through its association with other internal community characteristics. Bursik and Grasmick (1993a) find that unemployment, in association with other measures of economic deprivation, has a positive relationship with delinquency rates in 1960 and 1980. Bursik (1986) also reports that changes in unemployment are positively associated with changes in delinquency rates between 1930 and 1960. Additionally, Schuerman and Kobrin (1986) find that communities transitioning into high crime areas were characterized by increasing unemployment rates in Los Angeles.

While the unemployment rate has regularly been used as a measure of resource deprivation, it underestimates the number of people who are not employed. As an alternative, some researchers have used *joblessness* to measure economic deprivation (Krivo and Peterson, 1996; Shihadeh and Maume, 1997). Joblessness includes, in addition to those who are unemployed, the number of persons not in the labor force. The exclusion of persons not in the labor force is particularly relevant when studying urban neighborhoods where minority males are more likely to opt out of the labor market (Wilson, 1987; Shihadeh and Maume, 1997). Like unemployment, the jobless rate exhibits a positive association with crime rates (Krivo and Peterson, 1996; Shihadeh and Maume, 1997; Peterson et al., 2000).

The discussion thus far has illustrated the variety of ways in which socioeconomic status has been measured. Generally, at the neighborhood level, there is a positive association between poverty and crime, and violence in particular. However, Wilson

(1987, 1996) argues that social and economic changes in urban areas have resulted in the concentration of economic disadvantage in predominantly black urban communities. The concentration of these shifts has manifested itself in higher rates of poverty, inequality, unemployment, joblessness, female-headed families with children, public assistance dependency, and other social problems. Thus, there is substantial overlap among indicators of economic disadvantage. Land et al. (1990) argue that discrepancies in research findings using these measures are due, in large part, to the high degree of collinearity among structural indicators.

Examining homicide rates for states, SMSAs, and cities in 1960, 1970, and 1980, Land et al. (1990) use principal components analysis to create an index of *resource deprivation*. Resource deprivation consists of median family income, the poverty rate, the Gini index of income inequality, the percentage of the population that is black, and the percentage of children under 18 not living with both parents.[15] Using this index along with an index of population structure, Land et al. (1990) show that resource deprivation is positively associated with homicide rates in states, SMSAs, and cities in all three time periods. Furthermore, the significance of this finding increase as the unit of aggregation is reduced from states to cities. At the neighborhood level of analysis, the use of an economic disadvantage index has become commonplace in the literature.

Instability

The second major predictor of high crime areas has been residential instability (Figueira-McDonough, 1991). In Shaw and McKay's (1942) original specification of

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[15] Conceptually, resource deprivation and Wilson's (1987) concentrated disadvantage both refer to the coincidence of multiple indicators of low socioeconomic status. For this reason, the dissertation uses the terms interchangeably. Additionally, it should be noted that percent black is not a measure of disadvantage per se (Massey, 1998; Bray, 2003). However, the relationship between percent black and other indicators of disadvantage is so persistent that Land et al. (1990) lament the two may not be separable.

social disorganization, instability was conceptualized as population turnover. According to social disorganization theory, residential instability reduces the capacity of residents to form lasting primary relationships and weakens the supervisory capabilities necessary for parochial social control (Bursik and Grasmick, 1993b). The attenuation of these forms of social control is in turn expected to reduce public control networks. A similar argument is offered by Felson (1986) who notes that in the routine activities of community life, intimate handlers are the primary source of capable guardianship. Thus, where residential instability is greatest, and primary relationship networks the weakest, one expects a reduction in capable guardianship that frees offenders to act on suitable targets.

Shaw and McKay (1942) examined the population changes in local areas of Chicago. They found that areas nearest the central business district were being depopulated as commercial and industrial activity expanded. Additionally, they observed population increases in outlying areas of Chicago as people moved from one location to another. This was interpreted as evidence of the invasion and succession process described by Burgess (1925). Since that time, the concept of instability has been operationalized using several different measures such as population change (Bursik and Webb, 1982; Morenoff and Sampson, 1997), housing tenure (Heitgerd and Bursik, 1987; Sampson, 1985; Sampson and Groves, 1989; Miethe et al., 1991, Elliot et al., 1996; Sampson et al., 1997; Kubrin and Herting, 2003), the percentage of owner-occupied housing (Heitgerd and Bursik, 1987; Taylor and Covington, 1988; Sampson et al., 1997), and housing vacancies (Roncek and Maier, 1991; Krivo and Peterson, 1996).

Population change is measured as the difference in population size between two periods. Bursik and Webb (1982) find that the change in population size is negatively associated with juvenile delinquency rates between 1950 and 1960 in Chicago communities.[16] Thus, communities that experienced a net loss in population exhibited increases in delinquency during this period. However, population change was not associated with changes in delinquency during the 1940 – 1950 or 1960 – 1970 period. More recently, Morenoff and Sampson (1997) found that population change was negatively associated with homicide rates in Chicago between 1970 and 1990.[17]

Housing tenure is generally measured by the census as the percentage of the population age five and over who lived in the same house five years ago. Sampson (1985) finds that this measure, which he calls *residential mobility*, is positively associated with victimization rates for theft and violence in the National Crime Survey (NCS). Conversely, using a structural equation model with Chicago neighborhoods, Heitgerd and Bursik (1987) do not find a direct effect of stability on delinquency rates. However, they find that stable communities nearby areas undergoing racial transition do have higher delinquency rates. This finding suggests that community delinquency rates may not strictly be driven by internal dynamics. Rather, the dynamics of nearby areas may also have an influence on crime rates.

Miethe et al. (1991) examine homicide and robbery for 584 cities in the U.S. between1960 and 1980. They find that the percentage of the population that moved in the past five years is positively associated with robbery, but has no association with homicide rates. However, using the same measure at the neighborhood level Elliot et al. (1996) find a positive association with delinquency through its effects on informal social control and

[16] Bursik and Webb (1982) use the delinquency rate per 1,000 males age 10 – 17.

[17] Morenoff and Sampson (1997) also find that increases in homicide rates are associated with future population loss, suggesting the presence of a reciprocal effect between violent crime and community structure.

social integration.[18] Sampson et al. (1997) found that residential stability was negatively associated with violent crime, and positively associated with collective efficacy in 343 neighborhood clusters in Chicago. Additionally, collective efficacy largely mediated the association between stability and violent crime. However, Sampson et al. (1997) also found a small, but positive relationship between residential stability and homicide. When collective efficacy was included in the model, this relationship persisted and in fact intensified somewhat. Finally, in their study of St. Louis census tracts, Kubrin and Herting (2003) find that residential instability is positively associated with homicide rates.

In a slightly different operationalization of stability, Sampson and Groves (1989) use British Crime Survey data on the percentage of residents brought up within a 15 minute walk of their current residence. They find residential stability is associated with violent crime through its promotion of friendship networks and unsupervised peer groups. This dovetails with more recent efforts to integrate social disorganization and routine activities with respect to unstructured youth socializing (Osgood et al., 1996). Osgood and Anderson (2004) report that in a sample of approximately 5,000 eighth grade students in 36 schools parental monitoring is negatively associated with unstructured youth socializing, which in turn is positively associated with delinquency. The positive effect of residential stability on unsupervised peer groups could be interpreted as a similar mediating mechanism to that in Sampson and Groves's (1989) study. As noted above, stability is essential for the formation of primary relationship networks, which

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[18] Elliot et al. (1996) include population mobility as part of a disadvantage index that also included poverty, family structure, and ethnic diversity. This specification combines conceptually distinct structural indicators, rendering the determination of independent effects virtually impossible. However, the magnitude of the coefficient for the measure is quite large, consistent with the argument that the indicators act in a concentrated manner.

form the basis of youth peer groups. Thus, more stable communities would be expected to have a higher prevalence of youth socializing. In the absence of capable guardianship, we would expect youth groups to be positively associated with crime.

Owner-occupied housing is measured as the percentage of occupied housing units in which the owner lives. Heitgerd and Bursik (1987) find that owner-occupied housing is negatively related to a latent construct of household characteristics, which in turn is positively associated with delinquency rates.[19] Thus, there is a negative relationship between owner-occupied housing and delinquency. Taylor and Covington (1988) use owner-occupied housing as a component in their factor of stability.[20] For extremely disadvantaged Baltimore neighborhoods, they find that declines in stability are associated with increases in homicide and other violent crimes. However, Taylor and Covington (1988) also find stronger results for economic conditions and suggest that residential stability may act as a buffer against increasing levels of disadvantage.

Housing Vacancy is measured as the percentage of housing units that are not occupied. Strictly speaking, as a measure of instability, this indicator assumes that desirable neighborhoods will have high levels of housing occupancy. Conversely, if a community is not a desirable place to live, fewer housing units will be occupied by regular residents. Thus, where there are high levels of vacant housing, former residents have left the community and new residents are less likely to stay long. Roncek and Maier (1991) find that vacant housing is positively associated with crime rates across city

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[19] Heitgerd and Bursik (1987) operationalize household characteristics using a measurement model that includes owner-occupied housing, unemployment, and household density. The inclusion of unemployment as an indicator of the latent construct suggests that this measure is more closely associated with disadvantage than residential stability. It may be argued that, in economically deprived areas, residents are less likely to own their own home.

[20] The factor also included the proportion of married couple households and single unit structures (Taylor and Covington, 1988).

blocks in Cleveland, Ohio. Using a routine activities perspective, Roncek and Maier (1991) argue that recreational drinking establishments (i.e., bars and taverns) draw crowds that are less likely to know one another and therefore reduce capable guardianship. After controlling for the number of drinking establishments, vacant housing remains significant.[21] Krivo and Peterson (1996) find a significant relationship between vacant housing and violent crime in Columbus, Ohio census tracts as well. Furthermore, the standardized coefficient for vacant housing is larger than those for other factors such as the percentage renter-occupied housing, percent black, and percent young males. Finally, the relationship between vacant housing and violent crime persists after controlling for interaction effects between disadvantage and race.

The idea that neighborhood stability may act as a buffer against the deleterious forces of disadvantage is further described by Figueira-McDonough (1991). She argues that disadvantage and stability both influence the relationship networks of a community, but that the influences are not identical. Disadvantaged communities are expected to have fewer external links and secondary networks. These correspond to parochial and public levels of control in systemic social disorganization theory (Bursik and Grasmick, 1993). On the other hand, unstable communities are expected to have attenuated primary networks but greater levels of external linkages. These correspond to secondary and public social control levels in the systemic model (Bursik and Grasmick, 1993). That mobility erodes primary networks is also consistent with the absence of capable guardianship in routine activities theory (Cohen and Felson, 1979, Felson, 1986). Based on these propositions, Figuiera-McDonough (1991) creates a typology of urban

[21] The magnitude of the effect for drinking establishments is, however, larger than many of the structural characteristics in the model, including vacant housing.

communities and describes the relationship between structural characteristics and crime rates.

The established community is characterized by a stable and affluent population. This community is expected to have strong primary and parochial networks. As a result, the established community is expected to have the lowest delinquency rates. The parochial community is characterized by a stable and poor population. This community only has strong primary social controls, but is expected to have the second lowest crime rate in part due to its stability. The stepping-stone community has the second highest crime rate. This community is characterized by an affluent and unstable population, resulting in strong parochial and public controls without strong primary controls. The highest crime rate community discussed is the disorganized community, in which there is a poor and unstable population. This community is expected to have poorly functioning controls on all three levels of systemic organization.

The typology created by Figuiera-McDonough (1991) above is consistent with Wilson's (1987) discussion of the formation of the urban underclass. The out-migration of middle class families from less affluent minority communities results in the formation of socially isolated neighborhoods with high levels of concentrated disadvantage and other social dislocations. "A reasonable hypothesis concerning behavior is that in stable neighborhoods, people who are economically marginal and are struggling to make ends meet are more strongly constrained to act in mainstream ways than are their counterparts in high-jobless neighborhoods that feature problems of social organization" (Wilson, 1996: 70).

The Nature of Instability

An often overlooked discussion in the literature pertains to the nature of instability. As Shaw and McKay (1942) initially described them, unstable neighborhoods are those in which there is a high level of population turnover. This characterization of population mobility led to the common use of housing tenure as a measure of the concept. However, it is important to note that the ecological traditions of the Chicago school were developed within the historical context of urban growth and high rates of immigration into metropolitan areas. Few, if any, data existed regarding the ecological processes at work during periods of urban decline.

The critical issue is in the measurement of residential instability. The concept may be decomposed into three components: in-flow, out-flow, and the stable stock. During the early twentieth century, unstable communities had high-levels of in-flow and out-flow, with smaller proportions of stock. This is the classic conceptualization of a highly unstable community, within the context of urban growth. A relevant question to ask is whether or not these dynamics are sustained during periods of urban decline? Roderick McKenzie (1925) provides the theoretical foundation for explaining the cause and effect of urban decline.

McKenzie (1925) argues that communities tend to grow in a manner that, all else equal, will ultimately result in a state of equilibrium between the population and economic base. If, however, there is a disturbance to the system, such as an innovation in the economic base or forms of communication and transportation, the ecological system must readjust. Depending on the type of innovation that occurs, the process of readjustment may cause continued growth, or significant decline in the urban system.

Where a disturbance induces decline, the default outcome is “emigration and readjustment to a more circumscribed base” (McKenzie, 1925: 68).

When the impact of a malignant disturbance occurs, the process of readjustment inevitably changes the ecological structure of the community. In the face of population loss, and changes in the economic base, the networks and associations maintaining social order are inevitably altered. The result “when a community starts to decline in population due to a weakening economic base, [is] disorganization and social unrest” (McKenzie, 1925: 71). Furthermore, McKenzie argues that a shift to a weaker economic base will increase competition among the remaining population, forcing those who cannot adapt into either a lower socio-economic status or inducing them to opt out of the economy.

Incorporating these arguments into ecological theory provides a framework that addresses the structural influence on neighborhood crime rates during periods of both growth and decline in the urban system. The resulting perspective argues that stable patterns of urban growth or decline result in stable ecological structures across neighborhoods. However, when these dynamics are sufficiently altered by an exogenous shock, the structural distribution of the system is altered. Therefore, identifying the populations most affected by innovations and shifts in the economic base of the urban system may provide important information in predicting changes in the ecological distribution that were previously assumed to be stable.

With respect to the measurement of instability, this argument implies that housing tenure may act as a valid proxy for residential instability during periods of urban growth. As individuals and families enter and become assimilated to the urban system, the sorting processes described by Burgess (1925) will result in neighborhoods with higher levels of turnover. However, during periods of urban decline, the dynamics of the system are changed and unstable neighborhoods are those that experience the largest proportionate losses in population. Under these circumstances, traditional measures of housing tenure will indicate increases in neighborhood stability. A more realistic description would be that the community is withering into social isolation and concentrated disadvantage. Consistent with Wilson's (1987) description of urban underclass communities, instability measured as population out-flow is expected to be associated with increases in concentrated disadvantage.

Disadvantage and Racial Invariance

Crime rates have regularly been shown to be positively associated with neighborhood economic disadvantage (Bursik and Grasmick, 1993a; Krivo and Peterson, 1996; Sampson et al., 1997; Peterson et al., 2000; Kubrin and Herting, 2003). However, structural theories of crime rates assume that the influence of economic disadvantage is consistent across racial groups (Ousey, 1999).[22] Therefore, it is the differential exposure to violence-inducing contexts that creates racial differences in violence (Sampson and Wilson, 1995). Yet, the confounding of racial composition and economic status at the neighborhood level has made the assessment of this assumption difficult at best. As Sampson (1987: 354) and others have noted, "…racial differences are so strong that the worst urban contexts in which whites reside with respect to poverty and family disruption are considerably better off than the *mean* levels for black communities" (emphasis in original). For example, Jargowsky (1997) shows that between 1970 and 1990, less than five percent of poor whites lived in high poverty neighborhoods. Conversely, roughly

[22] Recall that two of Shaw and McKay's (1942) primary findings were that high delinquency areas were poor and persisted regardless of the racial and ethnic composition of the community.

twenty percent of poor blacks lived in such communities. Furthermore, poverty rates for non-Hispanic whites were approximately one-third of the poverty rates for blacks.

This confounding of race and economic status has recently generated a body of research addressing the racial-invariance assumption. Examining race-specific homicide rates across 125 U.S. cities, Ousey (1999) finds that there are significant differences in the magnitude of structural coefficients between blacks and white. Specifically, for poverty, unemployment, female-headed households, and a resource deprivation index, the influence on homicide is greater for whites than blacks. Ousey (1999) concludes that structural correlates of homicide are not racially invariant. However, using a similar dataset of 124 U.S. Central cities, Krivo and Peterson (2000) find that there is a non-linear association between disadvantage and black homicide rates.[23] As disadvantage increases, so do rates of lethal violence. However, this relationship weakens at higher levels of disadvantage. Thus, when economic disadvantage is squared, the difference between the influence of disadvantage on white and black homicide rates is reduced to non-significance.

Comparing block groups in Atlanta, Georgia, McNulty (2001) finds that the influence of disadvantage on violent crime is similar for black and white neighborhoods.[24] However, this relationship could only be compared at low levels of disadvantage because there were no white communities with comparably high levels of poverty. Examining the data across the entire distribution of disadvantage, McNulty (2001) finds a greater effect of disadvantage in white communities. He attributes this

[23] Ousey (1999) and Krivo and Peterson (2000) both sample U.S. cities in 1990 with total populations of 100,000 or more and with black populations of 5,000 or more. Due to the detection of outliers and missing data for cities in Florida, Krivo and Peterson sample is reduced to 124.
[24] McNulty (2001) defines predominantly black and predominantly white neighborhoods as those with 70 percent or more of the population in each racial category.

finding to the notion that there is a diminishing influence of disadvantage on violent crime rates at the upper end of the distribution. This finding is consistent with the non-linear association detected by Krivo and Peterson (2000).

McNulty and Bellair (2003) examine data from the National Longitudinal Survey of Adolescent Health, a nationally representative school-based cluster sample of students ages 11 to 20, to explore the racial invariance hypothesis. Where serious violence is concerned, they find a significant difference in offending across racial groups. When community disadvantage is controlled, the differences between whites and blacks are reduced to non-significance.[25]

Sampson and Bean (2006) summarize the research to date regarding the racial-invariance hypothesis into a few relevant "neighborhood facts". First, they note that inequality between neighborhoods is high and that economic disadvantage is related to the geographic isolation of minorities. Second, they find that neighborhood disadvantage is a robust predictor of violence rates, and that this relationship is observed across a variety of levels of aggregation. Third, when properly compared, there is little empirical evidence that the neighborhood correlates of violence act differently across racial groups.

Ecological Stability, Disadvantage, and Racial Composition

The review of the literature thus far highlights several important points regarding community crime rates. First, disadvantage is overwhelmingly associated with higher levels of violence. Second, in urban areas, minorities (predominantly blacks) live in contexts of greater economic disadvantage than their white counterparts. Third, differences in rates of violence across racial groups appear to be associated with

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[25] Interestingly, the differences between whites, Hispanics, Asians, and Native Americans are not explained by community disadvantage alone, but by a combination of family structure, social bonds, and gang involvement.

differential and restricted distributions of economic well-being. Finally, social and economic changes in urban areas since World War II have disproportionately affected minority neighborhoods so as to create an urban underclass. The combination of these observations and research findings is highly relevant to the study of community trajectories of crime.

The changes reported by Wilson (1987, 1996) and Massey and Denton (1993) are indicative of the lack of ecological stability, which is assumed by ecological theories of crime. Such forces have conspired to increase the number of people in the urban underclass, as well as the number of people living in underclass communities, thereby changing the ecological structure of the city (Jargowsky, 1997). Through these processes the differential distributions have been reinforced and the divide widened for urban communities. Thus, the findings of the literature paint a consistent portrait of neighborhood dynamics in urban cities. A destabilized system adjusts to changing economic circumstances, leaving behind those who are least assimilated into the fabric of the system. Historically, these communities are predominantly black communities in central cities. The result is the out-migration of middle class families (Wilson, 1987) and the residential segregation of minority families that attempt to leave and who cannot afford to move to much more affluent communities (Massey and Denton, 1993, Morenoff and Sampson, 1997).

Change Over Time

At present, the literature on changes in community crime rates over time has been predominantly confined to the study of consecutive cross-sectional periods over a range of years (Bursik and Grasmick, 1992). The strength of this approach lies in comparing statistical models across time periods and assessing the relative consistency of findings. On the other hand, the major weakness of this approach is that the model coefficients only describe the relative distribution of crime rates and structure across neighborhoods. The variation in crime rates is decomposed between communities. However, this approach ignores the fact that longitudinal variation in crime is influenced by processes that operate both across and within communities (Bursik and Grasmick, 1992). Thus, a full understanding of the ecological dynamics behind neighborhood crime rates must address both sources of variation.

As an alternative to using multiple cross-sectional models, residual change scores have been used by some researchers (see Bursik and Webb, 1982; Heitgerd and Bursik, 1987; Taylor and Covington, 1988). Residual change scores are obtained by regressing variable *X* at time *t* on data for the same variable at time *t-1* (i.e., $X_t = \alpha + \beta X_{t-1} + r$). The residual from this equation represents the change in variable *X* that is unexpected given the average change in the distribution across all communities. The residual change scores for both independent and dependent variables are then examined with ordinary least squares (OLS) regression. The strength of this approach is that residual change reflects the redistribution of communities for a given indicator, relative to the urban system. However, because the residual is standardized for all neighborhoods, it does not explain changes in the absolute level of crime (Bursik and Grasmick, 1992). For example, one neighborhood might exhibit relatively small residual change scores that reflect its stable role in the ecological system. However, such a neighborhood might display marked fluctuations in its levels of structural indicators and crime rates. Thus, while residual change scores are useful in detecting changes in the overall distribution of neighborhood characteristics, the method does little to explain within-community variation in crime rates.

To address the problem discussed above, recent studies have turned to the use of hierarchical models, and semi-parametric group-based procedures (Bursik and Grasmick, 1992; Kubrin and Herting, 2003; Griffiths and Chavez, 2004). Hierarchical models allow variations in the outcome to be decomposed into within- and between-neighborhood components (Raudenbush and Bryk, 2002; see chapter four for more detailed discussion of the HLM model). This strength is ideal for examining the dynamic processes associated with neighborhood crime trajectories.

As discussed above, ecological theories generally hold an assumption of stability in the processes producing neighborhood crime distributions. To examine this assumption, Bursik and Webb (1982) examine residual change measures for Chicago neighborhoods between 1940 and 1970. The findings indicate that changes in the ecological distribution of Chicago neighborhoods were not associated with changes in delinquency rates between 1940 and 1950. However, during the subsequent decade, changes in population size and racial/ethnic composition were associated with approximately one-third of the change in delinquency rates. Between 1960 and 1970, changes in household density and racial composition were again associated with changes in crime rates. Bursik and Webb (1982) argue that the associations between racial composition and stability were the result of changes in minority settlement patterns after 1950. However, the key theoretical propositions of Shaw and McKay were supported.

Heitgerd and Bursik (1987) extend this analysis by examining the association between external neighborhood changes and delinquency rates. Using the period 1960 to

1970, the authors find that changes in the racial composition of adjoining communities are significantly related to changes in the delinquency rate for moderately stable and very stable areas. Morenoff and Sampson (1997) explore these dynamics further, finding that population loss was associated with higher crime rates in Chicago neighborhoods between 1970 and 1990. Furthermore, evidence of a reciprocal effect was found such that areas with greater population loss experienced greater increases in violence. Finally, during this period, Morenoff and Sampson (1997) found that population movement differed for whites and blacks, with whites moving further away from violent areas.

Bursik (1986) examined Chicago data between 1930 and 1970. He found that ecological redefinition of Chicago communities with respect to stability and racial composition occurred primarily between 1950 and 1970. Bursik argues that the suburbanization of Chicago during the 1940s interacted with housing shortages in the city and the arrival of larger minority populations to produce greater instability in minority communities. In these communities, housing density increased as landlords subdivided rental properties to maximize profits. This type of market manipulation led to higher rates of turnover and, in turn, delinquency between 1950 and 1970. This work highlights the fact that "non-market-related processes may be able to alter the nature of ecological dynamics" (Bursik, 1986: 62). This concept can further be adapted to political decision-making processes as well (Bursik, 1989).

Examining Los Angeles between 1950 and 1970, Schuerman and Kobrin (1986) found several distinct patterns associated with structural changes and crime patterns. Neighborhoods experiencing rises in crime exhibited shifts from owner- to renter-occupied housing, as well as increases in multi-unit dwellings. Furthermore, these communities experienced increases in residential mobility and single-parent families, and decreases in low-skilled workers (indicative of increasing joblessness). The process suggested by the Los Angeles data is that neighborhoods experience changes in land-use and housing patterns first. These changes then begin a pattern of changing socio-demographic patterns and increase in crime rates. Additionally, Schuerman and Kobrin (1986) found that neighborhoods undergoing such changes quickly experienced the greatest increases in crime rates.

Bursik and Grasmick (1992) provide the first illustration of hierarchical modeling for neighborhood delinquency trajectories. They examine Chicago communities, again between 1930 and 1970. On average, neighborhoods experienced increasing delinquency rates between 1950 and 1970. Yet, there was a great deal of variation in the community-specific trajectories. Additionally, neighborhoods with higher average levels of unemployment had higher delinquency rates. Examining the linear trends in local trajectories, changes in delinquency were positively associated with changes in the percentage non-white, and negatively associated with changes in owner-occupied housing. Finally, the analysis finds that acceleration in delinquency trajectories is positively associated with changes in racial composition (from white to black), but negatively associated with unemployment. This last finding is consistent with the non-linear association between economic disadvantage and crime observed by Krivo and Peterson (2000) and McNulty (2001). These findings suggest that the role of economics, racial composition, and stability are important in explaining community crime trajectories. However, the structural indicators appear to make unique contributions to the shape of the trends.

Kubrin and Herting (2003) extend this analysis to homicide rates in St. Louis census tracts between 1980 and 1995. In keeping with the suggestion in Land et al. (1990), they produce factor scores for economic disadvantage and residential instability.[26] Additionally, they control for the population aged 15 to 24, population size, and the spatial correlation of homicide rates across communities, as well as for the changes in these factors between 1980 and 1990. Kubrin and Herting (2003) find that the initial levels of disadvantage, instability, and spatial autocorrelation are associated with homicide levels in 1980. However, contrary to Bursik and Grasmick's (1992) findings, Kubrin and Herting do not find significant relationships between the measures of structural change and homicide trends.[27]

While Kubrin and Herting (2003) provide a more fully specified model than Bursik and Grasmik (1992), the inconsistent findings may be a result of several different factors. First, Kubrin and Herting (2003) examine a fifteen-year period of time, and compute their measures of change using 1980 and 1990 census data. Therefore, changes occurring in St. Louis communities during the latter one-third of their study period are not examined. In contrast, Bursik and Grasmick (1992) examine a much longer period of Chicago history (40 years) and describe the ecological changes occurring within neighborhoods across the entire period. The null findings of Kubrin and Herting may therefore be the result of examining a shorter period of ecological change in St. Louis.

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[26] Disadvantage is comprised of the poverty rate, single parent families, median family income, the unemployment rate, and percent black. Residential instability is comprised of the percentage living in the same residence and the divorce rate.

[27] When homicides are disaggregated by type, Kubrin and Herting (2003) find a relationship between changes in disadvantage and trends in felony homicides. Neighborhoods with increasing disadvantage experienced greater increases in felony homicide during the late 1980s and early 1990s.

A second difference between these studies lies in their operationalization of social structure. Bursik and Grasmick (1992) use single indicators of racial composition, resource deprivation, and residential stability. In contrast, Kubrin and Herting (2003) combine multiple indicators using factor analysis to produce a two factor solution. Two potential problems arise from using this procedure. First, while factor analysis provides a solution to collinearity among relevant indicators, the resulting variable represents a measure of the common variation among the indicators. As such, the factor scores may mask important contributions to crime trends that are specific to individual indicators. The second problem in using the factorial solution lies in the ability to assess change over time across factor scores. Kubrin and Herting (2003) use principal components factor analysis with varimax rotation. This procedure yields a score with a mean of zero and standard deviation of one across communities. Replicating this procedure for 1980 and 1990 would produce two sets of scores with similar distributions (i.e., identical means and standard deviations). Therefore, the differences between scores over time represent the change in relative positions among communities, much like the residual change score. Again, the comparison of the solutions across periods does not describe the change in absolute levels of disadvantage. The differences between these two studies suggest the need to more closely examine the nature of structural changes in the separate indicators, as well as in a multivariate context.

The Influence of Space

The distribution of neighborhood characteristics across the city is not random. Rather, ecological theories argue that the sorting processes of city growth and decline shape the social environment of local communities. However, neighborhoods do not exist in a vacuum, isolated from other communities. They are functionally interdependent units of the larger city that interact with each other as the system evolves (Bursik and Grasmick, 1995). This fact is explicit in the concepts of invasion and succession. Additionally, systemic disorganization models recognize that the relationship networks underpinning local social control also extend beyond the neighborhood boundary (Bursik and Grasmick, 1995; Sampson and Groves, 1989). Therefore, it is likely that interaction between neighborhoods will also shape the regulatory capacity of a community. For this reason, the study of neighborhood change must take into account the spatial distribution of crime and social structure.

How do neighborhoods influence the characteristics and events in nearby communities? With respect to violent crime, the most prevalent rationale is the diffusive nature of violence (Baller et al., 2001; Morenoff et al., 2001; Messner et al., 1999; Cohen and Tita, 1999; Rosenfeld et al., 1999). The diffusion of violence may occur when violence is used as a means of informal social control (Black, 1998). While violence may be initiated between two people as a form of social control, it diffuses if violence is used in response to prior violent acts.

Homicide is a form of interpersonal violence that exhibits a great deal of dependence on the spatial distribution of relationship networks within and between neighborhoods. Most victims of homicide know who the offender is (Reiss and Roth, 1993). This implies that victims and offenders are members of the same interpersonal networks. In many cases, such networks are geographically constrained to specific areas (Morenoff et al., 2001). This is supplemented by the fact that most offenders commit homicide near their homes (Reiss and Roth, 1993). Therefore, to the extent that interpersonal networks extend beyond the borders of socially disorganized communities, the risk level of homicide is also expected to move outside of the community. When a phenomenon diffuses across an area, while maintaining its presence in the originating location, the process is called “expansion diffusion” (Cohen and Tita, 1999).

Homicide also represents a diffusion of violence when the act is performed in retaliation for previous violence (Morenoff et al., 2001). If the groups involved in such altercations must cross community boundaries to engage in such acts, then the retaliatory act may represent a diffusion of violence from one community the next. This diffusion process may be a by-product of gang-motivated or gang-affiliated violence (Rosenfeld et al., 1999). Additionally, such “turf” conflicts occur in the context of drug market competition for desirable selling locations. When a phenomenon diffuses from one location to another, leaving the originating location, the process is called “relocation diffusion” (Cohen and Tita, 1999).

The diffusion processes described above reflect direct diffusion. The force of contagion is endogenous to violence (Bray, 2003). While this is the purest sense of the diffusion of violence, these events may also diffuse indirectly through a mediating process. For example, violent crime in one neighborhood may influence changes in the social structure of surrounding areas. The adjacent communities would then be more likely to experience increases in crime resulting from increased disorganization. Morenoff and Sampson (1997) find evidence of this in their study of Chicago neighborhoods between 1970 and 1990. Specifically, communities located near high crime areas experienced greater population decline than other areas. This in turn led to higher concentrations of poverty and increased crime rates. Furthermore, population shifts varied across racial groups. Areas nearest high crime locations, increases in crime, and concentrated disadvantage experienced white population decline. However, the core ghetto communities experienced black population decline while neighborhoods on the periphery gained black population. These findings are consistent with the notion that violent crime and homicide in particular, may influence the social structure of surrounding communities, allowing further diffusion of crime in adjacent locations (Morenoff and Sampson, 1997).

The discussion above is not meant to suggest a unidirectional chain of events in which neighborhoods simply decay into a perpetual state of disorganization and crime. Remember that the local areas of the urban system are subject to the aggregate processes of city evolution. Thus, when innovations and policy decisions change the economic, communication, transportation, and political landscape in the city, neighborhoods in disarray may stabilize, or even improve over time (Griffiths and Chavez, 2004). Additionally, at the neighborhood-level, Suttles's (1972) description of the "defended community" illustrates that stable, cohesive communities may exhibit increased delinquency rates in response to the perceived threat of an undesirable group. Heitgerd and Bursik (1987) find evidence of this process in Chicago as some white communities experience elevated levels of juvenile delinquency in response to the encroachment of minority groups. Finally, violence is not the only phenomenon that may diffuse from one location to another. Sampson et al. (1999) find that collective efficacy – the shared belief in the ability of the community to facilitate solutions to common problems – also crosses neighborhood boundaries with regard to the supervision of children.[28] These considerations highlight the fact that neighborhoods do not simply come into being and then decline. Rather, communities are subject to development and decline according to city-wide evolution as well as forces exerted by surrounding areas (Jargowsky, 1997).

In addition to the diffusion of violence and its effect on neighborhood characteristics and crime, the stability of disorganized communities is likely to change over time. However, as Griffiths and Chavez (2004: 942) discuss, “Although the homicide rate in most U.S. cities changed rapidly over a short period in the late 1980s and early 1990s, only a small proportion of individual communities likely account for the surge.” In their study of Chicago communities between 1980 and 1995, these authors find three distinct trajectories of neighborhood homicide trends. The neighborhoods with the highest homicide rates clustered together in terms of their unit-specific trajectories, with the second highest rate communities at the periphery. The lowest homicide rate communities surrounded the other two groups. Additionally, Griffiths and Chavez (2004) were able to demonstrate that the homicide trends in the highest crime rate neighborhoods were primarily responsible for changes in Chicago’s crime rate during the study period. However, in examining the neighborhood trends in homicide, the authors do not control for any social structural characteristics.

From an ecological perspective, these arguments suggest that while neighborhoods are likely to cluster together along structural vectors, such clusters are not necessarily constrained to a single space in the city. Over time, the development of the city and interplay between local communities can cause the ecological distribution of

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[28] While this finding is set in the context of social disorganization and collective efficacy, it is also germane to the concept of capable guardianship from a routine activities perspective.

communities to shift. In addition to these dynamics, the clustering of high crime areas may also play a role in changing the spatial distribution of ecological indicators through direct diffusion and indirect structural processes. Therefore, it is expected that disorganized communities will continue to cluster together over time. However, the geographic location of these areas relative to other neighborhoods may change.

Several testable hypotheses may be derived from these arguments. First, it is expected that crime as well as structural characteristics of neighborhoods will cluster together throughout the study period. Second, controlling for spatial effects will reduce the magnitude of the effects of neighborhood characteristics. However, because the internal structure of the community is still hypothesized to be the primary regulatory mechanism, ecological features of the area will remain significant predictors of neighborhood crime. Third, because changes in violence and social structure are expected to be significantly associated over time, the trends in crime and ecological change are expected to cluster together.

Conclusion

The empirical literature generally finds support that neighborhood social structure is related to crime and violence. In particular, economic disadvantage has a persistent and strong positive association with crime. Additionally, residential instability is also positively associated with crime and victimization. Racial composition is also found to have an association with neighborhood crime rates. However, changes in the ecological stability of U.S. cities have contributed to the disproportionate concentration of disadvantage among minority populations, and especially African Americans. Therefore, much of the association between race and violence is likely due to economic disadvantage and not race-specific differences in the propensity for crime.

While most studies have examined neighborhood crime rates using cross-sectional data and methods, a few studies have attempted to assess the neighborhood correlates of crime trajectories. However, the results from these studies are mixed. Bursik and Grasmick (1992) find that changes in social structure are associated with community trajectories of juvenile delinquency in Chicago. However, Kubrin and Herting (2003) do not find that changes in structural measures are related to St. Louis homicide trends.

Recently, researchers have also begun exploring the spatial distribution of crime and violence across geographic areas. These studies generally find positive spatial autocorrelation among the level of crime rates, meaning that higher crime areas tend to be clustered together. Additionally, the when Griffiths and Chavez (2004) examined neighborhood homicide trajectories in Chicago, they also find positive autocorrelation in the trends. Furthermore, several studies have examined the spatial distribution of structural correlates of crime, as well as other neighborhood processes such as collective efficacy (Morenoff and Sampson, 1997; Morenoff et al., 2001; Baller et al., 2001). Generally, these studies find positive spatial autocorrelation in these neighborhood processes that is related to rates of crime and violence.

The two analytical chapters of the dissertation will explore these issues further for St. Louis neighborhoods between 1980 and 2000. The analysis will examine community homicide trends, and the changes in social structure that are associated with those trends. Additionally, the analysis will bring together methodologies for the study of both the longitudinal and spatial relationships between serious violence and neighborhood structure. The next section of the dissertation will discuss the data in more detail, before engaging in the analysis.

Chapter 3: Study Location, Data, Variables, and Analytic Strategy

Study Location

The dissertation examines data from the city of St. Louis, Missouri. At its peak in 1950, St. Louis City had a population of approximately 850,000 according to the U.S. Census and was the eighth largest city in the United States. Located on the western bank of the Mississippi River, St. Louis was the major industrial and manufacturing center of the region with the infrastructure for shipping goods and materials easily by rail or river. European immigration during the late 1800s and early 1900s had produced a predominantly white population of approximately 82 percent (Laslo, 2002).

Like many other Midwestern and Northeastern cities, employment opportunities in St. Louis during the 1950s were largely in manufacturing with a large proportion of workers in the automobile and auto-parts industry. Other major employers have included railroads and river freight companies, McDonnell-Douglas, Monsanto, as well as the Anheuser-Busch Brewery. However, the economic climate of St. Louis city became rapidly unstable after World War II, and the city underwent substantial changes.

During the 1960s, the federal highway project in St. Louis city was completed. Four interstate highways would eventually be constructed on city land. Interstate 64 bisects the city along a roughly east-west axis, running just south of the central business district and north of the major rail-yards. Interstate 70 extends northwest from downtown along the northern border of the city until eventually turning west beyond the city limits. Interstates 44 and 55 share common roadway just south of the central business district and part ways before leaving St. Louis. Interstate 44 extends southwest from the city, while interstate 55 continues south, roughly following the Mississippi River.

Coincident with the completion of these projects and throughout the 1970s, there were substantial changes in economic opportunities for city residents. Large numbers of manufacturing jobs were lost as factories moved westward to the surrounding counties where land was cheaper. Additionally, many residents moved out of the city to follow employment opportunities. Approximately 27.3 percent of the city population moved out of St. Louis during the 1970s. Also during this decade, the city implemented a school-desegregation plan that resulted in further population loss (Laslo, 2002).

The changes occurring in St. Louis continued between 1980 and 2000, although less rapidly than during the 1970s. In 1980, the population of the city was about 452,000 and would dwindle to 348,000 by the year 2000 according to the U.S. Census. The racial and ethnic composition of St. Louis also changed as a result of population out-migration. Whereas non-whites comprised approximately 18 percent of the population in 1950, the percentage grew to about 56 percent in 2000. The growth in the non-white population percentage was not simply due to population loss, however. Between 1950 and 1970, the non-white population of the city grew by over 100,000 before shrinking by about 50,000 during the subsequent thirty years (Laslo, 2002).

As a study location, St. Louis clearly represents a city in decline between 1980 and 2000. Having experienced economic and population losses that were rampant in the Midwest and Northeast, as well as other economic and social transformations that occurred across the U.S., the city was far from the prosperous river town of the 1950s. In many ways, St. Louis is a prime example of the changing urban structure after World War II in the U.S. as described by Wilson (1987, 1996).

Data and Variables

The data for the dissertation were obtained from three sources. The homicide data were collected for the St. Louis Homicide Project (SLHP) and Project Safe Neighborhoods (PSN) in St. Louis, Missouri.[29] The St. Louis Homicide Project Data span the years 1979 to 1997. Homicide records were collected from the St. Louis Metropolitan Police Department and the addresses of incidents were included in the data.[30] The data obtained from Project Safe Neighborhoods span the years 1998 to 2001 and were also collected from police department records to obtain the addresses of incidents. Homicide addresses for each year were geo-coded to the 2000 census tract boundaries for St. Louis. Incidents were then aggregated to produce total annual homicide counts for each tract. All geo-coding was performed using ArcView 3.2 software.

The third data source is the Geolytics, Inc. Neighborhood Change Database 1970 – 2000 (NCDB). This NCDB consists of census data covering the four decennial data collection periods from 1970 to 2000. During each decennial census, tract level boundaries are adjusted in response to population movements and changing demographics. Thus, data obtained directly from the U.S. Census Bureau is not always comparable over time unless adjustments are made to account for boundary changes. The NCDB is preferred in this study over primary source census data because the tract boundaries have been normalized to the 2000 census collection period.[31] Tract-level data is disaggregated to the block-level for each decennial census then aggregated to the 2000

[29] The author would like to thank Scott Decker and Richard Rosenfeld for providing access to the SLHP and PSN data for this study.
[30] The addresses included represent the location of the incident, and not the home address of the victim. Thus, the geographic data represent the distribution of homicide risk across the city and not the distribution of where victims live.
[31] See the Neighborhood Change Database 1970 – 2000 User's Guide, Appendix J, for a detailed description of the remapping procedures.

tract boundaries. In St. Louis, between 1980 and 2000, 103 out of 113 census tracts (91.2 percent) maintained consistent boundaries. Of the ten tracts that underwent boundary changes, five tracts experienced a change in both 1990 and 2000 census periods. Using the NCDB data allows these areas to be retained in the analysis using the normalized boundaries.

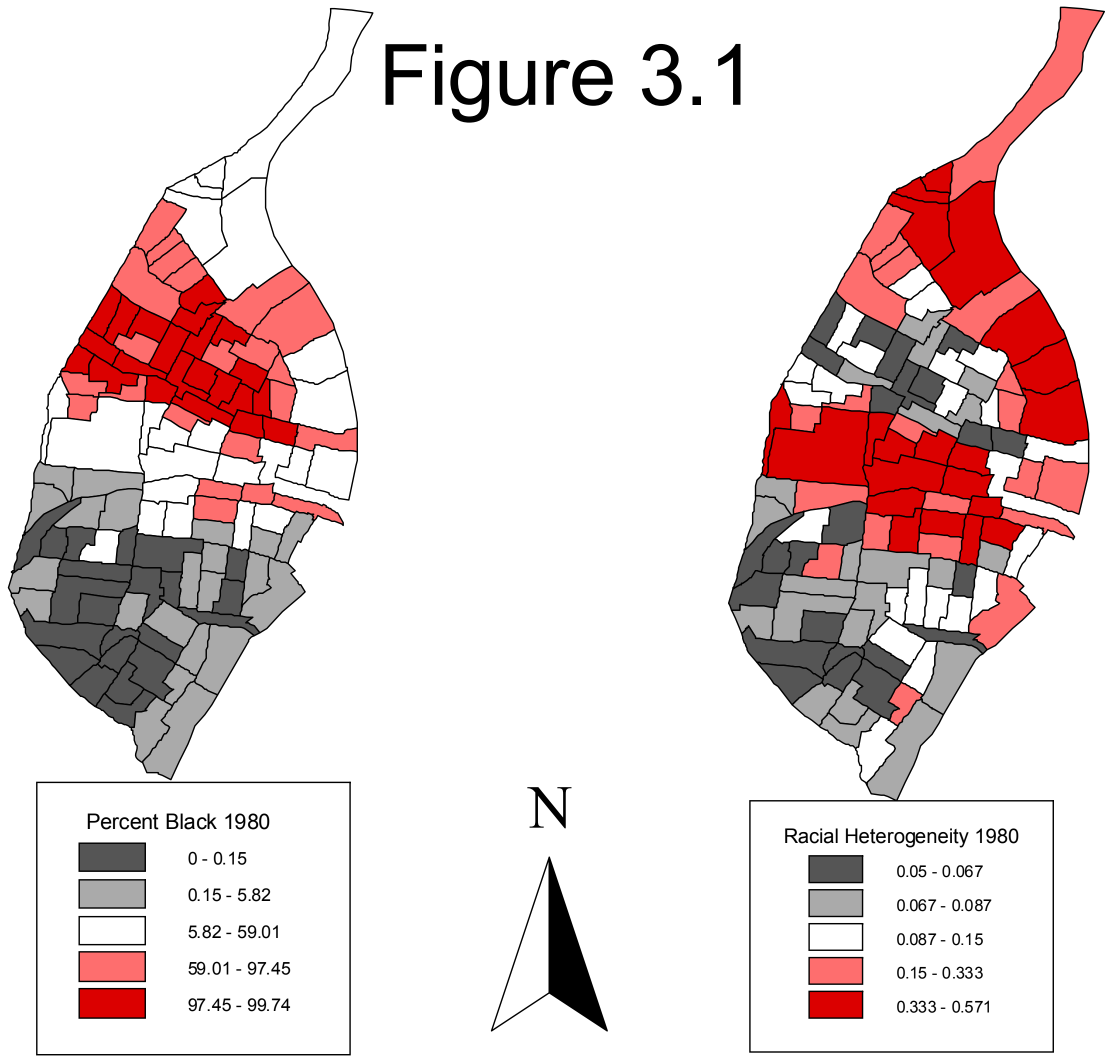
Using census data that have been geographically normalized allows the examination of census tracts over time and the computation of valid measures of change. Several variables from the NCDB data are used in this dissertation. Each variable relates to one of the major dimensions of social structure discussed by Messner and Rosenfeld (1999): social class, racial composition, family and age structure, and mobility.

Population Size is the count of individuals living in each census tract. The census uses five major categories to represent the racial composition of an area: white, black, Asian/pacific islander, native American/Aleutian, and other.[32] St. Louis city is largely comprised of whites and blacks (see figure 3.1), with the other racial categories comprising smaller proportions of the population. Two measures of racial composition are computed from the data. *Percent Black* is the percentage of the tract population that is black. The other measure of racial composition, *Racial Heterogeneity*, is designed to describe the distribution across all five racial categories. The measure is computed as:

$$\text{Racial Heterogeneity} = 1 - \sum_{i=1}^{5} \left(p_i^2 \right) \qquad (1)$$

[32] Individuals may be multi-racial. As such, in 2000, the census altered to racial composition data to include multi-racial categories under each of the five major categories (resulting in 36). Since these data were not previously collected, the 1980 and 1990 census cannot be made comparable to the 2000 data. Therefore, the dissertation only examines racial composition in the context of the five major race categories.

Figure 3.1


Percent Black 1980
0 - 0.15
0.15 - 5.82
5.82 - 59.01
59.01 - 97.45
97.45 - 99.74
N
Racial Heterogeneity 1980
0.05 - 0.067
0.067 - 0.087
0.087 - 0.15
0.15 - 0.333
0.333 - 0.571

where p_i^2 is the squared proportion of the tract population for each of the five racial categories (Blau, 1977; Britt, 2000). The measure ranges from 0, when the racial composition of the tract is homogeneous, to a maximum of 0.8, when the population is evenly distributed across racial categories.

In addition to indicators of racial composition, the dissertation uses two additional measures of population diversity. *Ethnicity* is measured as the percentage of the tract population that is Hispanic. *Percent Immigrant* is measured as the percentage of tract population that was not residing in the U.S. five years prior to the census collection.

Four measures of family and age structure are used. *Female-headed Families with Children Under 18* is measured as the percentage of all families in the census tract. The *Divorce Rate* is measured as the percentage of the population, fifteen years old or more that report being divorced. Additionally, *Percent Youth* is the percentage of the population between the ages of 15 and 24. Since males are disproportionately involved with violent crime, the dissertation includes *Percent Male Youth* in the same age group.

Increasingly employers demand a supply of workers with advanced levels of education, while the supply of jobs for those with little education has declined (Wilson, 1996). Therefore, the dissertation calculates *Percent High School Dropouts* as the percentage of the population age 25 and over that did not complete high-school. For the same age group, *Percent College Graduate* is used to assess the percentage of the population with a four-year degree.

Four measures of unemployment are examined. First, *Total Unemployment* measures the percentage of the civilian labor force aged sixteen and over that is unemployed. However, as Wilson (1987) argues, social and economic changes in urban areas disproportionately influenced poor and minority males. Therefore, the dissertation includes *Male Unemployment* measured as the unemployment rate among civilian males in the labor force, aged sixteen and over.

Wilson (1987) also argues that when unemployment is increasing, and legitimate employment opportunities are decreasing, the increased competition for jobs will cause some residents to opt out of the labor force. When this occurs, these residents are not included in the denominator of unemployment rate calculations. Thus, a community may maintain a consistent unemployment rate over time. However, the neighborhood may experience a large decline in economic well-being if the absolute size of the labor force is shrinking resulting from an increased lack of participation. For this reason, the dissertation also examines *Total Joblessness*, and *Male Joblessness*. For both indicators, joblessness is the percentage of the civilian population that is either unemployed or not in the labor force.

The *poverty rate* is defined as the percentage of the population with incomes below the census defined poverty level in the preceding year (e.g. income for 1989 is measured in the 1990 census). The poverty rate is a measure of the prevalence of absolute poverty in the neighborhood. However, the indicator does not provide information on the level of income in the community. Therefore, the dissertation also examines *average family income*, measured as the mean income across families within a census tract.[33] This measure allows comparison of income levels within high and low poverty rate areas. A final measure associated with income status is the percentage of households receiving *Public Assistance*.

[33] Family income is inflation-adjusted to 1980 dollars using the consumer price index (CPI).

In addition to objective measures of socio-economic status such as average income or poverty rates, Wilson (1996) argues that the loss of employment opportunities in central cities has constrained opportunities for workers in two important ways. First, labor markets were bifurcated into two sectors: technical and managerial positions requiring highly-trained and skilled workers, and service jobs requiring little or no skill. Second, the loss of inner-city jobs created a spatial mismatch between city residents and economic opportunities. For many low-income workers the result is a reliance on public transportation to commute to and from work. Therefore, this study measures the *Percentage of Service Workers* among those aged 16 and over who are employed. Additionally, the *Percentage of Workers using Public Transportation* is examined.

Population mobility in the city is measured using several indicators. The most direct measure of the out-migration of residents is *Population Change,* measured as the net change in tract residents. More indirect measures examine mobility with respect to length of residence. *Percent Same Residence* is measured as the percentage of the population age five and over that has lived in the same house for at least five years. To capture the movement of populations within the city, the dissertation uses the *Percent Living in St. Louis* five years ago, but in a different house.

In addition to these direct measures of population movements, social disorganization theorists have argued that the type and quality of housing in the neighborhood is associated with population turnover (Shaw and McKay, 1942; Schuerman and Kobrin, 1986). Similarly, the proximity of residents to each other and rate of turnover is expected to alter the routine activities of the community, particularly with respect to capable guardianship. Therefore, this study examines the percentage of housing units that are *Owner-occupied*, *Renter-occupied*, *Vacant*, and *Multi-Unit Dwellings* as indicators of population mobility and guardianship.

The measures discussed above represent aspects of the major domains of social structure and are consistent with current knowledge of the structural covariates of homicide (Land et al., 1990; Messner and Rosenfeld, 1999; Krivo and Peterson, 2000). Additionally, each of the measures is consistent with concepts derived from strain, routine activities, and social disorganization theories. A summary of these measures is provided below.

Measures of racial and ethnic composition include *Percent Black*, *Percent Hispanic*, *Percent Immigrant*, and the *Population Heterogeneity* index. Family and age structure measures include *Female-Headed Families with Children under 18*, *Divorce Rates*, *Percent Youth (15-24)*, and *Percent Male Youth (15-24)*. Krivo and Peterson (2000) argue for closer examination of the educational achievement, such as *Percent High School Dropouts* and *Percent College Graduates*, in studies of homicide since these variables are highly associated with economic potential. Additional measures of economic conditions and social class include *Unemployment Rates*, *Male Unemployment Rates*, *Poverty Rates*, *Average Family Incomes*, *Percent of Households on Public Assistance*, *Joblessness Rates*, Male *Joblessness Rates*, *Percent of Labor Using Public Transportation*, and *Percent Service Workers*. Finally, housing and population stability measures include *Population Change*, *Percent Same Residence*, *Percent Living in St. Louis*, *Owner-occupied Housing*, *Renter-occupied Housing*, *Vacant Housing*, and *Multi-unit Dwellings.*

Analytic Strategy

The dissertation uses several analytic strategies to address the research question. First, hierarchical linear models (HLM) are used to determine whether or not changes in social structure are significantly related to within-neighborhood homicide trends (Raudenbush and Bryk, 2002). Second, exploratory spatial data analysis (ESDA) techniques are used to examine the spatial structure of homicide trends and neighborhood characteristics. Finally, in a two-stage analysis, neighborhood trends in homicide produced in HLM are imported for spatial regression analysis to explain the clustering of homicide trajectories across St. Louis tracts. The methods are discussed in greater detail where appropriate.

Chapter 4: Neighborhood Trajectories of Homicide

The focus of this chapter is to explore the structural correlates of St. Louis neighborhood homicide trajectories. The analysis expands on the work of Kubrin and Herting (2003) in several key aspects. First, the period of analysis includes the years 1980 through 2000, thereby extending the series to twenty years. This represents a thirty percent increase in time points and covers the majority of the homicide decline in St. Louis. Second, the analysis examines the trajectory of neighborhood homicide trends within the context of the broader homicide trend for St. Louis City. In doing so, the dissertation examines variations in neighborhood trajectories during periods of significant increases and decreases for homicide trends city-wide. The third characteristic that differentiates the current study from that of Kubrin and Herting (2003) is the expansion of latent constructs such as disadvantage and instability into their component indicators. The purpose of this analysis is to examine in closer detail the relationships between broader domains of social structure, and the crime trends they are associated with.

The analysis will proceed in several steps. First, the dissertation will examine neighborhood homicide trends to determine, in general, the functional form of the dependent variable, and its degree of variability across tracts. Second, the analysis will examine the bivariate association between indicators of social structure and violent crime trends. To the extent that the levels and changes in these indicators are correlated with one another, latent constructs will be created through a factor analytic strategy and entered into multivariate models. Using this strategy, the trajectory parameters of homicide rates are explained through their association with changes in neighborhood social structure.

It should be noted that the analysis presented in this chapter is used to determine how structural changes are related to homicide trends. Additionally, the results will explore the nature of these relationships over time. These two aspects of the research are consistent with questions such as *what* is the nature of the relationship, and *when* is the relationship observed. Importantly, the analysis presented here cannot explain the geographic distribution of homicide trends and neighborhood structure. This aspect of the research is consistent with the question *where* are the relationships observed. This last portion of the research is reserved for the following chapter and an explicitly spatial analysis.

St. Louis Homicide Trends 1980 – 2000

Like many other large urban cities, homicide rates in St. Louis exhibited substantial fluctuations during the last twenty years of the twentieth century (see figure 4.1). After experiencing a sustained increase during the 1970s, violent crime peaked in 1981. A significant decline during the early portion of the decade was halted and reversed in the middle and late 1980s. During the early 1990s, violence reached a record high. Then, the tide of violence took and unexpected turn, subsiding quickly to a fifteen-year low by the year 2000. Yet, like other urban areas, these trends did not characterize all communities within the city.

Homicide is not randomly dispersed throughout St. Louis neighborhoods. Figure 4.2 shows the pooled distribution of homicides between 1980 and 2000, by census tracts. During this time period, the average community experienced 33.42 homicides (std. dev. = 30.08), or approximately 1.59 per year. Of the 113 tracts within the city, 57.52 percent (n

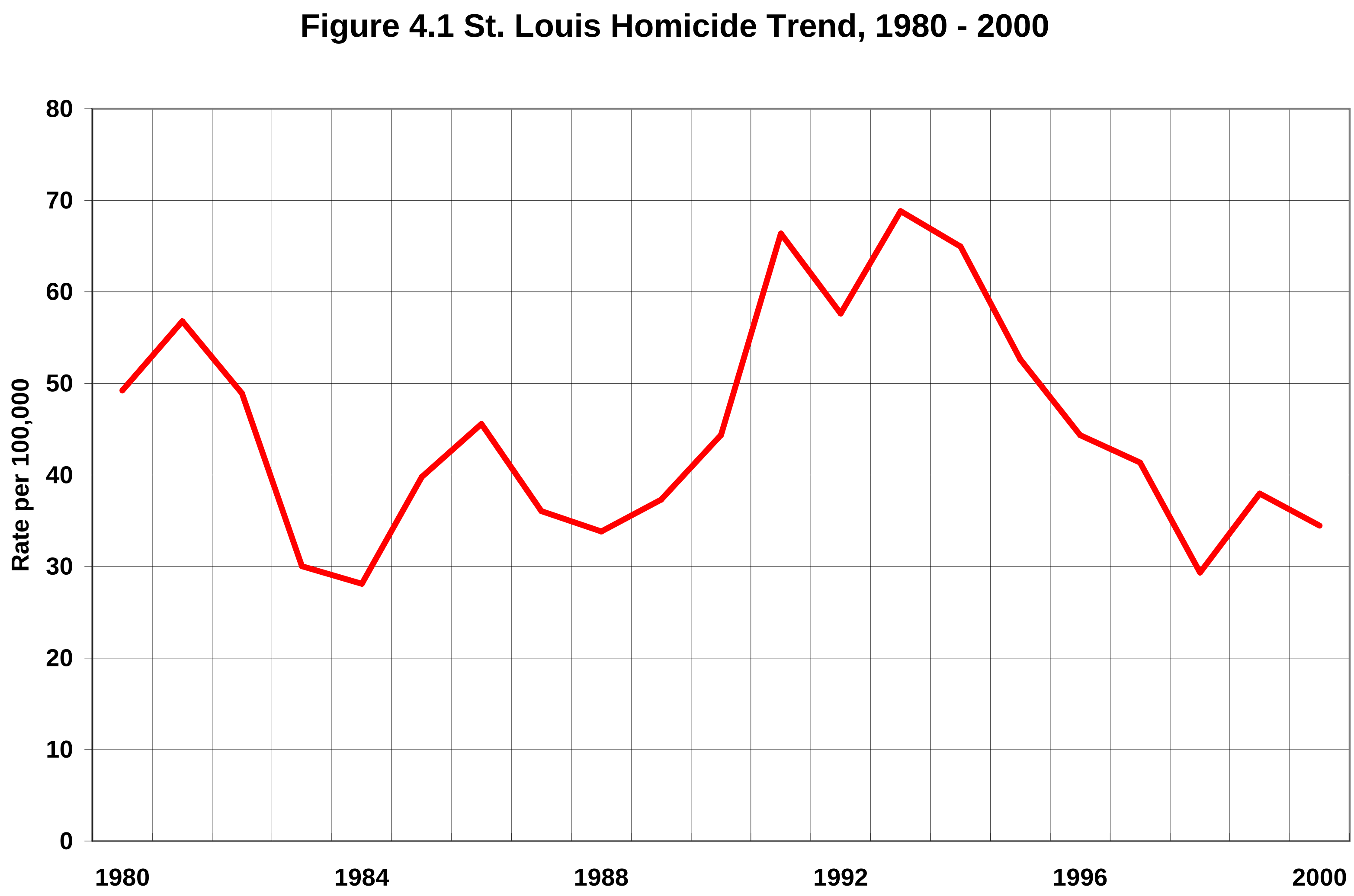
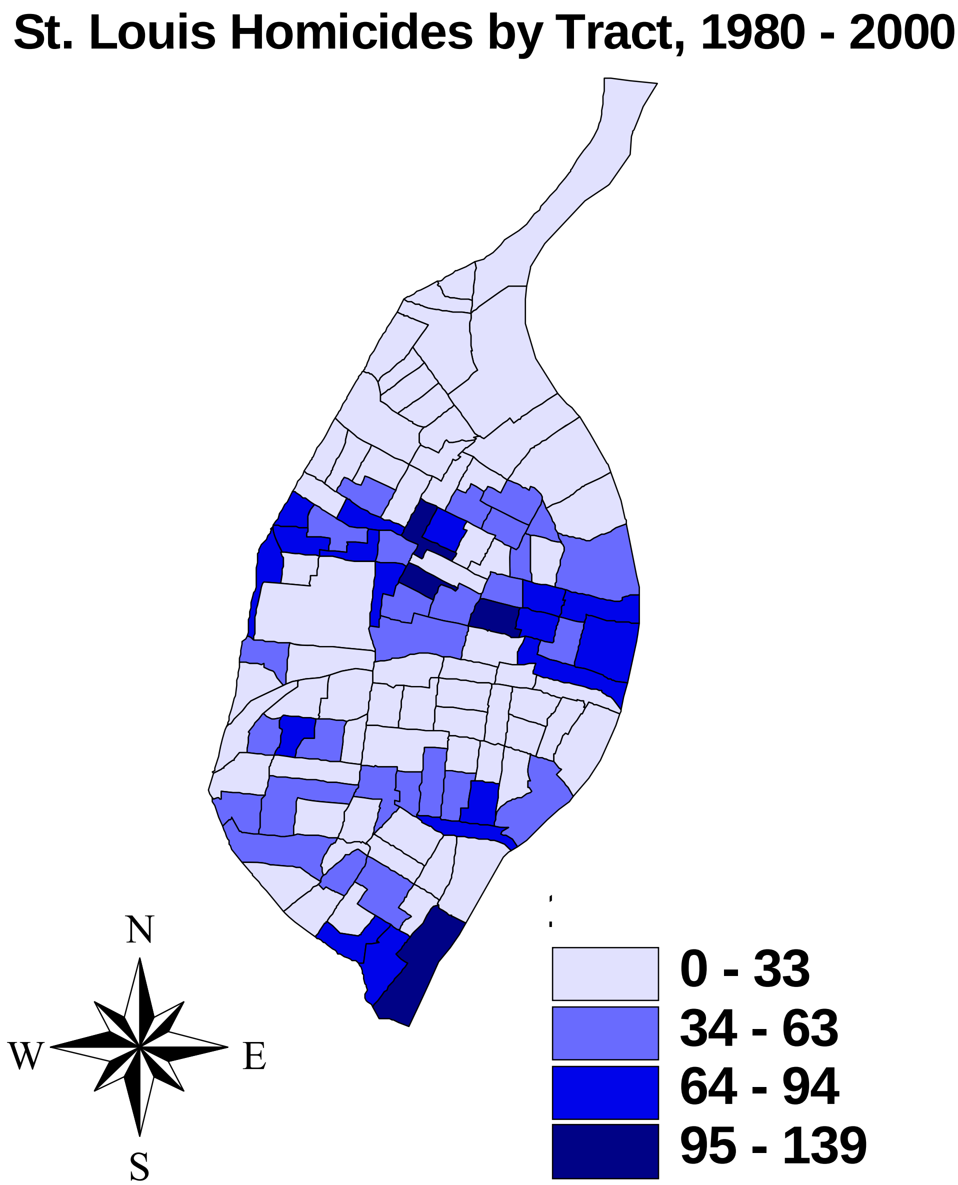


Figure 4.1 St. Louis Homicide Trend, 1980 - 2000
Rate per 100,000
80
70
60
50
40
30
20
10
0
1980
1984
1988
1992
1996
2000

Figure 4.2


St. Louis Homicides by Tract, 1980 - 2000
N
W
E
S
0 - 33
34 - 63
64 - 94
95 - 139

= 65) are at or below this level of violence. Of the remaining neighborhoods, 23.9 percent (n = 27) were within one standard deviation above the mean, and 15.0 percent (n = 17) were two standard deviations above the mean. Only four neighborhoods (3.5 percent) had homicide levels more than two standard deviations above the mean.

Geographically, the majority of violence occurs in a band of tracts located just north of the central city, and spanning the city from east to west. Of these 29 tracts, approximately half (n = 15) were more than 1 standard deviation above the mean level of homicide. Included in this group are three of the four most violence prone tracts in the city. However, homicide is not strictly concentrated in the northern half of the city. A group of communities (n = 19) in the southern half of the city also experienced above average levels of homicide. Although these tracts have lower levels of violence, and are less concentrated geographically than their counterparts in the north, they represent the second most dangerous areas in the city.

The homicide trend and geographic distribution show marked variation in both locations and levels of violence. However it is the intersection of location and trend that this study is most concerned with. The dissertation therefore turns to examining the distribution of homicide trends at the neighborhood level. Simply asked, how do homicide trends vary across local areas of St. Louis? And, are there significant differences across locations that can explain these differences?

To answer both of these questions, a two level hierarchical linear model (HLM) is estimated for 110 tracts in the city.[34] Due to the low number of homicides in many of the

[34] Prior research suggests that the inclusion of communities with less than 200 in population will result in unreliable rates (Rosenfeld et al., 1999; Kubrin and Herting, 2003). For this reason, the analysis excludes tracts 1214.00, 1222.00, and 1235.00. In 1980 these tracts had 334, 101, and 0 populations, respectively. In 2000, tracts 1222.00 and 1235 had 0 population, and tract 1214.00 had declined to a population of 122.

tracts, short-term variability within tracts is magnified. Therefore, a three-year moving average homicide count is calculated.[35] Annual population estimates were created using linear interpolation of the decennial census data at the tract level. The smoothed homicide counts and population estimates were then used to calculate the annual homicide rate per 1,000 for each tract. The distribution of annual homicide rates exhibits strong positive skew. Thus, the rates were transformed using a natural logarithm, and the logged homicide rate per 1,000 is the dependent variable.

The hierarchical linear model is a two level regression model that simultaneously examines variations in the outcome both within and between the units of analysis (Raudenbush and Bryk, 2002). In the current model, level 1 is used to fit a trajectory for homicide in each neighborhood of St. Louis. The level 1 equation is:

$$Y_{ti} = \pi_{0i} + \pi_{1i}T1 + \pi_{2i}T2 + \pi_{3i}T3 + e_{ti} \ , \tag{4.1}$$

where Y_{ti} is the logged homicide rate at time *t* in tract *i*, *T1* is a linear trend that corresponds to the years 1980 through 1986, *T2* is a linear trend that corresponds to the 1987 to 1993 period, and *T3* is a linear trend for the period from 1994 to 2000. The intercept π_{0i}, is the estimate of the logged homicide rate per 1,000 in 1980. The remaining regression parameters describe the homicide trend for neighborhood *i* during each of the periods described above, and e_{ti} is the residual for tract *i* at time *t*.

In level 2, the regression parameters π_{0i}, π_{1i}, π_{2i}, and π_{3i} are used as outcomes to describe the variation in homicide trends across tracts. The level 2 models are:

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[35] The three-year moving average (MA) was applied from 1979 through 2001, thereby preserving the study period of 1980 – 2000. Without the MA transformation, the HLM models failed to converge after 10,000 iterations. However, after MA smoothing, unconditional models converged after 14 iterations.

$$\begin{aligned}\pi_{0i} &= \beta_{00} + r_{0i}\\ \pi_{1i} &= \beta_{10} + r_{1i}\\ \pi_{2i} &= \beta_{20} + r_{2i}\\ \pi_{3i} &= \beta_{30} + r_{3i}\end{aligned}, \qquad (4.2)$$

where β_{00} is the average level of homicide across tracts in 1980, β_{10} is the average homicide trend between 1980 and 1986, β_{20} is the average homicide trend between 1987 and 1993, and β_{30} is the average trend between 1994 and 2000. The residuals in the level 2 models represent the neighborhood-specific deviations from the grand mean for each of the level-1 parameters. In this way, the HLM explains variations in homicide rates both within and between communities of St. Louis.

Traditional growth curve models used to describe and explain individual change generally use a polynomial function of time at level 1 (see Kubrin and Herting, 2003 for an example). Under this specification, the intercept represents the initial level of the outcome, and linear, quadratic, and higher order functions of time can be used to describe changes over time in the outcome. However, the level 1 model described above represents a spline regression in which a linear trend is estimated for sub-periods of the trajectory, and allowed to bend at predetermined points called knots. This level 1 model is preferred over a polynomial function of time for three reasons.

First, as shown in figure 1, St. Louis homicides follow an S-shaped trajectory between 1980 and 2000. In order to fit a polynomial function in level 1, linear, quadratic, and cubic time components must be used to approximate the trajectory.[36] However, the use of a cubic polynomial risks over-fitting the data, reducing the regression space to a point where variables entered in the level 2 equations cannot explain the small residual

[36] Higher order polynomials could be used. However, the interpretation of the regression coefficients, and level-2 parameter estimates becomes difficult.

differences in trend. Additionally, using a lower order polynomial, such as a quadratic, at level 1 does not have good face validity given the S-shape of the trends.[37]

Secondly, the S-shaped trend in observed homicide rates indicated three distinct periods of trend corresponding to major upswings and downswings in violence. Messner et al. (2005) examined the homicide trajectories between 1979 and 2001 for all cities of 250,000 or more in 2001. The purpose of their study was to identify cities that experienced epidemic-like increases and declines in homicides, and the years in which the trends experienced significant changes. The researchers found that St. Louis experienced such a boom-bust cycle in homicide trends. The analysis found that the city had a significant upturn in violence in 1986, and a subsequent downturn in 1993.

Finally, the next chapter of this dissertation will describe the spatial patterning of homicide trends and changes in social structure across St. Louis neighborhoods. To the extent that the geographic distribution of structural changes may explain the clustering of homicide trends, spatial regression will be used to describe those relationships. However, HLM cannot currently estimate a spatial regression in a multi-level context. Following Morenoff (2003), a two-stage procedure can be used with HLM to approximate this model. However, the procedure requires a single trend parameter to use as an outcome rather than a polynomial function with multiple parameters.[38]

The use of a spline regression at level 1 takes into account the three concerns described above. First, the spline estimates a linear trend for distinct sub-periods between

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[37] A cubic model was explored. However, the residual variances in the quadratic and cubic trend parameters were below 0.00001. When neighborhood characteristics were entered in the level 2 models, the only significant effects found were associated with the 1980 level of homicide, suggesting that the model was over-fitting the data. A quadratic model was estimated, but did not fit the data as well as the cubic, and was a poor approximation of the neighborhood trajectories.

[38] A complete discussion of this procedure is given in the next chapter.

1980 and 2000 without over-fitting the data. Second, the spline allows modeling the neighborhood trends that correspond to significant structural breaks in the city-wide trend. Third, the results from the spline regression can be used to approximate a spatial regression in the context of a multi-level model. For these reasons, the spline is preferred over traditional polynomial models.

Still, the spline strategy has several limitations that must be noted. First, Messner and colleagues (2005) estimated structural break points for the city of St. Louis, not for individual neighborhoods of the city. By using 1986 and 1993 as knots in the spline, the dissertation cannot assess the extent to which neighborhoods may have differed in the timing of their increases and decreases. It is possible, if not entirely likely, that homicide rates for some neighborhoods began trending upward before or after 1986. The same possibility exists for the 1993 turning point. Assessment of the differences in turning points across communities is therefore impossible because it is explicitly modeled in the spline.

A second limitation of the spline regression is the reduction in length for the time series in each section of the model. By breaking the time series into three sections, each linear portion of the trajectory corresponds to a specific 7-year period of time. By implication then, the level 2 portion of the model relates the structural changes for each period to between-neighborhood variation in 7-year homicide trends. Under this condition, the coefficient estimates for structural covariates pertain to relatively short-run trends in violence, rather than a 21 year period of time. Therefore, the analytical question is not whether changes in social structure are related to long-run crime trends over a 20 year period. Rather, the analysis will determine whether structural features of neighborhoods are related to relatively short-run upswings and downswings in violence.

Table 4.1 presents the results of an analysis of variance and an unconditional model described by equations 4.1 and 4.2. Analysis of variance is conducted with HLM by specifying the following level 1 and 2 equations:

$$\begin{aligned} &\text{Level 1}: Y_{ti} = \pi_{00} + e_{ti} \\ &\text{Level 2}: \pi_{00} = \beta_{00} + r_{0i} \end{aligned}, \qquad (4.3)$$

where π_{00} is the neighborhood-specific average log homicide rate, β_{00} is the average log homicide rate across neighborhoods, r_{0i} is the neighborhood deviation from the grand mean, and e_{ti} is the annual deviation from the within-neighborhood average. Therefore, this represents a one-way ANOVA. The results show that the average log homicide rate between 1980 and 2000, and across all tracts is $\beta = -0.147$ ($p < .001$). The average homicide rate per 1,000 is 0.86.[39] The random effects panel of the table shows the variance in the level 1 and level 2 residuals, var(e_{ti}) = 0.0762 and var(r_{0i}) = 0.1711, respectively.

A chi-square test is used to formally determine whether or not the residual variance component is significantly greater than zero. The test has degrees of freedom equal to n – 1, where n is the number of level 2 units (i.e. neighborhoods). In this case, $\chi^2 = 5251.992$ ($p < .001$) indicating that the variation in neighborhood average homicide

[39] The average homicide rate is calculated by exponentiating the fixed effect in the ANOVA. Exp(-0.147) = 0.863.

rates is significantly greater than zero. The 95 percent confidence interval for the neighborhood average homicide rates is (0.38, 1.94).[40] In addition to testing the

Table 4.1: Unconditional HLM of Log Homicide Rates per 1,000 in St. Louis Census Tracts with Robust Standard Errors, 1980 - 2000

Fixed Effects	*Coef.*	*S.E.*	*Coef.*	*S.E.*	
Intercept, β_{00}	-0.147***	0.040	-0.086	0.047	+
1980 - 1986 Trend, β_{10}			-0.032	0.005	***
1987 - 1993 Trend, β_{20}			0.043	0.005	***
1994 - 2000 Trend, β_{30}			-0.046	0.006	***
Random Effects	*Variance*	*Chi-sq*	*Variance*	*Chi-sq*	
Intercept, r_0	0.17110***	5251.992***	0.22117	1266.05	***
1980 - 1986, r_1			0.00188	277.845	***
1987 - 1993, r_2			0.00164	383.201	***
1994 - 2000, r_3			0.00258	448.538	***
Level 1 Error, e	0.07615		0.04784		
* p < .05 , ** p < .01 , *** p < .001				df = 109	

assumption of significant differences across neighborhoods in their average homicide rates, the ANOVA results can be used to calculate the intraclass correlation, which is the percentage of the variation in log homicide rates between neighborhoods. The intraclass correlation is 69.2 percent, indicating that the majority of the variation is between neighborhoods rather than within neighborhoods.[41]

The second model in table 4.1 is unconditional in the sense that it estimates the within-neighborhood trajectories of homicide, but does not include any additional

[40] The confidence interval is calculated as Exp[$\beta_{00} \pm 1.96\left(\sqrt{\tau_{00}}\right)$], where τ_{00} is the residual variance component.

[41] The interclass correlation is calculated as $\hat{p} = \dfrac{\tau_{00}}{\tau_{00} + \sigma^2}$, where sigma-squared is the residual variance in the level 1 error.

covariates in the model. The intercept, β_{00}, now represents the estimate of the average log homicide rate in 1980. The average homicide rate in 1980 is exp(-0.086) = 0.918 ($p < .05$). Between 1980 and 1986, there was an average decline of 3.1 percentage points in homicide rates. This was then followed by an average increase of 4.4 percentage points annually between 1987 and 1993. Finally, from 1994 to 2000 the average homicide rate dropped by 4.5 percentage points per year.[42] All of the trend parameters are significant below the .001 level.

The random effects portion of the model shows that there is significant residual variation at level 2 in the intercept, as well as in the trend parameters. Thus, not only do St. Louis tracts exhibit significant variability in their 1980 homicide rates, but also in their trajectories of homicide during the following 20 years. Comparing the residual level 1 error variance, the results show that modeling the trajectory explains 37.2 percent of the within-neighborhood variation in homicide rates.[43] To further examine the fit of the unconditional model to community homicide trends, figure 4.3 shows the observed and predicted average homicide rate per 1,000 during the study period. The spline regression fits the overall trend well. The correlation between observed and predicted values is 0.816 ($p < .001$). Additionally, the knots used to delineate structural breaks fit with the major turning points in the trend (Messner et al., 2005).

A number of recent studies have suggested that a small proportion of urban neighborhoods disproportionately contribute to fluctuations in violence in at the city level

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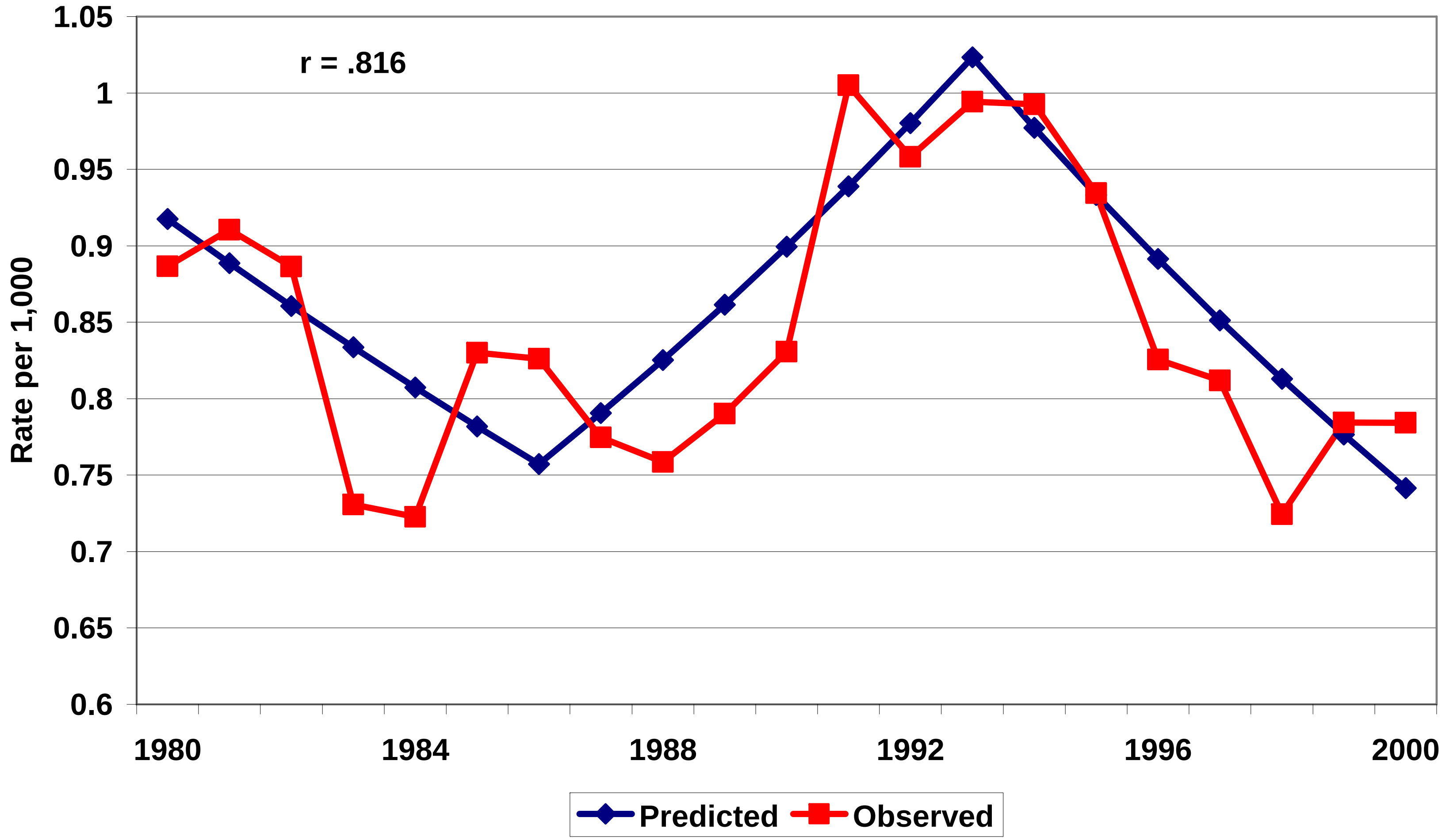
[42] The percentage change in homicide rates for each period is calculated by exponentiating the fixed effect, subtracting 1, and multiplying by 100. For example, the 1980 – 1986 decline is calculated as [exp(-0.086)-1]*100 = -3.1%.

[43] The reduction in residual variance serves as a rough estimate of model fit and is calculated as the difference between the level 1 error variances (Unconditional – ANOVA), divided by the level 1 error variance for the ANOVA. For the unconditional model this is (0.04784 – 0.07615) / 0.07615.

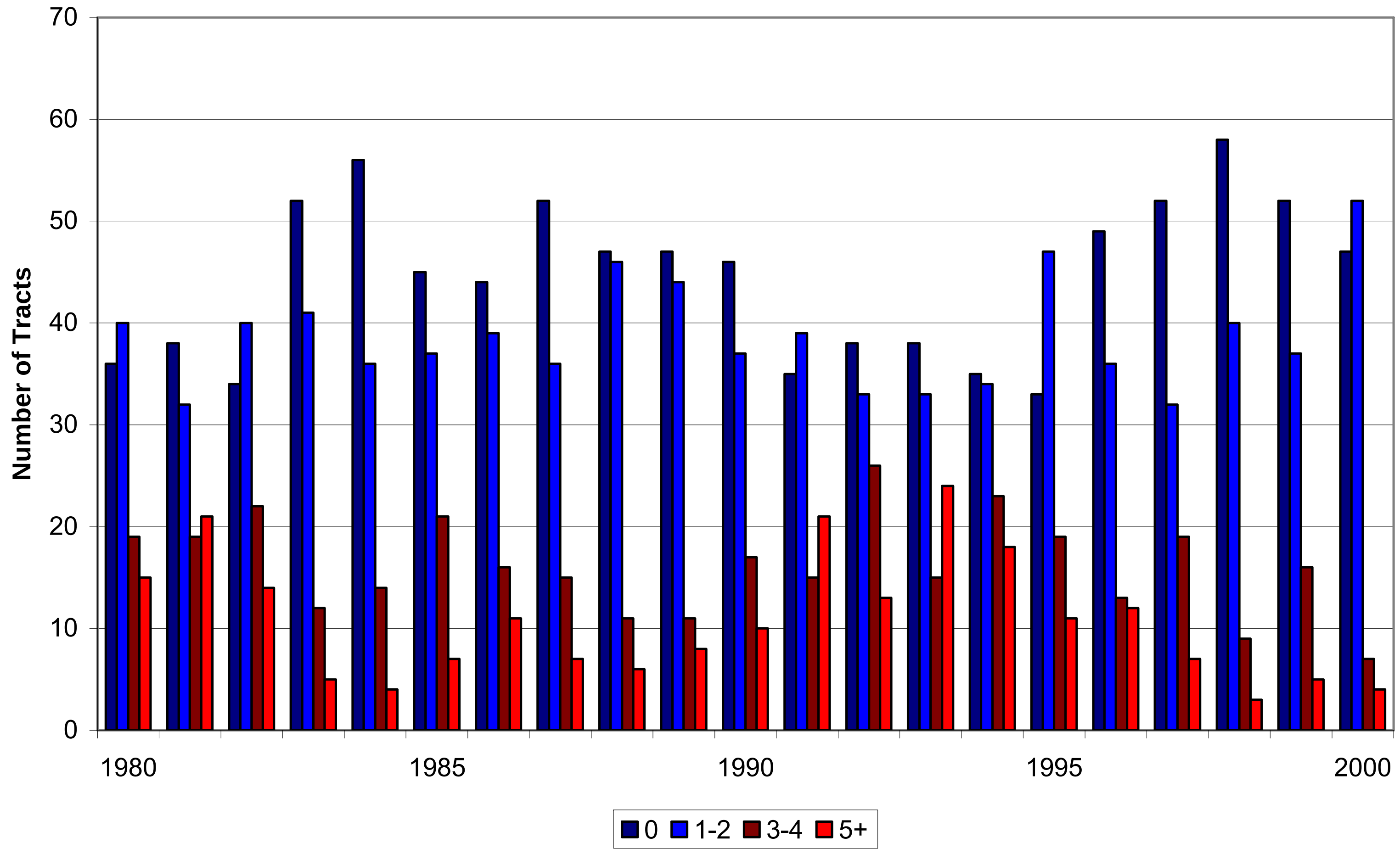
Figure 4.3: Observed and Predicted Homicide Trends in St. Louis Neighborhoods, 1980 - 2000 (n = 110)



(Griffiths and Chavez, 2004; Weisburd et al., 2004). To assess this possibility for St. Louis, the percentage change in homicide for the city accounted for by the 11 tracts (10 percent) with the largest magnitude of fluctuation is calculated. Between 1980 and 1986, 51.5 percent of the decline in homicide could be accounted for by 11 neighborhoods. This percentage dropped between 1987 and 1993 to 31.9 percent. After 1993, approximately 20.0 percent of the decline in homicide is attributable to the 11 tracts with greatest decline. Based on these results, homicide trends in St. Louis City also appear to be disproportionately influenced by a small number of communities with large fluctuations in violence. However, the smaller contribution to city-wide trends after 1987 indicates that there was a general rise in violence across St. Louis neighborhoods. This point is illustrated in figure 4.4. Beginning in 1987, the number of tracts with two or fewer homicides declined steadily until 1994 then increased steadily through 2000. At the same time, the number of areas with 3 or more homicides began increasing in 1987, reaching a peak in the mid 1990s, and then declining steadily through 2000.

The unconditional model presents a reasonably good fit to the data for St. Louis census tracts. The model also confirms that there are substantial and significant variations across the neighborhood-specific levels and trajectories. The purpose of the dissertation is to explain these variations as a function of community social structure. Therefore, the discussion turns to assessing the structural characteristics of St. Louis neighborhoods and the nature of changes in structure during the study period.

Figure 4.4: Frequency Distribution of St. Louis Neighborhoods by Number of Homicides, 1980 - 2000



Structural Change in St. Louis, 1980 – 2000

The characteristics of St. Louis neighborhoods underwent significant change between the years 1980 and 2000. Table 4.2 provides descriptive statistics for the indicators of social structure collected from the decennial census. Additionally, paired sample t-tests were performed to determine if there were significant differences across census periods.[44]

As discussed previously, St. Louis census tracts experienced significant net out-migration of population during the study period. In 1980, the average tract population was 4114.55. By 2000, the average tract population was reduced to 3164.25, an average loss of about 950 people, or approximately 23 percent of the population. Within the context of these losses, the majority of other social indicators also experienced significant changes.

The racial composition of St. Louis communities changed significantly, increasing from 44.14 percent black in 1980 to 56.65 percent black by 2000. As figure 4.4 shows, St. Louis was a hyper-segregated city in 1980 with 91 tracts (82.7%) that were either at least 80 percent black, or less than 20 percent black. During the two decades following 1980, figure 4.4 shows that the number of tracts with less than 10 percent black population dropped from 45 to 20. At the same time, there was relatively little growth in the number of communities with more than 90 percent black population (from 34 to 37 in 1980 and 2000, respectively). Instead, there were 44 tracts (40.0%) which became more racially diverse, with the average tract moving up by at least 1 category on the figure. However, while a substantial number of neighborhoods were becoming more racially

[44] Table 4.2 indicates whether or not the 1990 and 2000 sample means were significantly different from previous decades. Complete t-test results are presented in Appendix A

Table 4.2: Descritptive Statistics for Indicators of Social Structure, 1980 - 2000 (n = 110)

	1980		*1990*			*2000*		
Variable	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*		*Mean*	*Std. Dev.*	
Population	4114.55	1688.34	3602.25	1494.32	*	3164.25	1495.65	***
Percent Black	44.14	42.99	48.70	40.95	*	56.65	37.51	***
Percent Hispanic	1.20	1.28	1.17	1.35		1.71	1.54	***
Population Heterogeneity	0.14	0.17	0.19	0.19	*	0.25	0.20	***
Percent Immigrant	0.50	0.95	0.93	1.54	*	3.12	3.73	***
Percent Female-Headed Families	16.74	11.70	20.10	12.54	*	23.63	13.13	***
Divorce Rate	9.10	2.48	10.97	2.60	*	12.35	2.99	***
Percent Youth (15-24)	19.10	4.44	14.64	5.48	*	15.66	7.84	*
Percent Male Youth (15-24)	8.83	1.98	6.97	3.33	*	7.21	3.75	*
Percent High School Dropouts	21.79	14.04	20.43	15.71		14.61	12.94	***
Percent College Graduate (4-year)	9.47	7.88	14.10	10.97	*	16.83	13.29	***
Unemployment Rate	11.66	6.61	12.08	7.75		13.39	9.67	*
Male Unemployment	13.11	8.00	13.92	9.70		14.29	11.11	
Poverty Rate	22.02	14.47	25.52	15.54	*	26.48	13.73	*
Average Family Income (1980 Dollars)	17658.58	5696.24	18424.84	7015.92	*	20108.11	7114.60	***
Percent Households with Public Assistance	15.56	11.52	15.38	11.36		17.61	10.42	***
Joblessness Rate	50.77	8.23	48.25	10.87	*	48.49	12.40	*
Male Joblessness Rate	42.40	11.09	42.94	13.74		44.88	15.18	***
Percent Workers Using Public Transportation	19.81	9.13	14.82	10.15	*	13.28	8.98	***
Percent Labor as Service Workers	21.72	8.29	21.84	8.63		23.99	7.48	***
Percent Same Residence	58.89	11.66	56.24	11.24	*	51.57	11.43	***
Percent Living in St. Louis 5 Years Ago	28.22	8.44	28.04	7.54		29.51	8.84	**
Percent Owner-Occupied Housing	45.41	21.26	45.16	20.65		46.30	19.77	**
Percent Vacant Housing	11.86	9.10	15.85	8.53	*	17.61	9.26	***
Percent Renter-Occupied Housing	47.12	17.49	44.86	14.81	*	43.29	15.04	***
Percent Multi-Unit Housing	37.66	22.24	38.28	22.08		36.13	23.33	***

* Significant Difference from 1980
** Significant Difference from 1990
*** Significant Difference from 1980 and 1990

Figure 4.5: Frequency Distribution of St. Louis Neighborhoods by Racial Composition, 1980 - 2000 (n = 110)

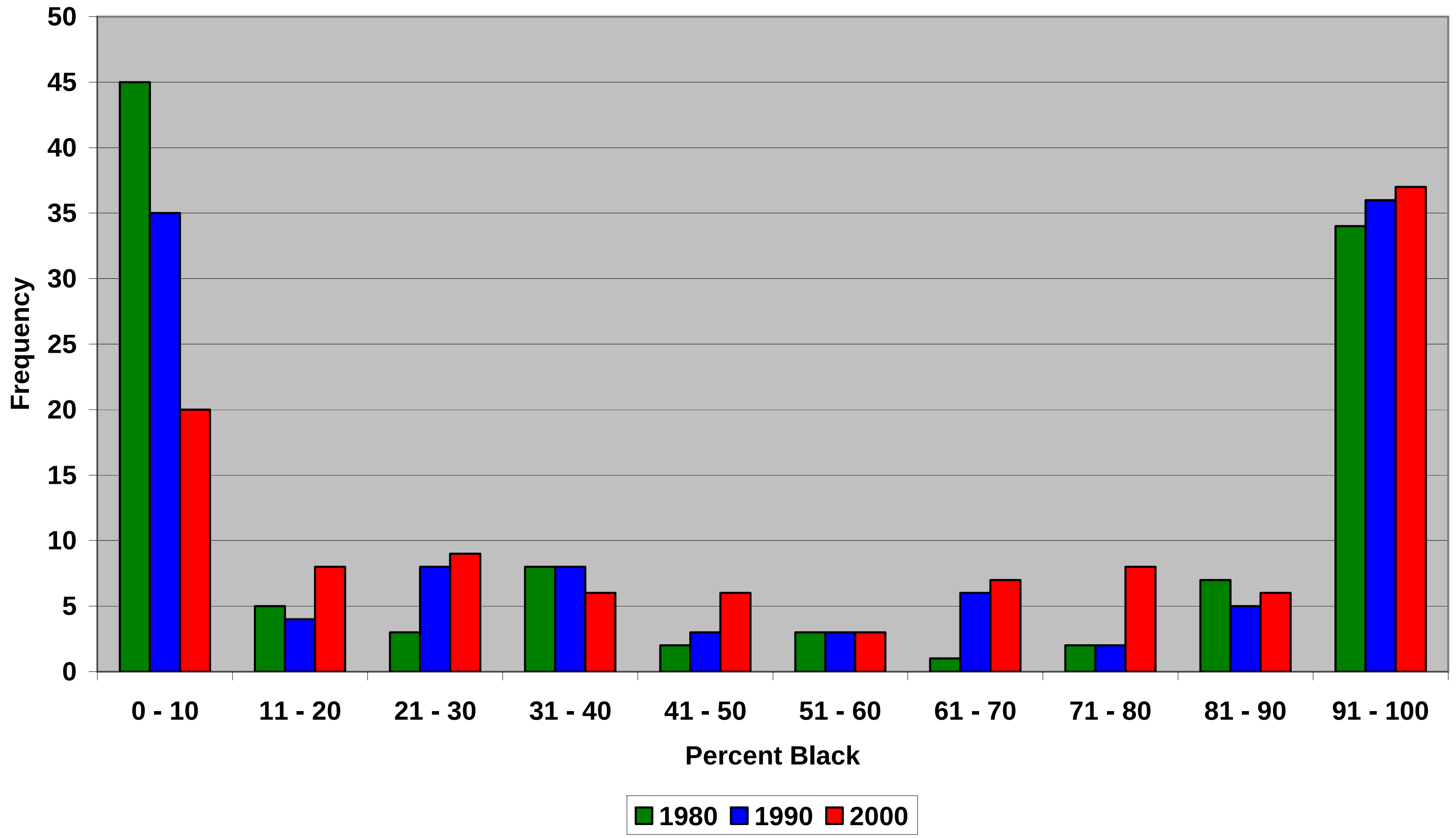


Table 4.3: Changes in Average Population Size and Racial Composition in St. Louis Census Tracts, 1980 - 2000 (n = 110)

	1980 Population	*Population Change*		*Percent Black Change*	
Non-Black (< 30%) n = 53	3964.21	-428.77		21.51	
Mixed (30 - 70%) n = 14	4026.57	-548.00		16.74	
Black (> 70%) n = 43	4328.51	-1724.12		0.04	
Levene's (2, 107)	0.631	6.689	**	45.090	***
ANOVA					
F (2, 107)	0.570	50.146	***	20.534	***
Post Hoc Difference Tests					
Non-Black - Black	-364.30	1295.34	***	21.48	***
Non-Black - Mixed	-62.36	119.23		4.77	
Mixed - Black	-301.94	1176.12	***	16.71	*

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

diverse, the majority (n = 59) remained stable, or experienced reductions in racial diversity (n = 7).

To further explore the nature of changes in racial composition, the neighborhoods were divided into three groups based on the percentage of blacks in the population for 1980: non-black (< 30%), mixed (between 30% and 70%), and black (> 70%). For these three groups, table 4.3 shows the average change in population and racial composition between 1980 and 2000, as well as the 1980 population size. Analysis of variance shows that the average population size in 1980 was not significantly different across non-black, mixed, and black communities.[45] However, these neighborhoods did differ significantly with respect to net population change and changes in racial composition. In particular,

[45] Levene's test for the homogeneity of variance across groups indicates that the within-group variation in population size is not significantly different. However, there were significant differences in variation for both net population change and change in racial composition between 1980 and 2000. Therefore, Tamhane's T2 test was used to test for significant pairwise mean-differences across groups.

predominantly black neighborhoods experienced three to four times the net population loss (average change = -1724.12) of predominantly white and mixed neighborhoods, respectively (average change = -428.77 and -548.00). At the same time, predominantly black tracts experienced an average of less than a one-half percentage point change in racial composition. In contrast, mixed tracts exhibited an average change in racial composition of 16.7 percent, while in predominantly non-black tracts the average increase was 21.5 percentage points.

The 1980 average racial composition for non-black and mixed communities was 3.67 and 42.76 percent, respectively. Based on these starting levels, the 1980 black population size for non-black communities was, on average, (3964.21 * .0367) 145.49, and the average for mixed communities was (4026.57 * .4276) 1721.76. Had all of the net population change been the result of non-black out-migration in these areas, the racial composition measure would have increased to 4.12 percent in 2000 for predominantly non-black communities and to 49.50 percent in racially mixed tracts.[46] This would result in a 0.45 and 6.74 percentage point increase in the percentage black population for non-black and mixed neighborhoods. Therefore, the change in racial composition for St. Louis can be characterized by two trends: the out-migration of large numbers of people from predominantly black communities, and the in-migration of significant proportions of blacks to non-black and racially mixed areas.

In addition to the change in racial composition across St. Louis census tracts, there were small, but significant increases in the percentage of Hispanics and those who were living outside the U.S. and Puerto Rico five years before (see table 4.2). The

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[46] The calculation for non-black tracts is [145.44 / (3964.21 – 428.77)] * 100 = 4.12%. The calculation for racially mixed tracts is [1721.76 / (4026.57 – 548)] * 100 = 49.50%.

percentage Hispanic increased roughly one-half percentage point between 1980 and 2000. The percentage of those living in foreign countries five years prior doubled between 1980 and 1990, from 0.50 percent to 0.93 percent. However, this number increased by approximately 230 percent in the following decade, to 3.12 percent in 2000. These trends coincided with changes in racial composition to significantly increase population heterogeneity from 0.14 in 1980 to 0.25 in 2000 ($t_{.05, 109} = 5.583$, $p < .001$). Thus, the hyper-segregation that historically characterized St. Louis city neighborhoods persisted through 2000, but showed signs of weakening as minority and immigrant populations began to diversify historically white neighborhoods.

During the study period, age and family structures changed significantly as well. There was a significant decline in the youth population (ages 15-24) during the 1980s. On average, this age group was reduced from 19.1 percent of the population to 14.64 percent, a 4.46 percentage point decline. Following this change, the average youth population remained stable during the 1990s, with the average changing only 1 percentage point from 14.64 to 15.66 percent.

With regard to family structure, the average neighborhood divorce rate grew steadily and significantly between 1980 and 2000. The average increased 3.25 percentage points, from 9.10 to 12.35 percent. Additionally, the average percentage of female-headed families with children under the age of 18 increased nearly seven percentage points during the study period. Significant increases were observed during both decades, and by 2000 nearly 24 percent of the families in the average neighborhood were headed by single females.

Table 4.2 also shows the neighborhood trends in education levels. The percentage of high-school dropouts was stable during the 1980s at roughly 20 percent. During the 1990s, the dropout rate declined by about four percentage points, to 14.61 percent in 2000. At the same time, the percentage of resident with a 4-year college degree increased steadily during both the 1980s and 1990s. While St. Louis communities had an average of 9.47 percent college graduates in 1980 this number had increased to 16.83 percent in 2000, a change of approximately 7 percentage points. These two trends indicate that the diversity of education levels in St. Louis neighborhoods was increasing between 1980 and 2000.

Economic indicators for St. Louis neighborhoods show signs of relatively small but significant changes between 1980 and 2000. Unemployment rates were stable during the 1980s and rose by approximately 1.3 percentage points during the 1990s, a significant increase. The male unemployment rate did not experience any significant changes during the study period. However, the male joblessness rate increased significantly during the 1990s, from 42.94 to 44.88 percent, while the total joblessness rate remained stable. This suggests that the increase in unemployment rates influenced both men and women, and that men were more likely to drop out of the labor force altogether.

There was a significant decline in the proportion of workers using public transportation to get to work during the 1980s, from nearly 20 percent at the beginning of the decade to about 15 percent in 1990. During the following decade, this trend slowed and the proportion dropped to 13.3 percent in 2000. Furthermore, the average proportion of workers employed in service work remains stable in the 1980s, at about 22 percent.

Yet there was a significant two percentage point increase in the average level of service workers during the 1990s, to about 24 percent in 2000.

During the 1980s, the average poverty rate increased by about 3.5 percentage points, from 22.02 to 25.52 in 1990. This was followed by a smaller and non-significant one percentage point increase in poverty rates during the 1990s. Average family incomes (in constant 1980 dollars) were trending up throughout the study period. During the 1980s the neighborhood average increased by approximately 750 dollars. Then during the economic boom of the 1990s the slope of this trend more than doubled as incomes rose from 18,245 in 1990 to 20,108 in 2000. Also during the 1990s, there was a significant increase in the percentage of households receiving public assistance payments, from 15.38 to 17.61 percent.

In addition to the large level of population out-migration discussed above, St. Louis communities also experienced a significant re-organization of the remaining residents. Between 1980 and 1990, the average neighborhood had approximately a 2.5 percentage point decline in the percentage of the population residing in the same house for five or more years. This trend then accelerated during the 1990s with nearly a 5 percentage point decline. The result in 2000 was a neighborhood average of 51.5 percent of residents living in the same house, where as this number had been nearly 59 percent in 1980. Coincident with the decline in same-residence status was a small, but significant increase in the percentage of the population living in St. Louis City for five or more years, from 28 to 29.5 percent during the 1990s. Since the proportion of those living in the same house was decreasing, but the proportion of those previously residing in the city was increasing, this provides further evidence of population migration both between and within St. Louis tracts.

With regard to housing and occupancy indicators, St. Louis neighborhoods have been characterized by both change and stability. The average percentage of owner-occupied housing units and multiple-unit dwellings has remained relatively stable between 1980 and 2000, both fluctuating within approximately one percentage point. However, the out-migration of population is clearly evident in the sharp increases for vacant housing units. The average vacancy percentage was 11.9 in 1980, but rose nearly 5.7 percentage points during the following two decades to 17.6 percent in 2000. At the same time, the proportion of renter-occupied housing units declined by approximately 3.8 percentage points, from 47.12 in 1980 to 43.29 in 2000. Therefore, while the ratios of single- to multiple-unit dwellings remained relatively stable over these 20 years, population migration reduced the overall number of occupied dwellings, and disproportionately so in rental housing.

Relating Social Structure to Homicide

As seen in figure 4.2, homicides in St. Louis are not randomly dispersed throughout the city. As discussed in chapter 1, the major schools of community- and macro-level theory argue that where economic disadvantage, family disruption, racial heterogeneity, restricted employment opportunities, and population mobility are greatest, crime rates are also expected to be high. Recall that the major theoretical arguments link social structure to crime through a variety of mechanisms such as a reduced capacity to generate social control (social disorganization / collective efficacy), generalized frustration from economic difficulties (Mertonian strain/relative deprivation), and increases in suitable targets or reductions in capable guardianship (routine activities). Regardless of the intervening mechanisms at work, all of these perspectives argue for an association between the structural characteristics of communities and crime rates. Therefore, this section of the dissertation examines the nature of the relationship between social structure and homicide rates across St. Louis census tracts.

Table 4.4 displays the correlations between indicators of community social structure and homicide rates for 1980, 1990, and 2000.[47] Due to positive skew in the data, the measures of percent Hispanic, population heterogeneity, percent immigrant, percent college graduate, and average family income were transformed using a natural logarithm. Overall, the correlations are in the expected directions, and the majority represent moderate to strong relationships. Additionally, most of the significant correlations persist across the three decennial measures of homicide rates.

Population size is not associated with homicide rates in 1980 and 1990. However, there is a weak negative relationship between population size and homicide in 2000 ($r = -.190$, $p < .05$), meaning that communities with larger populations experienced lower levels of violence per capita than smaller communities. Given the consistently strong and positive relationship between percent black and homicide, and the large out-migration of residents from predominantly black communities to other areas of the city, this evidence suggests that high homicide rate neighborhoods during the 1980s and 1990s lost enough population to induce a relationship between population size and homicide rates. This evidence is consistent with the findings of Morenoff and Sampson (1997) who found that

[47] Because year-to-year fluctuations in neighborhood homicides can produce instability in the calculation of rates, a 3-year average homicide rate was calculated, centered on the decennial observation (e.g. the rate for 1980 was calculated by averaging the rates for 1979, 1980, and 1981).

increases in homicide rates were associated with population declines in Chicago neighborhoods.

Table 4.4: Correlation Matrix for Indicators of Social Structure and Homicide Rates in St. Louis Neighborhoods (n = 110)

	3-Year Average Homicide Rates		
Variable	1980	1990	2000
Population Size	-0.116	-0.159	-0.190*
Percent Black	0.778***	0.833***	0.788***
Ln Percent Hispanic	-0.177	-0.479***	-0.484***
Ln Population Heterogeneity	0.216*	-0.051	-0.373***
Ln Percent Immigrant	-0.059	-0.252**	-0.390***
Percent Female-Headed Families	0.691***	0.711***	0.590***
Divorce Rate	0.168	-0.175	-0.192*
Percent Youth (15-24)	0.365***	0.348***	0.079
Percent Male Youth (15-24)	0.326**	0.349***	0.119
Percent High School Dropouts	0.125	0.084	0.161
Ln Percent College Graduate (4-year)	-0.339***	-0.433**	-0.589***
Unemployment Rate	0.729***	0.641***	0.569***
Male Unemployment Rate	0.697***	0.654***	0.526***
Poverty rate	0.809***	0.741***	0.665***
Ln Average Family Income	-0.616***	-0.625***	-0.510***
Percent Households with Public Assistance	0.754***	0.750***	0.710***
Joblessness Rate	0.565***	0.605***	0.613***
Male Joblessness Rate	0.701***	0.715***	0.613***
Percent Workers Using Public Transportation	0.814***	0.808***	0.678***
Percent Labor as Service Workers	0.717***	0.681***	0.670***
Percent Same Residence	-0.038	-0.033	0.140
Percent Living in St. Louis 5 Years Ago	0.247**	0.406***	0.366***
Percent Owner-Occupied Housing	-0.534***	-0.411***	-0.255*
Percent Vacant Housing	0.616***	0.696***	0.720***
Percent Renter-Occupied Housing	0.405***	0.266**	0.020
Percent Multi-Unit Housing	0.404***	0.251**	-0.037

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

As mentioned above, there is a consistently strong and positive relationship between racial composition and homicide rates. The coefficient of determination (r^2) indicates that percent black explains between 60 and 80 percent of the variation in homicide rates, depending on the year. As will be discussed later, predominantly black neighborhoods in St. Louis clearly exhibit the concentration effects of economic disadvantage that Wilson (1987, 1996) argues reflect ongoing social isolation from mainstream opportunities in the economy. Only two other community characteristics even approach the magnitude and persistence of the association between percent black and homicide: the poverty rate, and the percent of workers using public transportation to get to work.

Of the other racial and ethnic composition indicators, the logs of percent Hispanic and percent immigrant are both negatively associated with homicide rates in 1990 and 2000. Furthermore, the strength of this association increases over the course of the study period. Recall that St. Louis has very small proportions of both of these groups. However, there were significant increases in immigration during both decades, and significant increases in the Hispanic population during the 1990s. Thus, the communities in which these groups settled maintained low rates of violence as compared to other tracts.

Population heterogeneity exhibits significant associations with homicide rates in 1980 and in 2000, but not during the interim. Additionally, the association changes from being weakly positive in 1980 to moderately negative in 2000. Therefore, in the early years of the study, racially heterogeneous neighborhoods have higher homicide rates. However, by the end of the period diverse neighborhoods are more likely to have lower homicide rates.

Female-headed families with children have a persistent and strong positive relationship with homicide rates, although the relationship weakens slightly in 2000. Furthermore, the percentage of the population ages 15 to 24 has a moderately positive association with homicide rates in 1980 and 1990, while the divorce rate has a weak and negative correlation to homicide in 2000. Taken as a group, these bivariate relationships suggest that changes in age structure and family structure do not have stable relationships with violence between 1980 and 2000.

Of the two measures of education levels, the high school dropout rate has a positive, but non-significant association with homicide rates, and the proportion of college graduates shows a consistent negative correlation with homicide rates. Additionally, the magnitude of the relationship increases from 1980 to 2000. Therefore, while the dropout rate does not appear to have any association with levels of homicide, the college graduation rate does. Recall from table 4.2 that the average percentage of college graduates increased significantly between 1980 and 2000. This increase in education levels could have brought increased economic resources and social capital to St. Louis neighborhoods, thereby reducing economic strain and improving social networks among residents. The expected effect of this change would be a reduction in violent crime. However, an alternative explanation for the increasing magnitude of the correlation between graduates and violence is that college graduates were less likely to move to, or remain living in, neighborhoods with high crime rates. Therefore, as the prevalence of higher education increases and new economic opportunities arise, individuals and families are less likely to remain in dangerous areas. As these populations move to safer locations, the negative association between homicide rates and graduates will grow stronger.

Nearly all of the economic indicators exhibit consistently strong and positive correlations with homicide rates. Tracts with higher levels of unemployment and joblessness, poverty, households with public assistance, and workers in service positions or taking public transportation have higher levels of homicide between 1980 and 2000.

Additionally neighborhoods with higher incomes experienced lower homicide rates during the period. Most of these measures also display a weaker relationship with homicide rates after the crime decline of the 1990s than in prior periods. The results suggest that disadvantaged communities may experience greater fluctuations in violence. This possibility will be explored later.

With respect to population mobility, the percentage of residents ages five and older who lived in the same house five years before is not significantly related to homicide rates in any portion of the study period. However the percentage of residents who lived in a different house in St. Louis five years prior has a moderate positive correlation with homicide rates. A relatively weak relationship is found in 1980, but grows stronger by 1990 ($r = .406$, $P < .001$) before weakening slightly in 2000 ($r = .366$, $p = < .001$). This finding indicates those people moving out of poor, high crime areas were not able to move into the safest, and more expensive, communities. For many, the best available option is to move to an area that has less crime than their community of origin, but certainly not the safest. This finding is consistent with recent work in Chicago, in which the distance residents moved when leaving a high crime neighborhood was conditioned by the economic status of the neighborhood of origin (Morenoff and Sampson, 1997). Those with few resources to make such a move are constrained in their options of where to go, and generally settle in adjacent and nearby locations, with only slightly lower crime rates.

Finally, the nature of the housing market and tenure status of residents has a moderate to strong relationship with homicide rates. As expected, greater levels of owner-occupied housing are negatively correlated with lower crime rates in each decade.

However, the strength of that relationship diminishes over time. In contrast, the percentage of renter-occupied housing and multi-unit housing are positively related to homicide rates, but follow the same pattern of diminishing effects, becoming non-significant in 2000. In contrast, the percentage of vacant housing exhibits a persistent and strong positive relationship with homicide rates across the entire period. Thus, as more residents move out of the city, the level of owner-occupied housing increases among those without the resources to move. As violence subsided in the highest crime rate communities during the 1990s, this relationship diminished. Additionally, both the percentage of renters and multi-unit dwellings were decreasing during the study period, reducing the overall capacity for disruption by short-term residents who were not invested in, or connected to, the community.

Both of these trends generated a significant increase in the percentage of vacant housing. As more units became vacant, the proximity between residents of the neighborhood would be expected to decrease, reducing their capacity to provide assistance and guardianship for one another. Additionally, greater levels of vacant housing provide locations or “cuts” for individuals and groups to engage in clandestine activity (e.g. selling drugs), or other unstructured socializing among adolescents (Jacobs, 1999; Osgood and Anderson, 2004). The detrimental association between vacant housing and public safety also extends beyond simply providing a location for crimes to occur. As vacant housing increases, the very essence of a community begins to disappear. One cannot have a community where there are no residents.

Bivariate Models of Structural Effects on Homicide Trends

Across all of the domains discussed previously, most measures of social structure exhibit moderate to strong correlations, in levels, with decennial homicide rates in St. Louis neighborhoods. However, the primary purpose of this chapter is to assess the relationship between changes in social structure and crime trends. Therefore, the dissertation turns to a brief discussion of bivariate HLM models of homicide trajectories (see Appendix B for model results).

The unconditional piece-wise HLM is used as the baseline model. To explain the variations in homicide trends across the study period, each measure of social structure is entered into the level 2 models for the intercept (the 1980 homicide rate), and each of the spline components (1980 – 1986, 1987 – 1993, and 1994 – 2000 respectively). Thus the level 2 models take on the following form:

$$\begin{aligned}
\pi_{0i} &= \beta_{00} + \beta_{01}(W_i) + r_{0i} \\
\pi_{1i} &= \beta_{10} + \beta_{11}(W_i) + \beta_{12}(\Delta W_i) + r_{1i} \\
\pi_{2i} &= \beta_{20} + \beta_{21}(W_i) + \beta_{22}(\Delta W_i) + r_{2i} \\
\pi_{3i} &= \beta_{30} + \beta_{31}(W_i) + \beta_{32}(\Delta W_i) + r_{3i}
\end{aligned} \qquad (6),$$

where W_i represents the level of the covariate at the beginning of the period, and ΔW_i represents the change in the variable over the period for each spline section. For example, to study the association between changes in poverty rates and homicide trends, the intercept, or 1980 homicide rate, is modeled as a function of the 1980 poverty rate in neighborhood *i*. For the 1980 – 1986 trend (π_{1i}), the level 2 model contains the change in neighborhood poverty rates between 1980 and 1986, controlling for the 1980 poverty rate. The 1987 – 1993 trend component (π_{2i}) is explained at level 2 by the change in poverty rates between 1987 and 1993, controlling for the 1987 poverty rate. Finally, the

1994 – 2000 level 1 trend parameter (π_{3i}) is explained by the change in poverty rates during this period, controlling for the 1994 poverty rate.

The census data is collected every ten years, and therefore precludes using an exact measure of levels or changes during intercennsial years. Therefore, linear interpolation is used to estimate the annual levels of each structural indicator.[48] From these estimates, the change in each variable is calculated as the difference between ending and starting years of the period.

The results for population movement, as well as changes in racial composition and ethnic diversity indicate that each of these indicators is significantly associated with homicide trends between 1980 and 2000. However, the results also suggest that the timing and direction of these effects differ across measures. Population change is negatively associated with homicide trends between 1980 and 1993. Percent black is positively associated with homicide trends between 1987 and 1993, and negatively associated with homicide trends from 1994 to 2000. Conversely, increases in Hispanic populations and racial heterogeneity are negatively associated with homicide trends during the early 1980s. However, increases in Hispanic populations are negatively associated with violence trends during the 1987 to 1993 boom in homicide. The residual variance components for these models show that most of the indicators explain little, if any, of the variation in homicide trends over the unconditional model. However, controlling for the levels and changes in percent black reduces the residual variation in

[48] Linear interpolation is used as a conservative method for estimating intercennsial data for two reasons. First, ecological characteristics of neighborhoods do not generally exhibit dramatic changes quickly (although this is not always the case). Rather, changes in the population structure of a community tend to occur slowly and result in relatively slow changes from year to year. Second, the decennial data support the notion that, over a ten year period, neighborhood traits may change by a few percentage points, but rarely exhibit larger differences.

the intercept by 62.8 percent. Additionally, the residual variations in the 1987 to 1993 and 1994 to 2000 trends are reduced by 37.5 and 19.2 percent, respectively. Of these indicators, the level and change in percent black has the most power in explaining homicide trends.

Of the family and age structure variables, the levels of female-headed families with children under 18 and youth population are positively related to initial levels of homicide. Neighborhoods with larger proportions of female-headed families experienced larger increases and greater declines in homicide rates between 1987 and 2000. However the changes in this measure have only a marginally positive association with increases in crime during the late 1980s. Changes in youth populations are associated with homicide trends during this same period, but the relationship to homicide trends is negative. The level of divorce is not significantly related to initial levels of violence or subsequent trends. However, increasing divorce rates are negatively associated with the 1980 to 1986 decline in homicide. The random effects portions of the family and age structure variables indicate that the level of female-headed households explains approximately 48.6 percent of the variation in the 1980 log homicide rates, about 37.5 percent of the variation in the 1987 to 1993 trends, and about 15.4 percent of the variation in the post-1993 trends across neighborhoods. In comparison, total youth and male youth populations explain approximately 14.8 and 12.1 percent of the variation in 1980 levels of homicide, respectively. However, these indicators explain relatively little of the neighborhood variations in homicide trends.

In the education models, the level of high-school dropouts is not related to initial homicide rates or trends. However, there is a negative association between the change in dropout rates and homicide trends during the second period of the study, and a positive association after 1993. Higher levels of college graduates were related to lower initial homicide rates. These neighborhoods also experienced flatter homicide trajectories between 1980 and 1993. However, the change in college graduate rates is not associated with crime trends during these two periods. It is only during the final period of the study that increases in college graduate rates are associated with greater declines in homicide. Neither of these models exhibits large reductions in residual variation for the homicide trends over the unconditional model. However, the log of college graduates in 1980 does reduce the intercept variation by 15.5 percent over the unconditional model.

Of the economic indicators used, all are positively related to 1980 homicide rates in levels. Changes in unemployment are positively associated with crime declines in the early 1980s. While high poverty rate communities have greater fluctuation in homicide over time, the change in poverty rates is not significantly associated with the trends. For communities with increasing proportions of households receiving pubic assistance, homicide rates did not drop as quickly between 1980 and 1986, but increased more quickly between 1987 and 1993. Additionally, the change in male joblessness was positively associated with homicide trends between 1980 and 1986, but total joblessness was not. Changes in the proportion of workers using public transportation and employed in service positions are positively associated with changes in homicide after 1993. However, changes in public transportation are also associated with changes in neighborhood violence between 1980 and 1986.

The residual variance components for these models show that the poverty rate, households receiving public assistance, and workers using public transportation explain about 69.7 percent, 69.8 percent, and 70.0 percent of the 1980 homicide rate across neighborhoods, respectively. Additionally, total unemployment and the poverty rate explain the greatest amount of residual variance in homicide trends between 1980 and 1986 (26.7 and 15.8 percent, respectively). During the second period of study, each of the economic measures explains between 18.8 and 25.0 percent of the variation in neighborhood homicide trends, with the exception of total joblessness (12.5 percent residual variation explained). Finally, after 1993, each of the models explains small portions of the variation in neighborhood homicide trends. However, the change in workers using public transportation explains the most, with approximately 30.8 percent less residual variation when compared to the unconditional model.

Where the indicators of housing and mobility are concerned, all of the indicators except for the percent living in the same residence and owner-occupied housing are positively related to 1980 levels of homicide. However, only the changes in three measures are significantly related to homicide trends during the study period. Changes in the percent living in a different house in St. Louis five years ago and changes in owner occupied housing have a marginally positive relationship to violence trends after 1993. However, both the levels and changes in vacant housing are related to changes in homicide rates in every section of the model. Higher levels of vacant housing are associated with exaggerations in the homicide trends, both upward and downward. The changes in vacant housing are positively associated with homicide trends through 1993. However in the last period of the study, increases in vacant housing are associated with greater declines in homicide rates.

For residents living in a different house in St. Louis five years ago, the model explains approximately 25.0 percent of the variation in 1987 to 1993 neighborhood homicide trends, but relatively little of the variation in either the intercept or the other trend parameters. The owner-occupied housing model accounts for 23.1 percent of the neighborhood variation in both 1980 levels of homicide and post 1993 trends. However, there is little reduction in the variance components for the 1980 to 1993 periods of study. The vacant housing model explains more of the variation in homicide levels and trends than other housing and mobility measures. Levels and changes in vacant housing explain approximately 45.7 percent of the variation in 1980 homicide rates, 10.5 percent of the variation in trend prior to 1987, 25.0 percent of the 1987 to 1993 trend, and 26.9 percent of the neighborhood variation in trends during the late 1990s.

In summary, in bivariate models of homicide trends, the levels and changes in many of the structural measures are significantly related to both levels and trends in St. Louis neighborhood homicide rates. While the changes in measures from every domain of social structure are associated with trends in violence, the timing and direction of these relationships varies from one indicator to the next. Consistent with cross-sectional studies of homicide rates, structural measures explain a greater proportion of neighborhood variation in 1980 homicide rates than the subsequent trends. In stark illustration of the correlation between race and economic disadvantage, percent black, unemployment, poverty rates, households with public assistance, male joblessness, and workers using public transportation explain between 53.1 and 68.7 percent of the variation in 1980 homicide rates. While these indicators also explain more of the variation in homicide trends than other indicators, the reduction in residual variance is substantially less, indicating that changes in these measures are not as strongly correlated with homicide trends as they are in levels. In addition to the race and disadvantage indicators above, changes in female-headed families with children under 18 and vacant housing also explain non-trivial proportions of the homicide trends, with vacant housing showing the most consistent association throughout the study period.

The finding of significant associations at the bivariate level indicates that multivariate analysis is warranted to study the conditional relationships between changes in social structure and homicide trends in St. Louis. Therefore, the dissertation will explore the interrelationships between measures of social structure next. This will be followed by the multivariate analysis.

Intercorrelation of Neighborhood Characteristics over Time

Socioeconomic and demographic characteristics of St. Louis census tracts are not independently distributed across the city. Rather, a number of structural indicators are highly correlated across the urban landscape. Figure 4.6, for example shows the distributions of racial composition, average family income, and male joblessness in 1980. As illustrated in the figure, communities with predominantly black populations are located in the northern half of the city. These communities also exhibit the highest proportions of male joblessness and lowest income levels. Therefore, before attempting to estimate the association between structural characteristics and homicide trends, the dissertation examines the intercorrelation between neighborhood traits.

Table 4.5 provides the correlations of decennial census measures of economic disadvantage, residential instability, and ethnic heterogeneity, pooled across 1980, 1990, and 2000 and across 110 tracts for a total of (3 x 110) 330 observations (see appendix C for a complete correlation matrix of independent variables). Strong positive correlations exist between percent black, female-headed families with children under 18, unemployment, poverty, public assistance payments, male joblessness, workers using public transportation, and workers employed in service positions. Additionally, each of these measures exhibits a strong negative correlation with average family incomes. This evidence shows that St. Louis neighborhoods exhibit similar patterns of concentrated disadvantage and social dislocation as Wilson (1987, 1996) describes.

In addition to the intercorrelation of disadvantage indicators, four indicators of population instability have moderate to strong correlations as well. Owner-occupied housing and the percent living in the same residence have a moderate positive relationship. Additionally, owner-occupied housing has a very strong negative correlation to renter-occupied and multi-unit housing. Furthermore, renter-occupied housing and multi-unit housing have a strong positive correlation. This indicates that communities with high levels of home-ownership have lower levels of multi-unit dwellings and rental-occupancy, as well as higher levels of residents who have lived there longer.

Due to the high correlation among these indicators, multicollinearity would likely be problematic in a regression context.[49] Therefore, the data were reduced using a principal components factor analysis, with varimax rotation to ensure the resulting factors are orthogonal. In order to be able to create meaningful measures of change between 1980 and 2000, the factor analysis was performed using the pooled data. Thus, a factor

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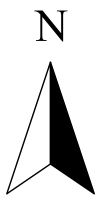
[49] The OLS assumption of independence among the explanatory variables of an equation also hold true for hierarchical models (Raudenbush and Bryk, 2002). HLM assumes that, at level 2, the explanatory variables are also uncorrelated with each other and the level 2 error term.

Figure 4.6: Spatial Distributions of Selected Measures of Social Structure in St. Louis Neighborhoods, 1980



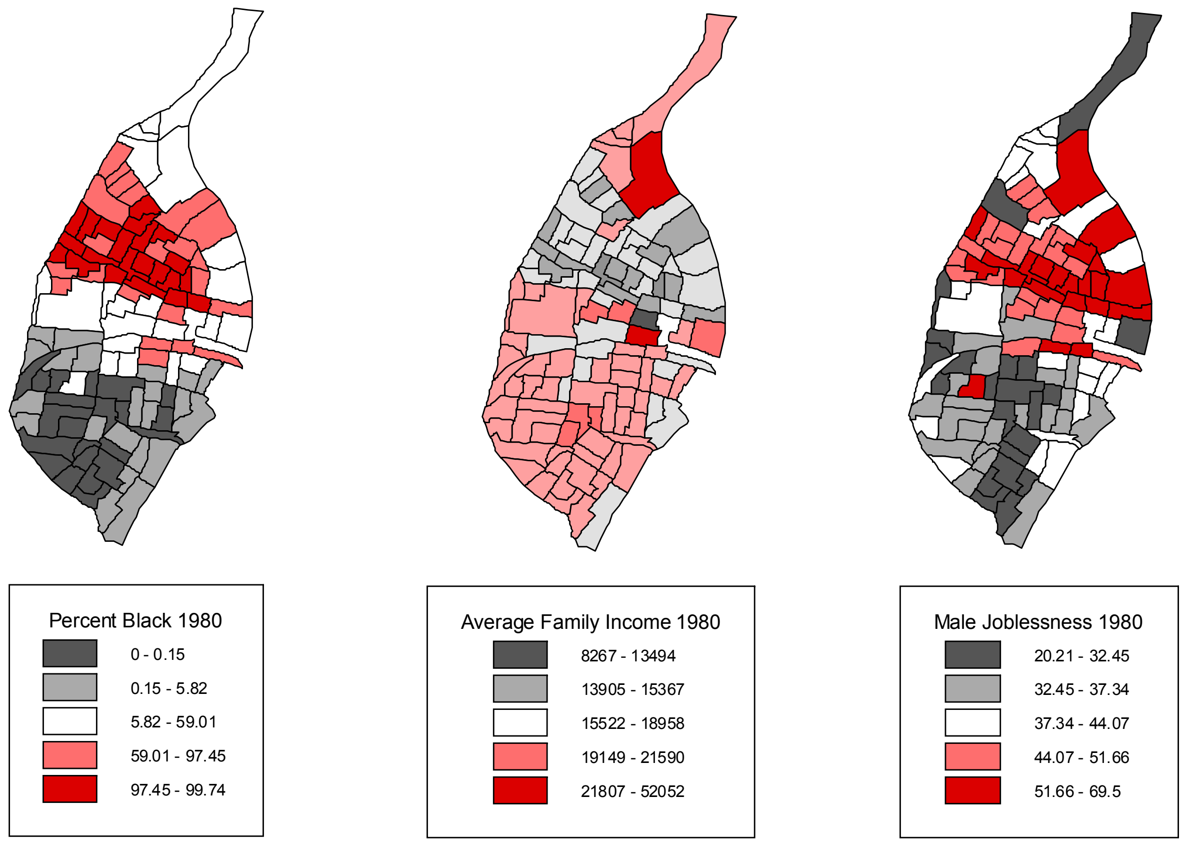


Table 4.5: Correlation Matrix of Pooled Indicators of Disadvantage and Instability and Ethnic Heterogeneity in St. Louis Census Tracts (n = 330)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Percent Black	1																
2. Percent Female Headed Families	.711***	1															
3. Unemployment	.688***	.667***	1														
4. Poverty Rate	.731***	.844***	.785***	1													
5. Ln. Average Family Income	-.537***	-.671***	-.651***	-.740***	1												
6. Percent Public Assistance Households	.798***	.830***	.765***	.879***	-.739***	1											
7. Male Joblessness	.717***	.587***	.745***	.725***	-.629***	.731***	1										
8. Percent Labor Using Public Transpotation	.727***	.584***	.620***	.675***	-.651***	.739***	.687***	1									
9. Percent Labor as Service Workers	.768***	.623***	.686***	.713***	-.670***	.785***	.690***	.647***	1								
10. Vacant Housing	.552***	.706***	.594***	.763***	-.541***	.704***	.564***	.516***	.536***	1							
11. Ln Percent College Graduates	-.409***	-.352***	-.506***	-.440***	.701***	-.554***	-.558***	-.504***	-.605***	-.254***	1						
12. Percent Owner-Occupied Housing	-.260***	-.491***	-.296***	-.549***	.356***	-.416***	-.329***	-.460***	-.171**	-.564***	-.062	1					
13. Percent Renter-Occupied Housing	.125*	.315***	.133*	.367***	-.219***	.236***	.185**	.358***	.023	.299***	.159**	-.952***	1				
14. Percent Multi-Unit Housing	.095	.263***	.089	.327***	-.069	.159**	.152**	.273***	-.059	.379***	.269***	-.893***	.884***	1			
15. Ln Percent Hispanic	-.494***	-.260***	-.373***	-.267***	.240***	-.324***	-.376***	-.422***	-.314***	-.147**	.283***	.017	.030	.014	1		
16. Ln Percent Immigrant	-.288***	-.058	-.117*	-.053	.288***	-.175**	-.204**	-.297***	-.188**	.027	.451***	-.157***	.179**	.226***	.361***	1	
17. Ln Population Heterogeneity	-.130*	.140*	-.058	.126*	.134*	-.037	-.169**	-.150**	-.182**	.216***	.399***	-.372***	.355***	.425***	.386***	.465***	1

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

score was produced for each census tract and each census year. The resulting solution has a mean that is conceptualized as the average latent construct across communities and over time.

Table 4.6: Principal Components Factor Analysis of Social Structure in St. Louis Census Tracts, 1980 - 2000 (n = 330)

Variable	*Disadvantage*	*Instability*	*Heterogeneity*
1. Percent Black	0.809	0.086	-0.260
2. Percent Female Headed Families	0.832	0.254	0.057
3. Unemployment	0.850	0.045	-0.093
4. Poverty Rate	0.906	0.285	0.050
5. Ln. Average Family Income	-0.807	-0.067	0.158
6. Percent Public Assistance Households	0.930	0.137	-0.081
7. Male Joblessness	0.802	0.111	-0.242
8. Percent Labor Using Public Transportation	0.715	0.311	-0.380
9. Percent Labor as Service Workers	0.862	-0.113	-0.143
10. Vacant Housing	0.738	0.328	0.156
11. Ln Percent College Graduates	-0.635	0.316	0.356
12. Percent Owner-Occupied Housing	-0.322	-0.921	-0.102
13. Percent Renter-Occupied Housing	0.119	0.943	0.063
14. Percent Multi-Unit Housing	0.055	0.953	0.113
15. Ln Percent Hispanic	-0.286	-0.060	0.709
16. Ln Percent Immigrant	-0.047	0.070	0.743
17. Ln Population Heterogeneity	-0.018	0.386	0.734

The results of the factor solution are presented in table 4.6. As the table shows, a three factor solution provided the best fit to the data and explains 76.2 percent of the shared variation across the indicators.[50] The first factor represents *economic disadvantage*, and is comprised of indicators of Wilson's (1996) concept of concentrated disadvantage (factor loadings in parentheses): percent black[51] (.809), female-headed families with children under 18 (.832), unemployment (.850), poverty rates (.906), the

[50] Divorce rates, male youths, and the percent living in a different house in St. Louis 5 years prior did not fit the factor structure and were dropped from the analysis. Additionally, the percent living in the same residence 5 years prior loaded well on the instability factor, but was not retained in the model because it did not have a significant relationship with homicide rates in either the cross-sectional correlations or the bivariate HLM models.

[51] Conceptually race and income are distinct (Bray, 2003). However, as noted previously and evidenced in table 4.5 there are very strong correlations between percent black and other indicators of economic disadvantage.

natural log of average family income (-.807), households with public assistance (.930), male joblessness (.802), workers using public transportation (.715), workers in service sector jobs (.862), vacant housing (.738), and the natural log of percent college graduates(-.635). The second factor represents *population instability*, and is comprised of owner-occupied housing (-.921), renter-occupied housing (.943), and multi-unit dwellings (.953). Finally, the third factor, representing *racial and ethnic heterogeneity*, was comprised of the natural logs of percent Hispanic (.709), percent immigrants (.743), and population heterogeneity (.734).[52]

The disadvantage, instability, and racial and ethnic heterogeneity components represent the three major components of classic social disorganization theory (Shaw and McKay, 1942). Linear interpolation was used to estimate levels of each measure during intercennsial years. These estimates were then used to calculate changes in the components between 1980 and 1986, 1987 and 1993, and 1994 and 2000. Table 4.7 provides descriptive statistics for the levels and changes in each measure.

In 1980, the average neighborhood was less disadvantaged than other communities and in other years (1980 mean disadvantage = -0.150). However, by the end of the century, the average tract was slightly more disadvantaged than other tracts and years (2000 mean disadvantage = 0.204). A paired sample t-test indicates that there were significant differences between decennial periods (1980 – 1990 $t_{109} = -2.187$, $p = .031$; 1990 – 2000 $t_{109} = -5.409$, $p = .000$). Examination of the change in disadvantage shows

[52] Population heterogeneity is calculated using the proportion of tract population that is black, giving cause for concern that percent black is actually entered into the factor analysis twice. However, the proportion of the population that is black is only one of several components in the population heterogeneity indicator and is only weakly correlated with population heterogeneity (see table 4.5). Were the empirical overlap in these two measures severe, they would load on the same component of the factor solution. Replications of the factor analysis in which either percent black or population heterogeneity were included without the other produced nearly identical solutions to the solution reported here (see table 4.6).

that communities became more disadvantaged at an accelerating rate. Between 1980 and 1986, the average change in disadvantage was 0.057. However, by the 1994 to 2000 period the increase in disadvantage was nearly three times greater, at .155. (t_{109} = -2.566, p = .012).

Table 4.7: Descriptive Statistics for Factor Scores, 1980 - 2000 (n = 110)

	1980		*1990*		*2000*	
Factor	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Disadvantage	-0.150	0.975	-0.054	1.036	0.204	0.962
Instability	0.085	1.044	0.068	0.957	-0.153	0.988
Race/Ethnicity	-0.510	0.653	-0.133	0.838	0.643	1.092

Descriptive Statistics for Factor Scores Changes, 1980 - 2000 (n = 110)

	1980 - 1986		*1987 - 1993*		*1994 - 2000*	
Factor	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Disadvantage	0.057	0.274	0.106	0.207	0.155	0.301
Instability	-0.010	0.176	-0.071	0.107	-0.133	0.173
Race/Ethnicity	0.226	0.445	0.346	0.352	0.466	0.542

In contrast to disadvantage, St. Louis neighborhoods became more stable over time. While there was no significant increase in stability between 1980 and 1990 (t_{109} = 0.592, p = .555), neighborhoods became significantly more stable between 1990 and 2000 (t_{109} = 8.034, p = .000). Additionally, changes in instability display the same acceleration during the study period as seen for disadvantage. Between 1980 and 1986, the average change for instability was -0.010. By the 1994 to 2000 period the rate of change had increased to -0.133 (t_{109} = 4.658, p = .000).

Racial and ethnic heterogeneity also changed significantly during the study period. The average heterogeneity score in 1980 was -0.510. This increased significantly by 1990 to -0.133 (t_{109} = -5.325, p = .000). During the following decade, the average increased yet again to 0.643 (t_{109} = -9.020, p = .000). Finally, as with disadvantage and instability, racial and ethnic heterogeneity increased at an accelerating rate between the 1980 to 1986 period and the 1994 to 2000 period ($t_{109} = -3.608$, $p = .000$).

In sum, the results of the factor analysis highlight several important changes in the structural characteristics of St. Louis neighborhoods. First, communities became significantly more disadvantaged over time. Second, these tracts became more stable as well, particularly during the 1990s. Third, racial and ethnic heterogeneity increased significantly between 1980 and 2000. Finally, for all three measures, the magnitude of change was significantly greater during the latter half of the study period.

Multivariate Models of Structural Effects on Homicide Trends

The final analysis for this portion of the dissertation will examine the conditional relationships between structural change and homicide trends for St. Louis census tracts. Consistent with the bivariate models, this analysis uses a spline HLM to model these relationships for the three periods corresponding to major upswings and downturns in city-level homicide rates. The results will indicate to what extent changes in social structure are associated with short-run homicide trends, controlling for structural characteristics in other domains.

As discussed previously, it is expected that increases in disadvantage will exaggerate upswings in neighborhood crime rates, and attenuate downswings. It is also expected that as communities become more unstable, they will also exhibit larger upswings in violence and smaller downward trends. The relationship between racial and ethnic diversity and crime trends is less clear. If increases in heterogeneity are associated with increasing economic disadvantage, then classic social disorganization and racial threat hypotheses would predict increases in violent crime (Shaw and McKay, 1969; Bursik and Webb, 1982). However, to the extent that increasing heterogeneity is associated with the movement of middle-class minorities and immigrants into safer communities, one would expect to find flatter trajectories of neighborhood violence. This type of change would translate into lesser declines and lesser increases as city-wide trends fluctuate. In the bivariate models, percent male youth has a positive relationship to initial homicide rates. Additionally, young males are disproportionately involved in violent crime. Therefore, the level and change in percent male youth is included along with disadvantage, instability, and heterogeneity in the multivariate models. It is expected that as the percentage of male youth increases in a community, there will be greater increases and smaller declines in violent crime.

Table 4.8 shows the correlation matrices of variables entered in the level 2 models. The majority of correlations are weak to moderate in magnitude, with many below 0.4. However, the change measures for disadvantage, instability, and heterogeneity have moderate to strong correlations. Variance inflation factors were calculated from a separate OLS regression of the level 2 models to assess the degree of multicollinearity present among the variables. In all cases, the VIF statistics were below 2.5, with the majority being below 2.0 which suggests that multicollinearity is not a problem in the model.

The correlations also highlight some of the structural changes occurring in St. Louis neighborhoods during the study period. For example, the correlation between changes in disadvantage and changes in instability between 1980 and 1986 is $r = -0.643$ ($p = .000$). Thus, communities that experienced increases in disadvantage also experienced decreasing instability, consistent with the out-migration hypothesis. Conversely, neighborhoods that were becoming more affluent experienced increasing instability. This association persists during later periods as well although it becomes slightly weaker ($r = -0.538$ $p = .000$, and $r = -0.554$ $p = .000$ for 1987 – 1993 and 1994 – 2000 respectively).

The relationship between instability change and changes in heterogeneity also exhibits a persistent negative association that becomes stronger during the study period. Between 1980 and 1986, these variables correlate at $r = -0.473$ ($p = .000$). Therefore, communities experiencing increasing instability also experienced declines in racial and ethnic heterogeneity. Conversely, communities that became more diverse experienced more stable populations. Furthermore, the magnitude of the correlations between these two variables in later periods is greater, showing that this relationship strengthened over time. Finally, the relationship between disadvantage changes and changing heterogeneity is moderate to strong and positive in each period. Therefore, as tracts became more disadvantaged, they were also becoming more diverse with respect to racial and ethnic distributions. Between 1980 and 1986, the correlation is $r = 0.410$ ($p = .000$). As with instability and heterogeneity changes, this relationship becomes stronger later during the study period.

In summary, the correlation matrices illustrate several important inter-relationships among structural indicators in St. Louis communities. First, changes in disadvantage, instability, and heterogeneity have moderate to strong correlations between 1980 and 2000. Second, where levels of disadvantage increased, communities also became more stable, as well as more racially and ethnically heterogeneous. Third, these relationships persist throughout the study period.

The analysis now turns to the examination of the multivariate models of neighborhood homicide trends in St. Louis. Table 4.9 presents five models of homicide trajectories: one each for disadvantage, instability, racial/ethnic heterogeneity, and model for male youth ages 15 to 24, as well as a full model that includes all of these measures. As with the bivariate models, the level and change in each covariate is entered to explain the homicide trends for the relevant section of the study period.

Model 1 displays the bivariate results for disadvantage and homicide trends. The level of disadvantage is significantly related to the 1980 homicide rate as well as to each of the trends. Consistent with other cross-sectional research, there is a large and positive association between the level of disadvantage and homicide rates in 1980 ($\beta = -0.401$, $p < .001$). For the 1980 to 1986 trend, more disadvantaged neighborhoods experienced greater declines in violence ($\beta = -0.016$, $p = .003$). However, this relationship is reversed during the 1987 to 1993 period, indicating that highly disadvantaged neighborhoods had greater than average increases in homicide rates ($\beta = 0.024$, $p < .001$). As with the first trend component, disadvantaged communities experienced greater than average declines in homicide rates in the post-1993 trend ($\beta = -.014$, $p = .012$). Thus, the level of disadvantage is consistently related to the magnitude of neighborhood crime trajectories. Areas with higher levels of economic disadvantage experience greater increases and larger declines than their less disadvantaged counterparts.

In contrast to levels of disadvantage, the changes in this variable are not consistently related to homicide trends in St. Louis census tracts. Rather, changing levels

Table 4.8: Correlation Matrix of Factor Scores and Youth Population, 1980 - 2000 (n = 110)

1980 - 1986	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Disadvantage	1.000							
2. Instability	0.004	1.000						
3. Race/Ethnicity	0.129	-0.062	1.000					
4. Percent Male Youth	0.480***	-0.069	0.416***	1.000				
5. Δ Disadvantage	-0.096	0.217*	-0.184	-0.028	1.000			
6. Δ Instability	0.130	-0.425***	0.350***	0.102	-0.643***	1.000		
7. Δ Heterogeneity	-0.399***	0.357***	-0.284**	-0.200*	0.410***	-0.473***	1.000	
8. Δ Percent Male Youth	-0.026	0.100	0.057	-0.131	0.282**	-0.209*	-0.058	1.000
1987 - 1993	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Disadvantage	1.000							
2. Instability	0.062	1.000						
3. Race/Ethnicity	-0.127	0.214*	1.000					
4. Percent Male Youth	0.392***	0.010	0.183	1.000				
5. Δ Disadvantage	-0.144	0.037	0.134	0.082	1.000			
6. Δ Instability	-0.023	-0.216*	0.107	-0.001	-0.538***	1.000		
7. Δ Heterogeneity	-0.453***	0.093	0.100	-0.283**	0.547***	-0.538***	1.000	
8. Δ Percent Male Youth	-0.107	0.142	0.088	0.399***	0.327***	-0.226*	0.124	1.000
1994 - 2000	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Disadvantage	1.000							
2. Instability	0.052	1.000						
3. Race/Ethnicity	-0.247**	0.189*	1.000					
4. Percent Male Youth	0.312**	0.057	0.071	1.000				
5. Δ Disadvantage	-0.202*	-0.094	0.331***	0.059	1.000			
6. Δ Instability	-0.043	0.078	-0.107	-0.001	-0.554***	1.000		
7. Δ Heterogeneity	-0.275**	-0.172	0.217*	-0.130	0.535***	-0.548***	1.000	
8. Δ Percent Male Youth	0.197*	-0.111	-0.189*	-0.102	-0.229*	0.240*	-0.102	1.000

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

Table 4.9: Multivariate HLM Results of Social Structure and Homicide Rates Standard Errors in Parentheses (n = 110)

Fixed Effects	*Unconditional Model*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
1980 Base Rate, π_{0i}						
Intercept, β_{00}	-0.086+ (0.047)	-0.026 (0.028)	-0.097* (0.044)	-0.074 (0.052)	-0.746*** (0.215)	0.061 (0.193)
Disadvantage, β_{01}		0.401*** (0.035)				0.415*** (0.026)
Instability, β_{02}			0.130** (0.043)			0.129*** (0.034)
Heterogeneity, β_{03}				0.023 (0.072)		-0.007 (0.046)
Male Youth, β_{04}					0.075** (0.023)	-0.011 (0.020)
1980 – 1986 Trend, π_{1i}						
Intercept, β_{10}	-0.032*** (0.005)	-0.035*** (0.005)	-0.031*** (0.005)	-0.033*** (0.007)	-0.010 (0.028)	-0.068+ (0.038)
Disadvantage, β_{11}		-0.016** (0.005)				-0.023*** (0.006)
Instability, β_{12}			-0.007 (0.006)			-0.004 (0.006)
Heterogeneity, β_{13}				-0.011 (0.008)		-0.014 (0.009)
Male Youth, β_{14}					-0.002 (0.003)	0.004 (0.004)
Δ Disadvantage, β_{15}		0.022 (0.017)				0.014 (0.022)
Δ Instability, β_{16}			0.005 (0.025)			0.028 (0.033)
Δ Heterogeneity, β_{17}				-0.021+ (0.012)		-0.018+ (0.011)
Δ Male Youth, $\beta 18$					0.005 (0.003)	0.006+ (0.003)
1987 – 1993 Trend, π_{2i}						
Intercept, β_{20}	0.043*** (0.005)	0.043*** (0.005)	0.041*** (0.005)	0.050*** (0.007)	0.016 (0.014)	0.070*** (0.042)
Disadvantage, β_{21}		0.024*** (0.004)				0.022*** (0.006)
Instability, β_{22}			0.003 (0.005)			0.002 (0.004)
Heterogeneity, β_{23}				0.007		0.010+

				(0.005)		(0.005)
Male Youth, β_{24}					0.003 (0.002)	-0.003+ (0.002)
Δ Disadvantage, β_{25}		0.017 (0.019)				0.036 (0.023)
Δ Instability, β_{26}			-0.027 (0.034)			-0.063+ (0.035)
Δ Heterogeneity, β_{27}				-0.014 (0.013)		-0.037+ (0.021)
Δ Male Youth, β_{28}					-0.010** (0.003)	-0.004 (0.004)
1994 – 2000 Trend, π_{3i}						
Intercept, β_{30}	-0.046*** (0.006)	-0.052*** (0.006)	-0.049*** (0.006)	-0.046*** (0.008)	-0.018 (0.015)	-0.022 (0.016)
Disadvantage, β_{31}		-0.014* (0.005)				-0.008 (0.006)
Instability, β_{32}			-0.020*** (0.005)			-0.022*** (0.006)
Heterogeneity, β_{33}				0.002 (0.006)		0.012* (0.006)
Male Youth, β_{34}					-0.004+ (0.002)	-0.004+ (0.002)
Δ Disadvantage, β_{35}		0.039* (0.016)				0.029 (0.023)
Δ Instability, β36			-0.014 (0.028)			-0.006 (0.039)
Δ Heterogeneity, β_{37}				-0.001 (0.009)		-0.010 (0.010)
Δ Male Youth, β_{38}					-0.005 (0.003)	-0.003 (0.003)
Random Effects	*Variance*	*Variance*	*Variance*	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.0657***	0.2043***	0.2223***	0.1974***	0.0484***
1980 – 1986 Trend, r_1	0.0019***	0.0017***	0.0019***	0.0020***	0.0019***	0.0016***
1987 – 1993 Trend, r_2	0.0016***	0.0011***	0.0017***	0.0016***	0.0015***	0.0010***
1994 – 2000 Trend, r_3	0.0026***	0.0022***	0.0022***	0.0026***	0.0024***	0.0018***
Level 1 Error, e	0.0478	0.0478	0.0478	0.0478	0.0478	0.0478

+ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

of disadvantage are only significant during the 1994 to 2000 period ($\beta = 0.039$, $p = .020$), although the direction of the relationships are consistent for the prior trends. The results indicate that while average homicide rates were declining by approximately 5.1 percent annually, a neighborhood in which disadvantage increased by one standard deviation experienced a decline of only 1.3 percent annually, holding the 1994 level of disadvantage constant.

The residual variance components in model 1 show that the level of disadvantage explains 69.0 percent of the variation in 1980 homicide rates. Additionally, the model reduces the residual variance of the trends by 10.5, 31.25, and 15.4 percent for the 1980 – 1986, 1987 – 1993, and 1994 – 2000 periods, respectively. Consistent with the results found in bivariate models, the level of disadvantage explains a substantial portion of the cross-sectional variation in homicide rates. However, the changes in disadvantage explain small but non-trivial portions of the variation in homicide trends.

The evidence is therefore mixed with respect to changing levels of disadvantage. Recall that an increase in economic hardship was expected to be related to greater upswings and attenuated downswings in violence. The St. Louis data between 1980 and 2000 indicate that this relationship is positive, but not significant between 1980 and 1993. However, during the 1990s decline in violent crime, changes in disadvantage are associated with smaller declines.

Model 2 shows the relationship between levels and changes in residential instability and homicide trends. As with levels of disadvantage, more unstable communities had higher levels of homicide in 1980 ($\beta = 0.130$, $p = .004$). However, neither the level, nor the change in residential instability is associated with homicide trends between 1980 and 1993. During the last period of the study, the level of instability is negatively associated with homicide declines ($\beta = -0.020$, $p < .001$), but changes in this measure are not significant in the bivariate model.

In the random effects portion of model 2, the 1980 level of instability explains only 3.7 percent of the variation in 1980 homicide rates. Since there were no significant relationships between instability and homicide trends during the first two trend periods, it is not surprising that model 2 explains almost none of the community-level variation in homicide trends. However, the 1994 level of instability was able to explain about 15.4 percent of the variation in post-1993 changes in violence.

These results suggest that while the residential instability has a significant and positive relationship to homicide rates in cross-sectional models, the changes in this measure are not associated with homicide trends. Thus in the bivariate model, the analysis finds no support for the hypothesis that increases in instability would be positively associated with homicide trends. In fact, although the coefficients are not significant, changes in residential instability have a negative sign from 1987 through 2000. The implication of this will be discussed below.

Model 3 shows the results for the racial and ethnic heterogeneity factor. The level of ethnic heterogeneity is not significantly associated with the 1980 homicide rate. Additionally, the initial levels of heterogeneity are not related to their respective trends in violence for any section of the model. However, the change in ethnic heterogeneity has a marginally negative association with homicide declines between 1980 and 1986 ($\beta = -0.021$, $p = .077$). Therefore, communities with growing level of Hispanic and immigrant populations, or increasing levels of racial diversity experienced greater than average declines in homicide rates in the early 1980s. The average annual decline during this period was 3.2 percent. For a neighborhood with a one standard deviation increase in ethnic heterogeneity, the decline was 5.3 percent annually. Coupling this result with the lack of significant relationships in other periods of the study, there is little evidence that changes in ethnic heterogeneity are strongly associated with homicide trends.

Model 3 indicates only marginal effects of the change in racial and ethnic heterogeneity on homicide trends. This is supported in the residual variance components portion of the model. Levels and changes in racial and ethnic heterogeneity do not explain the variation in homicide trends over the unconditional model. This is further evidence against the hypothesis that changes in ethnic heterogeneity are associated with homicide trends.

Model 4 shows the bivariate association between percent male youth and homicide rates. The initial level of homicide is positively associated with male youth populations ($\beta = 0.075$, $p = .002$). Additionally, the 1994 level of male youth has a marginal and negative association with the final decline in homicide rates ($\beta = -0.004$, $p = .003$). Therefore neighborhoods with larger proportions of young males in the population experienced slightly greater declines in homicide during this period. However, the only significant relationship between homicide trends and the change in male youth occurs between 1987 and 1993 ($\beta = -0.010$, $p = .004$).

The residual variance components in model 3 have been reduced by only small amounts. The percentage of male youths and changes over time explain about 7.0 percent of the variation in 1980 homicide rates. Additionally, the model explains roughly 6.3 and

7.7 percent of the variation in homicide trends during the second and third periods, respectively.

In model 5, the neighborhood homicide trajectories are explained by disadvantage, instability, ethnic heterogeneity, and the percent male youth. The 1980 homicide rate continues to be positively related to levels of disadvantage ($\beta = 0.415$, $p < .001$) and residential instability ($\beta = 0.129$, $p < .001$). However, when controlling for these two variables and ethnic heterogeneity, the percent male youth is no longer significantly associated with homicide rates. Additionally, the model shows that the level of disadvantage is persistently related to the magnitude of fluctuations in homicide rates between 1980 and 1993. However, after controlling for the levels and changes in other covariates, the coefficient for the 1994 level of disadvantage is reduced to non-significance ($\beta = -0.008$, $p = .164$).

In addition to the 1980 level of disadvantage, the change in ethnic heterogeneity and change in male youth are significantly related to the 1980 to 1986 homicide trends. Increases in ethnic heterogeneity are associated with greater declines in homicide rates in St. Louis neighborhoods ($\beta = -0.018$, $p = .099$). Additionally, communities with increases in male youth populations experienced smaller declines during this period ($\beta = 0.006$, $p = .058$).

Between 1987 and 1993, several additional covariates have marginally significant relationships to increases in homicide. Neighborhoods with higher starting levels of ethnic heterogeneity experienced steeper increases than the sample average ($\beta = 0.010$, $p = .052$). However, in areas that experienced increases in ethnic diversity, homicide rates increased at a lower rate ($\beta = -0.037$, $p = .074$). Additionally, tracts with higher proportions of young males in 1994 saw smaller increases in violence (β = -0.003, p = .091). Finally, in neighborhoods where residential instability increased, homicide trends were lower than the average (β = -0.063, p = .075).

During the last period of the study, communities with higher levels of instability in 1994 experienced greater than average declines in homicide (β = -0.022, p < .001). Additionally, tracts with higher levels of ethnic diversity experienced less than average declines (β = 0.012, p = .041). Finally, neighborhoods with greater percentages of young males had steeper than average declines during this period (β = -0.004, p = .076). However, in model 5 none of the changes in social structure are associated with the decline in homicide in St. Louis communities after 1994.

The residual variance components of model 5 show that these variables explain about 77.2 percent of the 1980 homicide rate across tracts. However, as with the bivariate models, changes in social structure explain less of the variation in trajectories of violence. The model reduces the residual variation by 15.8 percent between 1980 and 1986, by 37.5 percent between 1987 and 1993, and by 30.8 percent after 1993.

Discussion of Results

The current analysis extends the community-effects literature by examining whether or not changes in measures of social structure explain homicide trajectories over time at the neighborhood level. Furthermore, the analysis examines specific indicators to compare their relative abilities to explain changes in violent crime. In general, the results provide supportive evidence that levels and changes in social structure are associated with neighborhood trends in violence.

Consistent with prior research, the level of economic disadvantage is positively associated with the level of homicide in St. Louis neighborhoods. However, the results indicate that highly disadvantaged communities also experienced more volatile fluctuations in homicide over time. Furthermore, there is some evidence that changes in the level of disadvantage were related to community trends in violence during the latter half of the 1990s. However, this finding is reduced to non-significance when residential instability, ethnic heterogeneity, and the male youth population are controlled for.

The level of residential instability was also positively related to homicide rates as expected. However, there is only weak evidence that changes in stability are associated with crime trends, and only during the 1987 to 1993 period of the study. During this period neighborhoods that became more stable experienced greater increases in homicide rates. In contrast to what would be expected by social disorganization theory, this finding is more consistent with Wilson's population out-migration and social isolation thesis.

Figure 4.7 shows the homicide trend, population change, change in residential instability, and change in racial and ethnic heterogeneity, by tract between 1987 and 1993. The greatest increases in homicide rates occurred in tracts on the northeast side of the city. These communities experienced the greatest population loss, while South St. Louis neighborhood experienced smaller net changes. However, tracts with increases in residential stability also experienced average to above average upswings in violence. The final panel indicates that in North St. Louis, neighborhoods were becoming more racially and ethnically homogeneous, while communities on the southeast side of the city were increasing their level of diversity over this period.

Thus, figure 4.7 suggests that two separate processes may be at work in St. Louis neighborhoods. Neighborhoods on the north side of the city were the most highly disadvantaged areas of the city, and were racially homogeneous, predominantly black communities. As argued by Wilson, these areas experienced greater population out-migration relative to other parts of the city. As residents moved out of these areas, it is likely that local relationship networks were disrupted, reducing the capacity of the community to regulate behavior. Furthermore, severe losses of population reduce the proximity between neighbors, thereby attenuating their collective capacity for guardianship and mutual assistance. Thus, these tracts represent areas in which the community itself was beginning to dissolve and social controls weakened, allowing greater increase in violence.

In contrast to the process described above, some communities on the southeast side of St. Louis also experienced above average increases in homicide between 1987 and 1993. While these areas did not suffer the degree of population loss witnessed in other parts of the city, they underwent greater structural changes with regard to increasing disadvantage as well as racial and ethnic heterogeneity. As residents moved out of North St. Louis neighborhoods, some relocated to neighborhoods in South St. Louis. In these areas, residential instability was reduced as it pertains to the housing market. However, there was still a non-trivial turnover in population as some previous residents chose to move out. The results of these processes were smaller net reductions in population size.

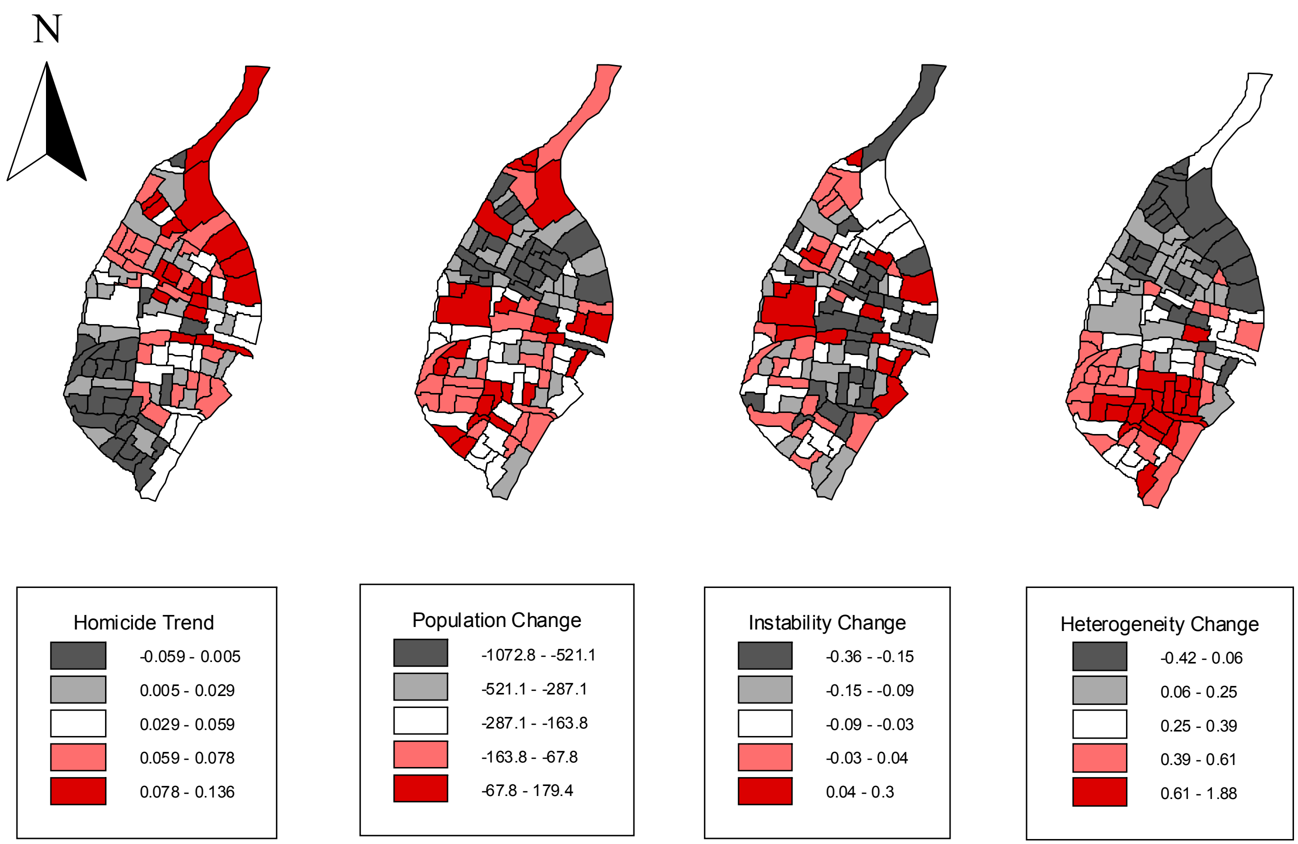
Additionally, the migration of residents from northern to southern neighborhoods, in conjunction with the out-migration of more tenured residents from southern tracts, caused an increase in racial and ethnic diversity, as well as economic disadvantage. For these communities, the processes of structural change appear more consistent with the traditional social disorganization perspective. Thus, while homicide rates increased at an above average rate in these areas, they did not experience the severe upswings of northern neighborhoods.

From these data, there appears to be a weak association between changes in social structure and crime trends. However, this may be due in part to differential processes at work in different parts of the city. Where population out-migration and social isolation are most severe, the traditional concepts of community begin to dissolve and the routine activities are disrupted in ways that reduce level of social control in the neighborhood.

However, for communities where population movement takes on the form of turnover, the sheer proximity of neighbors provides a greater capacity to control behavior through increased guardianship from a routine activity perspective. Still, where population turnover results in increases in racial and ethnic heterogeneity, as well as economic disadvantage, community relations are likely to become more strained and fragmented. The result of this process is a breakdown in regulatory capacity that allows some increases in violent crime, yet smaller than in areas where there is little community left to speak of.

The analysis also suggests that changes in social structure are not associated with homicide declines during the latter half of the 1990s. This result is unexpected, but points to the largest limitation of the analysis. The dissertation explores the association between measures of neighborhood social structure and crime trends. As with much of the literature relating social structure to homicide, the dissertation assumes a link between structure and local relationship networks, as well as routine activity patterns. However,

Figure 4.7: Change in Neighborhood Violence and Social Structure, 1987 - 1993



the data do not include any measures of additional neighborhood contexts that could be associated with crime trends. Specifically, measures of drug market activity, gang activity, physical disorder, police enforcement tactics, and incarceration rates are not available at the neighborhood level between 1980 and 2000 for St. Louis.

Due in large part to the dramatic nationwide increase in violence of the late 1980s and early 1990s, there were substantial shifts in policies aimed at crime control. The war on drugs has produced a significant increase in incarceration rates, as well as substantially more severe sentencing guidelines. Innovations in law enforcement, such as New York City's Compstat program, Boston's Operation Ceasefire, and Richmond's Project Exile have spurred changes in policing tactics toward targeting high-risk populations and communities. It is precisely these types of policies and initiatives, in conjunction with the attenuation of crack markets that have been promoted as the leading causes of the reduction in violent crime during the latter 1990s (Levitt, 2004; Rosenfeld, 2004).

It is therefore not surprising to find no association between changes in community social structure and the post-1993 crime drop in St. Louis. To the extent that crime control policies were effectively implemented at the neighborhood level, one would expect these other contextual factors to have significant associations with homicide trends. Therefore, the analysis suffers from omitted variable bias in this respect. The question that remains unanswered is whether or not structural changes would explain the residual variation in homicide trends after removing the influence of these other factors.

In addition to the limitation discussed above, the current analysis suffers from an additional limitation. The neighborhoods of a city are not independent observations in a research sample. Rather, they are functionally interdependent units of the urban system. Residents move in and out of different neighborhoods on a daily basis as they travel to and from work and leisure activities. Additionally, the use of administratively defined units such as census tracts holds the implicit assumption that such boundaries are meaningful to the populations residing within. However, the more likely reality is that the residents of one community have relationship networks that extend beyond census tract boundaries and are influenced by others residing outside of the neighborhood. For these reasons, the residents and events occurring in one community would be expected to both influence, and be influenced by, residents and events occurring in other neighborhoods. Yet the analysis in this chapter does not address this possibility and assumes that St. Louis neighborhoods are independent observations. To address this limitation, the dissertation will now examine the spatial distribution of neighborhood crime trends and structural characteristics.

Chapter 5: The Spatial Distribution of Homicide Trends and Social Structure

The analysis thus far has determined that neighborhood characteristics of social structure in St. Louis, Missouri are related to local trends in homicide rates. Additionally, the changes in neighborhood characteristics have marginally significant relationships with trajectories of violence. Lastly, the analysis provides evidence that suggests the processes relating structure to homicide may not be operating consistently in all parts of St. Louis. This section of the dissertation seeks to describe and explain the spatial distribution of homicide trends and structural changes in St. Louis between 1980 and 2000.

As noted previously, the HLM models provide answers to questions of “what” and “when” with respect to the relationships between structure and homicide trends. Still, the HLM strategy cannot address questions of “where” in this research. In contrast, the methods used in this chapter of the dissertation can examine the geographic distribution of homicide trends. Additionally, the methods allow estimation of the nature of the relationship between neighborhood structures and trajectories of violence. It should be noted that both approaches provide estimates of the nature of the relationship between structure and homicide trends (the “what”). Thus, while there is an expected degree of overlap between the results presented, neither strategy can address all three of the issues on its own. Whereas the previous chapter used methods suited to assessing the timing of changes (the “when”), this chapter uses methods suited to assessing “where” those changes occurred.

There are several research questions associated with this analysis. First, do neighborhood homicide trajectories cluster together in space? Second, do indicators of social structure cluster together as well? Third, in the presence of spatially autocorrelated homicide trends, can this clustering be explained by the distribution of structural characteristics within neighborhoods? Finally, to the extent that trajectories of violence exhibit spatial autocorrelation after controlling for the structures within communities, is there evidence consistent of a contagion or diffusion effect of violence? This chapter addresses each of these questions sequentially.

The Spatial Distribution of Homicide Trends

Between 1980 and 2000, homicides in St. Louis were generally clustered together in two small regions of the city (see figure 4.2). Communities located outside of these areas enjoyed periods of relatively little serious violent crime. Consistent with the findings from Chicago and Seattle, this pattern suggests that a relatively small number of tracts in St. Louis are responsible for the majority of annual fluctuations in St. Louis homicide rates (Griffiths and Chavez, 2004; Weisburd et al., 2004).

To decompose the levels of homicide over time, figure 5.1 provides four maps of neighborhood homicides rates per 1,000 in 1980, 1987, 1994, and 2000 respectively. The maps are color-coded by quantiles, and show that in each of these years, a small group of tracts in North St. Louis were consistently well above the mean homicide rate. Additionally, a few neighborhoods in South St. Louis exhibit above average homicide rates. However, these communities do not appear to exhibit persistently elevated levels of homicide. This provides some evidence that St. Louis homicide trends are being driven primarily by a few high crime areas, rather than by general trends in all communities.

Figure 5.1: Quantile Distributions of St. Louis Census Tract Homicide Rates, 1980 - 2000

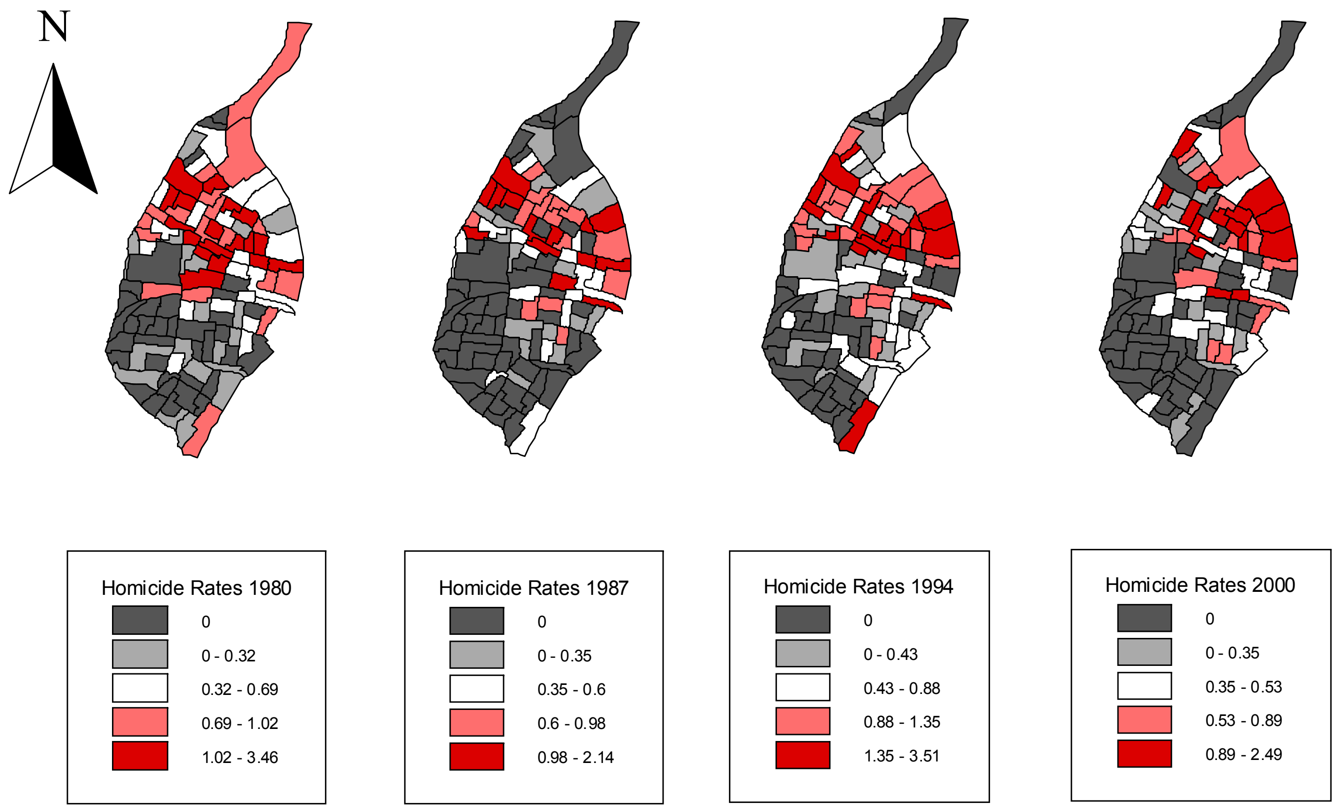
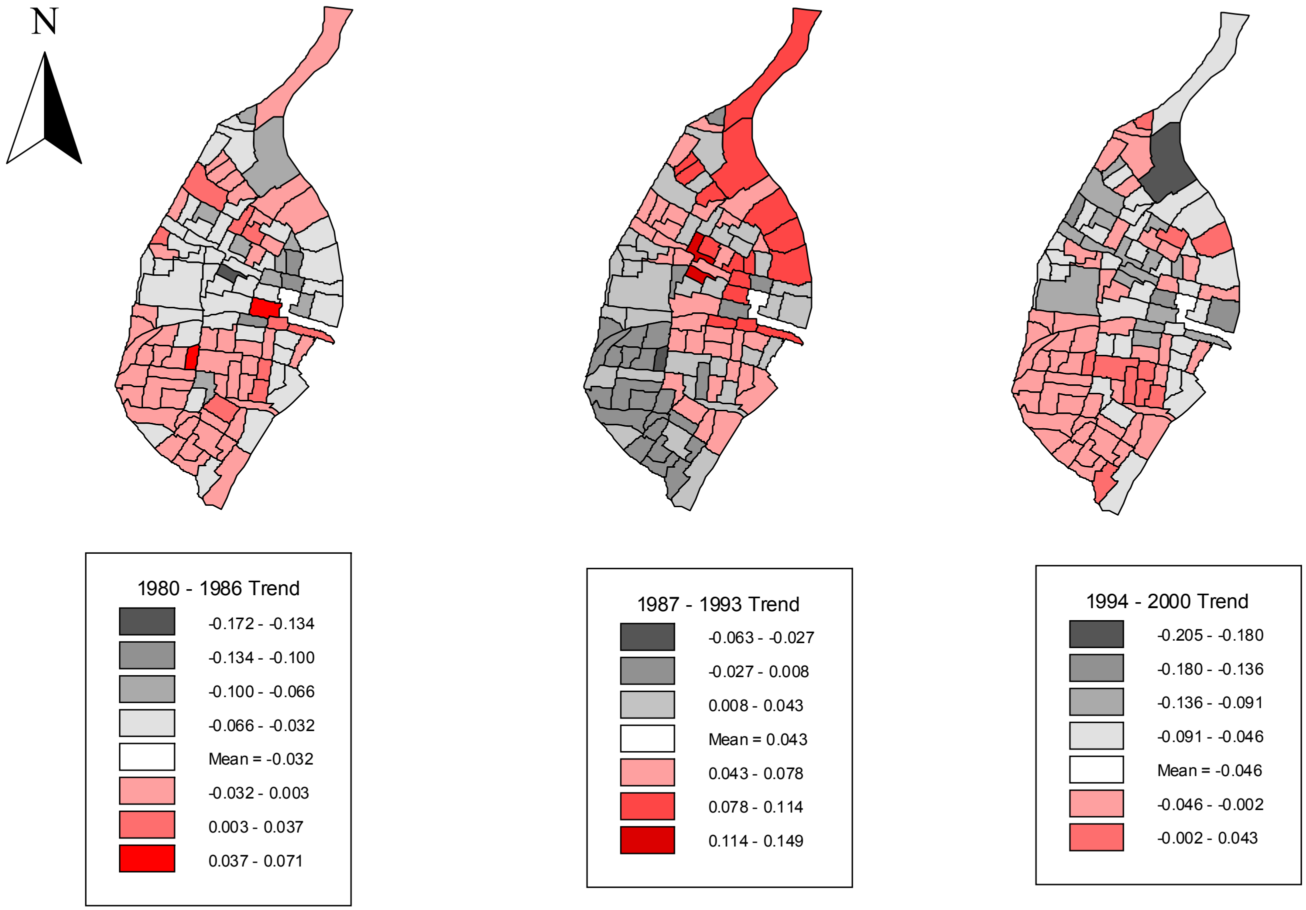


Figure 5.2: The Spatial Distribution of Homicide Trends in St. Louis Neighborhoods, 1980 - 2000



To asses whether or not neighborhood homicide trends cluster together in space, the analysis begins by obtaining estimates of within-tract homicide trajectories from the unconditional HLM model presented in Chapter 4. From this model, a linear trend parameter is available for each neighborhood, during each of the periods defined by structural breaks in the overall trajectory of the city. Figure 5.2 indicates the direction and magnitude of these trends for the 1980 – 1986, 1987 – 1993, and 1994 – 2000 periods of study. The figures show that the highest crime rate neighborhoods of North St. Louis experienced greater upswings and declines in homicide rates than lower crime rate communities. Furthermore, the southern communities with medium levels of violence exhibit somewhat exaggerated trends in homicide, but less so than their high crime counterparts to the north.

Based on these trend data, the degree of clustering among homicide trends may be formally tested through the use of a Moran's *I* statistic (Baller et al., 2001; Cliff and Ord, 1981). Moran's *I* is a statistic that measures the degree of spatial autocorrelation across geographic units. Positive values of *I* indicate that locations with similar values of a variable are clustered in close proximity to each other, while negative values indicate that dissimilar values of the variable are clustered in space (i.e. the familiar checkerboard pattern). When Moran's *I* is statistically equal to zero, this indicates that the geographic pattern of values is random across units. Moran's *I* is calculated as the following:

$$I = \sum_i \sum_j w_{ij}\left(x_i - \overline{X}\right)\left(x_j - \overline{X}\right) / \sum_i \left(x_i - \overline{X}\right)^2 , \qquad (2.1)$$

where x_i is the linear homicide trend in tract *i*, x_j is the linear homicide trend in tract *j*, $\overline{X}$ is the average homicide trend across all tracts, and w_{ij} is a spatial weights matrix. In less formal terms, Moran's *I* is analogous to testing time series data for serial correlation in two dimensions of space (Moran, 1950).

The spatial weights matrix, w_{ij}, represents an N x N adjacency matrix in which any *(i,j)* element is one if units *i* and *j* are adjacent, and zero otherwise (Anselin, 1988). In this case, an adjacent unit *j* is defined as sharing a common border or vertex with unit *i*. This is known as a first-order queen weighting structure.[53] The number of neighbors for each tract is therefore dependent on how many shared boundaries and corners they have with other tracts. The weights are row-standardized for each neighborhood *i*, causing the sum of the weights to equal 1 for each tract. As it pertains to the calculation of Moran's *I*, the homicide trend in each community is therefore correlated to the weighted average of its adjacent neighbors.[54]

Table 5.1 shows Moran's *I* for the initial levels and trends in neighborhood homicide rates. All of the coefficients are positive and significant.[55] Neighborhoods with high levels of homicide are persistently clustered together, with the greatest degree of clustering occurring in 1980 and 1994 when St. Louis homicide rates were at their peaks. Additionally, the areas with the greatest fluctuations in community-level trends tend to be clustered together as well. Although the degree of clustering for the trends is moderate in

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[53] In addition to queen weights, the analysis was performed with several other weighting schemes. Rook weights count neighbors as those tracts sharing common borders, but not vertices. K-nearest neighbor weights calculate the distance between tract centroids, and counts the K-nearest tracts as neighbors to any given location. In this case 5 and 10-nearest neighbor weights were used as well. Results are substantively identical when alternate weighting schemes are used. Therefore, only the results from queen weights are presented, here.

[54] Moran's *I* is not the only available measure of spatial autocorrelation. Additional measures such as Geary's *C* (contiguity ratio) have been available for many years (Geary, 1954). However, the GeoDa software does not allow calculation of other measures of spatial autocorrelation. Therefore, it is unknown whether or not these results would be robust to a different measure of association.

[55] All spatial analyses were performed using GeoDa v0.9.5-i5 software. The significance test for Moran's *I* is performed using a randomized permutation procedure. The statistic is recalculated 999 times to create a reference distribution which is then compared to the sample test statistic. Each Moran's *I* statistic was tested up to 10 times, with no substantive changes in the results.

magnitude, tracts with the greatest increases and declines in homicide are not randomly dispersed throughout the city. Rather, these communities are expected to be in relatively close proximity to one another. Furthermore, the Moran's *I* coefficient for the 1987 level (I = .347, p < .001) is smaller than in the other periods, while the 1987 to 1994 trend (I = .323, p < .001) is larger than during the other two periods. This evidence is consistent with the findings that a few neighborhoods contribute disproportionately to both the levels and fluctuations in city-level homicide rates.

Although the degree of spatial autocorrelation is moderate in magnitude, it is sufficient to reject the null hypothesis that homicide trajectories are randomly distributed throughout the city. Figure 5.2 illustrates this point by showing standard deviational maps of neighborhood homicide trajectories during the three periods of the study. Between 1980 and 1986, the majority of high crime tracts were experiencing substantial declines

Table 5.1: Moran's *I* for Homicide Rates and Trends, 1980 - 2000

Homicide Rates	*Moran's I*
1980	.451***
1987	.347***
1994	.441***
2000	.316***

Homicide Trends	*Moran's I*
1980 - 1986	.264***
1987 - 1993	.323***
1994 - 2000	.299***

*** p < .001

in violence. There were a few areas that experienced relatively flat homicide trends or even slight increases. However, a comparison with figure 5.1 shows that these communities had very low rates of violence to begin with.

Between 1987 and 1993, the communities with the greatest increases in homicide rates were those that had experienced large declines earlier in the decade. These neighborhoods in North St. Louis are also the areas that persistently have the highest levels of homicide throughout the study period. However, on the southeast corner of the city, a number of neighborhoods were experiencing greater than average increases in homicide during this period as well. As discussed in the previous chapter, these were tracts that were going through the greatest changes in racial and ethnic heterogeneity, as well as moderate increases in disadvantage. Therefore, small increases in crime rates are to be expected in these locations.

During the final period from 1994 to 2000, the homicide trends in North St. Louis reverse direction again, and large reductions on violence are observed throughout the period. Much of Southwest St. Louis remains stable with low levels of homicide. However, a few of the neighborhoods that showed slight increases between 1987 and 1993 continue their upward trends becoming substantially more violent in the latter half of the 1990s. For these communities, there were moderate increases in racial and ethnic heterogeneity, but substantial increases in economic disadvantage during the period.

The data show that the greatest fluctuations in neighborhood homicide rates occurred in North St. Louis city census tracts, while there were a few communities in the southern city that experienced persistent increases in homicide rates throughout the study period. In combination, the maps and Moran's *I* statistics clearly show that homicide trends in St. Louis city are clustered together in two particular areas of the city.

Due to the positive spatial autocorrelation of homicide trends in St. Louis neighborhoods and the observed relationships found between social structure and homicide trends, one would expect to find that the levels and changes in structural indicators are also correlated across tracts. Moran's *I* can be used to test these hypotheses as well. Table 5.2 shows the Moran's *I* statistics for the levels and changes of the structural covariates in 1980, 1987, 1994, and 2000, respectively.

Table 5.2: Moran's *I* for Levels and Changes in Structural Covariates in St. Louis Neighborhoods, 1980 - 2000

Levels	*1980*	*1987*	*1994*	*2000*
Disadvantage	.672***	.670***	.650***	.611***
Residential Instability	.569***	.593***	.600***	.592***
Ethnic Heterogeneity	.289***	.519***	.600***	.584***
Male Youth	.198**	.188**	.178**	.126*
Changes	*1980 - 1986*	*1987 - 1993*	*1994 - 2000*	
Disadvantage	.128*	.355***	.293***	
Residential Instability	-.011	.064	.138*	
Ethnic Heterogeneity	.354***	.529***	.433***	
Male Youth	.089*	.012	-.079	

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

The Spatial Distribution of Structural Characteristics

All of the structural indicators exhibit positive spatial autocorrelation, and nearly all are significant below the .05 level.[56] Economic disadvantage has the greatest magnitude of autocorrelation in 1980 (I = .672, p < .001). However, the magnitude of clustering diminishes somewhat by 2000 (I = .611, p < .001) indicating disadvantage was not as concentrated as in previous years. This is confirmed by Moran's *I* for the change in disadvantage. Between 1980 and 1986, neighborhood changes in economic disadvantage were not highly concentrated in specific communities. However, during the second two

[56] Appendix D provides the Moran's *I* statistics for each of the individual indicators of social structure. Again, due to the high degree of multicollinearity among these indicators, the analysis makes use of the factor scores described in the previous chapter.

periods of the study, changes in economic disadvantage were more highly concentrated, indicating that increases and decreases in disadvantage were more concentrated.

Residential instability exhibits a moderate to strong degree of spatial autocorrelation throughout the study period. In 1980, Moran's *I* was .569 ($p < .001$). Yet there was a marginal increase to .592 ($p < .001$) in 2000. Changes in residential instability generally displayed spatial randomness, indicated by small and non-significant *I* statistics between 1980 and 1993. However, there was a weak degree of positive autocorrelation across neighborhoods between 1994 and 2000 ($I = .138$, $p < .05$).

The ethnic heterogeneity component had only a weak positive correlation across St. Louis neighborhoods in 1980 ($I = .289$, $p < .001$). Yet, there was a distinct change in the spatial distribution of ethnic heterogeneity over the course of the study. By 1994, diversity was strongly correlated in space ($I = .600$, $p < .001$). In contrast to disadvantage and residential instability, the Moran's *I* statistic for the changes in heterogeneity exhibit moderate to strong correlations across tracts.

Male youth populations were only weakly correlated across St. Louis neighborhoods. In 1980, Moran's *I* was .198 ($p < .01$). Over the course of the following two decades, the spatial autocorrelation in this indicator decreased to .126 ($p < .05$) in 2000. However, the changes in male youth populations did not exhibit significant clustering except a weak positive correlation between 1980 and 1986 ($I = .089$, $p < .05$). Thus, the weak concentration of male youths in St. Louis communities became more dispersed throughout the city over this twenty-year period. Additionally, tract-level changes in this variable were generally randomly distributed after 1986.

In summary, the structural characteristics of these neighborhoods exhibit significant degrees of spatial autocorrelation in both levels and changes. Economic disadvantage was generally concentrated in North St. Louis city in 1980. Over time, this concentration became more dispersed as communities in Southeast St. Louis became more disadvantaged (figure 5.3). Residential instability was generally most concentrated in the central east-west corridor of the city during the study period. Changes in stability were randomly dispersed across tracts, except for a small group of neighborhoods that became more residentially stable in South St. Louis (figure 5.4). The largest structural change in these communities was associated with changes in ethnic diversity. In 1980 the largest concentrations of diversity were in the central east-west corridor of the city, and in the northernmost neighborhoods. However, during the subsequent decades, the concentration of ethnic heterogeneity shifted to South St. Louis, with a strong concentration in a handful of communities (figure 5.5).

These results show that social structure also exhibits spatial clustering in much the same way that homicide trends do. Given the moderate relationship between structural characteristics and crime trends, the next step in the analysis is to determine the extent to which the distribution of disadvantage, instability, heterogeneity, and age structure are associated with the spatial patterning of homicide trends.

Structural Explanations for the Spatial Distribution of Homicide Trends

Neighborhood homicide trends exhibit positive spatial autocorrelation throughout the study period. The purpose of this section of the analysis is to determine whether or

Figure 5.3: Changes in Disadvantage for St. Louis Census Tracts, 1980 - 2000

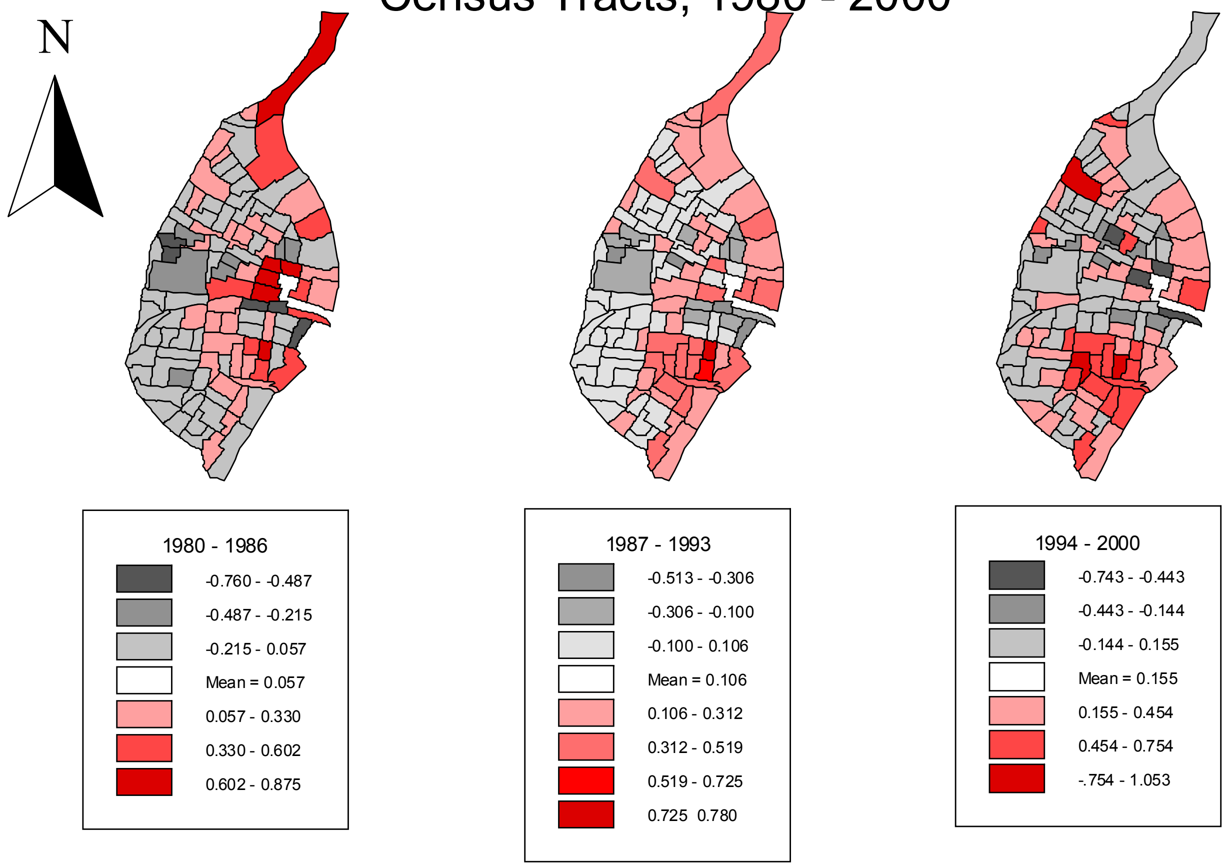


Figure 5.4: Changes in Instability in St. Louis Census Tracts, 1980 - 2000

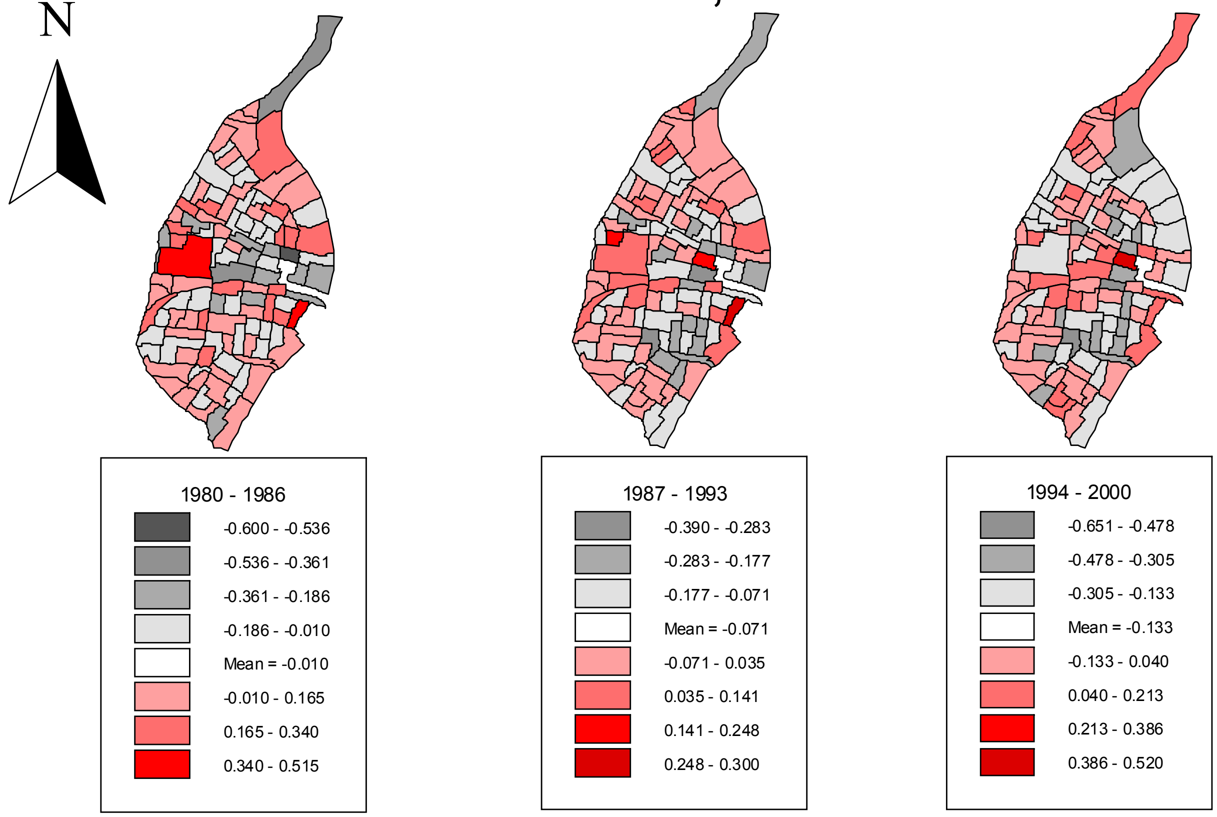
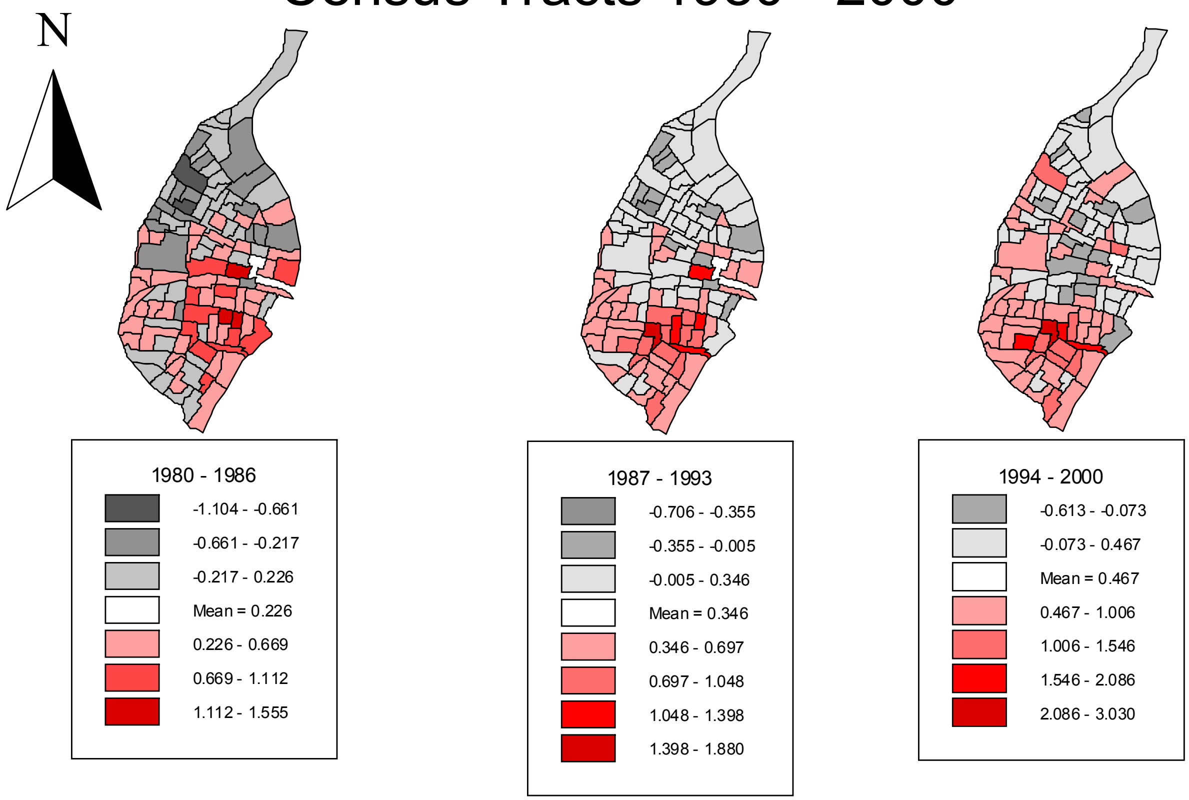


Figure 5.5: Changes in Heterogeneity in St. Louis Census Tracts 1980 - 2000



not the structural attributes of communities explain this distribution. Since the greatest fluctuations in violence occur in tracts that are close to each other, there are three possible reasons why such a pattern may exist (Baller et al., 2001). First, it is possible that these neighborhoods have similar social structures. To the extent that the structure of the community is related to its homicide trend, one would expect to see positive spatial autocorrelation of trajectories where there is positive spatial autocorrelation of structural indicators. This is referred to as the *structural similarity* model. If structural similarity is related to the geographic distribution of homicide trends, then controlling for the relevant measures of social structure will reduce the spatial autocorrelation of model residuals to non-significance. However, if the model residuals continue to exhibit spatial autocorrelation, then two additional possibilities exist to explain the spatial pattern of the outcome and an alternative specification will be needed.

Assuming that there is significant spatial autocorrelation in the residuals after controlling for structural characteristics, one alternative specification is the *spatial disturbance* model (Baller et al., 2001). In this model, residual spatial autocorrelation is modeled as part of the error term. The implication of this alternative specification is that a key variable has been omitted from the original model, which if controlled for would reduce the residual autocorrelation to non-significance. Formally, the spatial disturbance model is:

$$y = \beta X + \varepsilon \text{, where } \varepsilon = \lambda W \varepsilon + u \qquad (5.1)$$

In this model, *y* is the homicide trend to be explained, and *X* represents the explanatory variable(s) to be included in the regression. However, the error term ε is modeled to account for spatial autocorrelation, using a spatial weights matrix *W*, a parameters estimate for the autocorrelation λ, and a random residual error u (Anselin, 1988; Anselin and Bera, 1998).

In contrast to the spatial disturbance model, there is another alternative specification. Residual spatial autocorrelation may be explained through the introduction of an additional covariate that represents the weighted average of the dependent variable for spatial neighbors (assigned through the adjacency matrix). The new variable is referred to as a spatial lag, and the alternative specification is referred to as a *spatial effects* model (Baller et al., 2001). Implicit in the design of the spatial effects model is the assumption that the dependent variable exhibits a diffusion or contagion process whereby the homicide trend in one neighborhood would be expected to influence the homicide trend in an adjacent community. Additionally, because the spatial effects model incorporates a spatial lag of the dependent variable, the errors cannot be considered independent of one another. Therefore, the spatial effects model essentially subsumes the spatial disturbance specification.

Formally, the spatial effects model is:

$$y = \rho Wy + \beta X + \varepsilon \quad , \tag{2}$$

where y is the homicide trend to be explained, X is the explanatory variable(s) as specified in the OLS model, and Wy is the spatially lagged dependent variable using a spatial weights matrix W. The parameter ρ, is the coefficient estimate for the spatial lag. As discussed above, since the spatial lag of y is included in the model, the error terms become correlated by default. Thus the prediction errors are estimated as $(I - \rho W)^{-1} u$ (Anselin, 1988; Anselin and Bera, 1998).

To determine which alternative specification is appropriate, Lagrange Multiplier tests are performed using estimates from the original OLS model (Anselin, 1988; Baller et al., 2001). The LM test has been derived for both the spatial effects and spatial disturbance model, allowing comparison of the test results to indicate which alternative is preferred. If the LM – Lag test is significant, and the LM – Error test is not, then the preferred alternative specification is the spatial effects model. In the event the LM test results are reversed, then the spatial disturbance model would be the preferred specification.

There are occasions when both the LM – Lag and LM – Error tests return significant results. Anselin et al. (1996) provide two additional tests when this occurs. These are referred to as Robust Lagrange Multiplier tests (RLM). When standard LM tests indicate a preference for both a spatial disturbance model and a spatial effects model, the RLM tests are examined. The results from these tests are robust to the presence of the alternative specification. In other words, the RLM – Lag test provides a more appropriate test when there is significant error correlation, and the RLM – Error test does the same when there is a spatial lag correlation for the dependent variable (Anselin et al., 1996).

Table 5.3 presents the results from the OLS models replicating the level 2 HLM models from the previous analysis. Essentially this approach represents a two-stage modeling strategy for incorporating spatial dependence in multilevel models. The dependent variable is the level 1 trend coefficient estimated in the unconditional HLM model of homicide trajectories. This technique has been used previously in cross-sectional multilevel research and is adapted here for growth curve models (Morenoff, 2003).

Model 1 regresses the 1980 to 1986 neighborhood trend coefficients onto the levels and changes in social structure. The results show that the level of disadvantage has a significant negative association with homicide trends ($\beta = -0.016$, $p < .001$). Controlling for the additional covariates in the model, the average tract experienced a 4.4 percent average annual decline in homicide rates. For a tract that was one standard deviation above the mean on economic disadvantage, the decline was a 5.9 percent annually. None of the other covariates in the model are significant at even a permissive level of .10. However, the parameter estimates are consistent in their direction and marginally consistent in magnitude. Model 1 explains 22.2 percent of the variance in homicide trends between 1980 and 1986. This is slightly larger than the reduction in residual variance seen in the HLM model (15.8 percent). However, the results remain generally consistent with the multi-level models.

The diagnostic tests for residual spatial autocorrelation are provided below the parameter estimates in table 5.3. Moran's *I* for the residuals is 0.140 ($p = .002$).[57] This is a substantial reduction in spatial autocorrelation from the original Moran's I of 0.264. However, a marginal degree of spatial clustering remains in the residuals. Therefore, examination of the LM specification tests is necessary. The LM – Lag test and LM – Error tests are both significant. In this case, the robust LM tests must be consulted. Unfortunately, neither of the robust LM tests are significant. Based on these results, the

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[57] The Moran's *I* value reported for residuals is calculated in the same manner as previously discussed. However, the permutation method of determining significance is no longer appropriate since these are residuals. Therefore, the significance test is based on a normal approximation (Anselin and Bera, 1998).

Table 5.3: OLS results for Neighborhood Homicide Trends and Spatial Diagnostics, Standard Errors in Parentheses (n = 110)

Variable	*1980 - 1986*	*1987 - 1993*	*1994 - 2000*
Constant	-0.045*	0.060***	-0.024*
	(.019)	(.012)	(.010)
Disadvantage	-0.016***	0.021***	-0.009*
	(.004)	(.003)	(.004)
Δ Disadvantage	0.019	0.010	0.026+
	(.015)	(.017)	(.016)
Instability	-0.005	0.002	-0.018***
	(.003)	(.003)	(.004)
Δ Instability	0.020	-0.052	0.023
	(.026)	(.034)	(.028)
Ethnic Heterogeneity	-0.005	0.006	0.012*
	(.006)	(.004)	(.005)
Δ Ethnic Heterogeneity	-0.008	-0.025*	-0.001
	(.009)	(.011)	(.009)
Male Youth	0.001	-0.002	-0.003**
	(.002)	(.001)	(.001)
Δ Male Youth	0.0004	-0.002	-0.002
	(.002)	(.003)	(.002)
R-sq	0.222	0.423	0.395
Log Likelihood	228.909	247.05	213.471
AIC	-439.817	-476.10	-408.943
Diagnostic Tests			
Moran's *I*	0.140**	0.010	-0.047
LM - Lag	5.252*	0.005	0.006
LM - Error	5.560*	0.027	0.610
RLM - Lag	0.021	0.175	2.821
RLM - Error	0.330	0.198	3.425

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

distribution of structural characteristics in St. Louis neighborhoods does not fully explain the spatial distribution of homicide trends during this period.

Model 2 presents OLS results for the 1987 to 1993 period of study. Again, the 1987 level of disadvantage is significant and positively related to increases in homicide rates ($\beta = 0.021$, $p < .001$). The sample average increase in violence was 6.2 percent annually. However, for a neighborhood one standard deviation above the mean on disadvantage, the increase was approximately 8.4 percent annually. Additionally, changes in racial and ethnic heterogeneity were significant and negatively associated with homicide trends ($\beta = -0.025$, $p < .05$). Thus, a tract that experienced a one standard deviation increase in diversity had only a 3.6 percent annual increase in homicide rates during this period. No other coefficients were significant in this model. However, as with model 1, the results are generally consistent with the HLM level 2 results.

Model 2 explains 42.3 percent of the variation in homicide trends during the 1987 to 1993 period. Moran's *I* for residual spatial autocorrelation is 0.010 and is not significant, indicating that when these covariates are controlled for, the spatial distribution of homicide trends is explained. This is confirmed by the lack of significance in the LM – Lag and LM – Error tests.

Model 3 is the OLS estimates for the 1994 to 2000 period. As in previous periods, the coefficient for the 1994 level of disadvantage is significant ($\beta = -0.009$, $p < .05$). Thus, the sample average decline in homicide rates was 2.4 percent annually. For a neighborhood that was one standard deviation above the mean on disadvantage, there was a greater decline of 3.2 percent annually. In addition to the initial level of disadvantage, changes in disadvantage have a marginal but positive association with trends in violence

($\beta = 0.026$, $p < .10$). Where economic disadvantage was increasing, violent crime did not decline as quickly as in other tracts. The 1994 level of residential instability is negatively related to homicide trends during this period ($\beta = -0.018$, $p < .001$), and the 1994 level of ethnic heterogeneity is positively associated with homicide trends ($\beta = 0.012$, $p < .05$). Additionally, communities with larger proportions of male youth also experienced greater than average declines in violence ($\beta = -0.003$, $p < .01$).

Overall, model 3 explains 39.5 percent of the variation in homicide trends in the late 1990s. Moran's *I* for the residuals from this model is -0.047, and is not significant. Additionally, the LM tests for alternative specifications are not significant. Based on these results, the covariates in the model explain the spatial distribution of homicide trends after 1993.

Returning to model 1, both of the LM – Lag and LM – Error specification tests were significant. However, neither of the robust tests was significant. The combined test results are inconclusive for determining the appropriate alternative specification, and suggest the need for closer scrutiny of the model. A Jarque-Bera test for the normality of the errors is a chi-square test, with 2 degrees of freedom (Anselin, 2005). The value of the test statistic is 21.105 ($p < .001$) indicating that the errors are not normally distributed. To test for heteroskedasticity, the Kroenker-Bassett test is used and is robust to non-normal errors (Anselin, 2005). This test statistic is 18.615 ($p < .05$) and indicates that the residuals do not exhibit constant variance.

Inspection of the residuals indicated that one tract, 1192.00 was an outlier, with a large negative residual. This tract had the largest estimated decline during the 1980 to 1986 period in the HLM models ($\beta = -0.172$) and was subsequently under-predicted by the model. After removing this tract and re-estimating the model, non-normality and heteroskedasticity remained significant. In addition to inspecting the data for outliers, scatter plots of the residuals with covariates not included in the model did not yield any indication of a relationship between the residuals and another structural covariate. However, as discussed previously no data pertaining to non-structural variables are included in the model and it is likely that one of these variables would explain the non-normality and heteroskedasticity of errors. Additionally, the inclusion of such variables would be expected to improve the model fit above its current state, and might reduce the residual spatial autocorrelation further.

Still, the LM tests for both the spatial effects (Lag) and spatial disturbance (Error) models are significant. The LM test for the error model is slightly more significant, suggesting that this might be the preferred specification. Since the determination of the preferred alternative specification is likely to be confounded by omitted variables, the dissertation presents the results of both spatial effects and spatial disturbance models in table 5.4.

The spatial effects model includes a spatial lag of the homicide trends. For each tract this is simply a weighted-average homicide trend of the neighboring tracts. The results show a marginal improvement in model fit over the OLS model, with a log likelihood of 231.555 and an Akaike Information Criterion (AIC) of -443.111.[58] The coefficient for the spatial lag is positive and significant ($\beta = 0.321$, $p < .01$). Additionally, the coefficient for the level of disadvantage remains significant ($\beta = -0.013$, $p < .001$), but has been reduced in magnitude slightly. Several of the other covariates exhibit small

[58] In spatial dependence models R^2 is a pseudo- R^2 and is therefore not comparable to the original OLS estimate (Anselin, 2005).

Table 5.4: Spatial Effects Model for Neighborhood Homicide Trends, 1980 - 1986

	Spatial Effects		Spatial Disturbance	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*
Constant	-0.027	.018	-0.034	.018
Disadvantage	-0.013***	.004	-0.016***	.004
∆ Disadvantage	0.021	0.014	0.023	.014
Instability	-0.002	.003	-0.003	.004
∆ Instability	0.017	.024	0.009	.024
Ethnic Heterogeneity	-0.003	.005	-0.004	.006
∆ Ethnic Heterogeneity	-0.010	.008	-0.012	.009
Male Youth	0.0004	.002	0.00004	.002
∆ Male Youth	0.0006	.002	0.0005	.002
Spatial Lag	0.321**	.124	--	--
Lambda	--	--	0.382**	.123
R-sq	0.274		0.289	
Log Likelihood	231.555		232.144	
AIC	-443.111		-446.288	

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

reductions in their magnitudes, although they remain non-significant. These results show that between 1980 and 1986, neighborhood homicide trends were associated with both the internal structure of the community, but also with the trends in adjacent areas. Thus, tracts located near places with greater declines in violence also experienced larger declines.

While, the spatial effects model suggests that St. Louis communities had a significant influence on homicide trends in neighboring areas, it is possible that this model is not the appropriate specification. The spatial effects model not only includes the spatial lag of the dependent variable, but also allows for the correlation of errors across tracts in the same manner as the spatial disturbance model (Anselin, 1988; Baller et al., 2001). In this way, the spatial lag model subsumes the spatial error specification. For this reason, table 5.4 presents the results of the spatial disturbance model as well.

The spatial disturbance model for the 1980 to 1986 period shows an improvement in model fit over the OLS model, as well as a marginal improvement over the spatial effects model. The log-likelihood is 232.144, and the AIC is -446.288. Additionally, lambda is the parameter estimate for the spatial autoregressive parameter and is both large and significant ($\beta = 0.382$, $p < .01$). However, disadvantage continues to have a significant negative association with homicide trends ($\beta = -0.016$, $p < .001$). The remaining coefficients remain non-significant.

Due to the marginal improvement in model fit of the spatial disturbance model over the spatial effects model, and the relative stability of the coefficients in comparison with the OLS model, these results suggest that the spatial error model could be the preferred specification. Under these circumstances, the spatial distribution of homicide trends between 1980 and 1986 could further be explained if relevant omitted variables were entered into the model. As discussed in the previous chapter, such variables might include drug market activity, gang activity, law enforcement interventions, or incarceration rates. However, the reader should take this interpretation cautiously since the OLS model diagnostics indicated there were additional specification errors that could not be sufficiently addressed within the scope of this study.

Discussion of Results

The analysis presented in this section of the dissertation examines the spatial distributions of homicide trends and social structure in St. Louis neighborhoods between 1980 and 2000. The key questions to be answered include: 1) Do neighborhood-level homicide trends exhibit geographic clustering? 2) Do indicators of social structure exhibit geographic clustering? 3) When internal measures of neighborhood structure are controlled for, do homicide trends exhibit any residual spatial autocorrelation? 4) If residual spatial autocorrelation is detected among the homicide trends, is this likely to be due to a diffusion effect of homicide, or a non-structural variable that was not included in the model?

The answer to the first question is that neighborhood homicide trends do exhibit positive and significant spatial autocorrelation throughout the study period. However, the magnitude of the clustering is moderate, and increased substantially between 1987 and 1993, the period of time when homicide rates were increasing significantly in St. Louis city.

Examination of the census data on social structure also shows that many covariates exhibit moderate to strong positive autocorrelation across tracts when measured in levels. However, the changes in structural measures are less strongly clustered together. Disadvantage and instability are strongly clustered together in space during this 20 year period. Yet changes in disadvantage are moderately autocorrelated after 1987, whereas residential instability only has a weak positive Moran's *I* during the last seven years of the study. On the other hand, ethnic diversity exhibits a weak to moderate spatial autocorrelation in 1980, but the change in this measure exhibits relatively strong clustering between 1987 and 1993, and a moderate degree of autocorrelation from 1994 to 2000. Finally, youth age structure has only a weak positive degree of clustering in levels, and no significant autocorrelation for its changes. Taken together, these findings suggest that the spatial distribution of homicide trends may, in part, be explained by the geographic distribution of social structure and its change over time.

When homicide trends are explained by measures of neighborhood structure, the analysis shows that there is significant residual spatial autocorrelation remaining during the 1980 to 1986 period of the study. However, from 1987 through 2000, the levels and changes of structural characteristics are associated with homicide trends. For all three periods, the level of disadvantage is significant, consistent with the previous findings that economically deprived neighborhoods suffered greater fluctuations in crime trends than other communities. Between 1987 and 1993, increases in racial and ethnic heterogeneity were associated with smaller increases in homicide rates. However, after 1994 higher levels of disadvantage, instability, ethnic diversity, and male youth were all associated with greater declines in homicide. Yet the only change measure associated with homicide trends was for disadvantage and shows that where this variable increased, homicide rates did not decline as much as the sample average.

For the 1980 to 1986 period, there was significant residual spatial autocorrelation after controlling for neighborhood structure. However, diagnostic tests could not determine conclusively if the correlation was inherent to homicide trends themselves, or associated with an omitted variable. The spatial regression models find significant effects for both a spatial lag and a spatial error term. Yet, the spatial disturbance model fits the data slightly better and offers cautious speculation that an omitted variable could explain the residual autocorrelation during this period.

One of the most often observed correlates of neighborhood problems, including violence is economic disadvantage (Sampson et al., 2002). St. Louis is no different than other cities in this regard. The level of disadvantage is the only covariate for which there are persistent associations with homicide trends during the twenty years of this study. However, other measures of social structure only exhibit weak to moderate relationships with violence trajectories, and inconsistently over time. For example, changes in ethnic heterogeneity have a significant and negative relationship with homicide trends, but only between 1987 and 1993. Importantly, the levels and changes in social structure do explain the spatial distribution of homicide trends after 1987. Yet, they do not explain the distribution of homicide trends during the early 1980s. Several possible explanations are available to reconcile these inconsistencies.

The ecological structure of St. Louis neighborhoods underwent significant changes between 1980 and 2000. However, the magnitude of these changes was relatively small, with the greatest alterations occurring between 1987 and 1994. Therefore, to the extent that changes in social structure redefine the position of a neighborhood in the urban landscape, the relatively small changes observed during the early 1980s are not likely to have as much of an impact on crime trends. Rather, it is more likely that the unobserved contextual features of St. Louis tracts, discussed above, are explaining the majority of the spatial and temporal distribution of homicide trends.

Conversely, after 1987 ecological structures began to change more rapidly. With these larger changes, several neighborhoods underwent dramatic alterations with regard to economic disadvantage and ethnic diversity. With more neighborhoods undergoing larger changes, the association between social structure and homicide trends may be more apparent. Alternatively, there may be a threshold effect for structural change on violent crime rates. Small shocks to a system of neighborhood networks due to changes in the social structure may be absorbed or diffused throughout the community without resulting in serious disruptions of local social control. However, it is likely that at a certain point large enough structural changes could result in the breakdown of local relationship networks, guardianship, and social control. This possibility is beyond the scope of this dissertation to address.

Another possible explanation for the inconsistency of relationships is that the structural relationships in adjacent communities are related to homicide trends in a specific tract. This possibility was explored using a bivariate Moran's I plot in which the spatially-weighted average of structural covariates was correlated with the observed homicide trends for each neighborhood. In results not shown, only the spatial lag of changes in disadvantage between 1980 and 1986 was significantly correlated with homicide trends ($I = -0.088$, $p < .05$). Thus communities surrounded by locations that were increasing in economic disadvantage also experienced greater declines in homicide rates.

The OLS regression results for these models showed that when the spatial lag of disadvantage was included in the model, the coefficient for the spatial lag was marginally significant and negative ($\beta = -0.010$, $p < .10$). However the residuals continued to display heteroskedasticity, although the magnitude of the Kroenker-Bassett test was reduced slightly. Still, the LM diagnostic tests for alternative specifications were inconclusive.

When the spatial lag of the homicide trend was included in the spatial effects model, the lag of disadvantage change was reduced to non-significance. This suggests that the association observed in the OLS model was mediated by the within-neighborhood relationships between disadvantage and homicide trends. However, the spatial disturbance model was consistent with the OLS specification and continued to show a significant association between the spatial distribution of unobserved factors and homicide trends. Therefore, these data do not suggest that the internal structure of St. Louis neighborhoods has much of an influence on violent crime rates in adjacent communities.

Several of the coefficient estimates appear to be in the wrong direction. For example, increases in racial and ethnic diversity are associated with smaller increases in homicide during the 1987 to 1993 period. Additionally, increases in residential instability and male youth populations are associated with greater declines in homicide rates between 1994 and 2000. These findings suggest a third explanation in that social structure was changing in response to homicide trends, rather than influencing homicide trends.

Figure 5.6 provides standard deviation maps of the percentage change in population during the three periods of study. Clearly the neighborhoods of North St. Louis experienced the greatest percentage decline in population size in every period. Such a large exodus of residents is expected to disrupt local relationship networks, reduce guardianship, and spur a general reduction in social control. However, it may also be the case that crime rates began to increase in these communities due to other contextual

Figure 5.6: Precentage Change in Population in St. Louis Census Tracts, 1980 - 2000

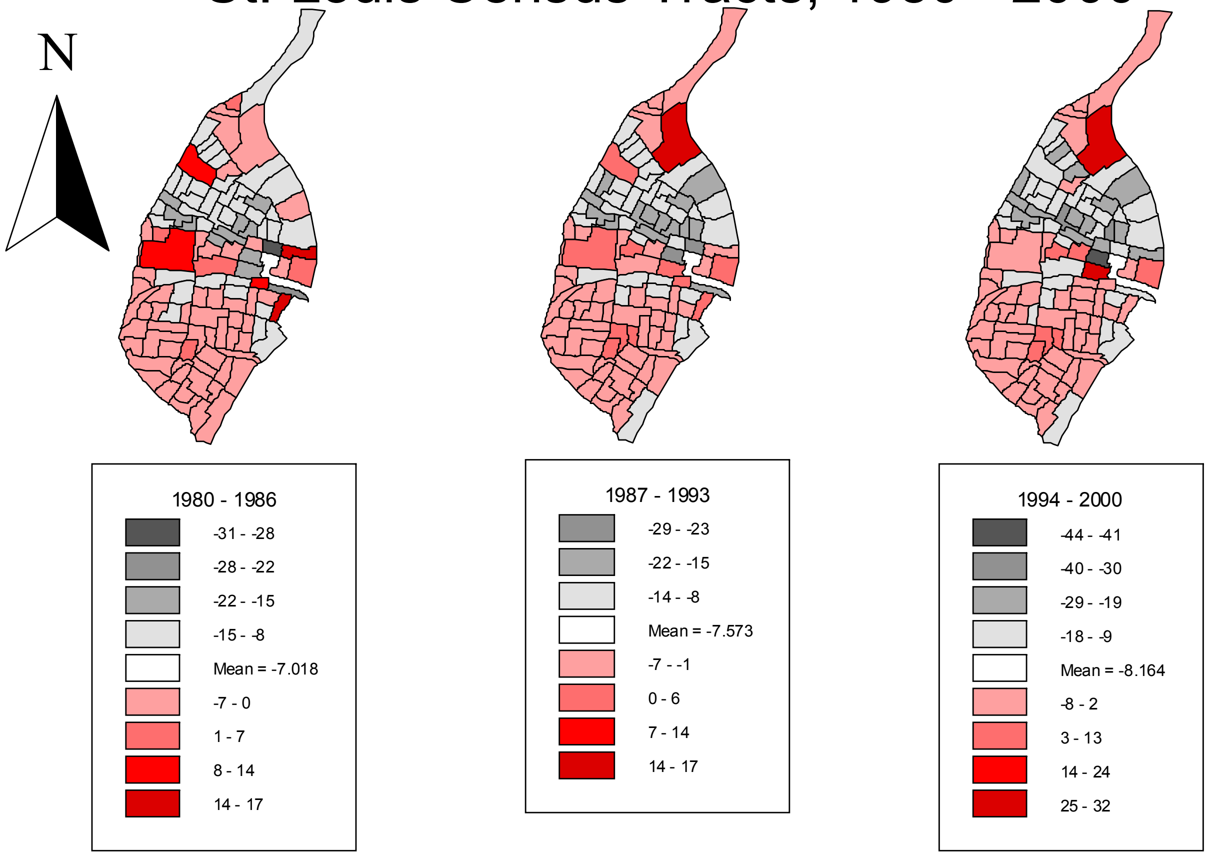
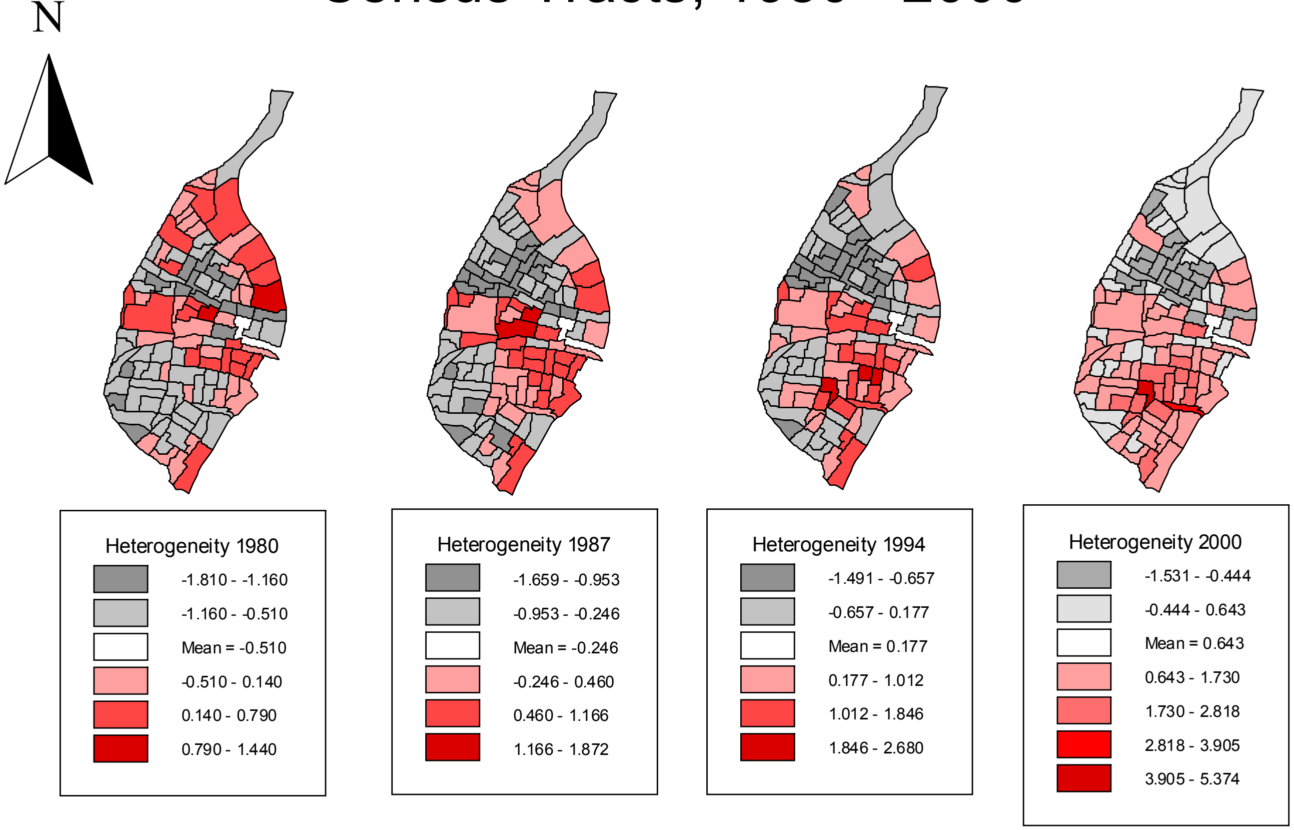


Figure 5.7: Population Heterogeneity in St. Louis Census Tracts, 1980 - 2000



factors that, in turn, spurred residents to leave the community and resettle in other parts of the city.

Figure 5.7 supports this idea of reciprocal effects when the ethnic diversity of St. Louis tracts is observed over this twenty year period. In 1980, the most diverse neighborhoods were located in North St. Louis city, with a small group of heterogeneous populations in the southeastern city. During the subsequent decades, there was substantial redistribution of these populations in the city. By the year 2000, the most ethnically heterogeneous neighborhoods were located predominantly in South St. Louis, with a strong concentration on the southeast side of the city. Furthermore, in North St. Louis, neighborhood population became more homogeneous. By the year 2000, virtually all north city tracts had more than 50 percent black population, and several neighborhoods were 94 percent black or greater.

Thus, the findings are largely consistent with research by Morenoff and Sampson (1997) in which they found that increases in homicide rates were associated with population loss in Chicago neighborhoods. The communities with the greatest increases in violent crime were those that experienced the largest out-migration of residents. However, affluent and minority populations tended not to move as far, generally only to the periphery of where violence was occurring. In this particular case, a substantial portion of this population moved into South St. Louis communities where white populations were moving out.

As residents from other locations in St. Louis moved into these communities, the structural characteristics of the community experienced significant changes. Economic disadvantage increased substantially. Racial and ethnic heterogeneity increased as well.

So, while homicide trends in North St. Louis city may have caused substantial population loss and allowed violence to spread. South St. Louis communities experienced minor increases in crime rates after 1994, which were associated with increases in economic disadvantage and ethnic diversity.

Consistent with the HLM results presented in the previous chapter St. Louis neighborhoods experienced two different forms of structural changes that were associated with violent crime trends. The clear finding is that economic disadvantage is associated with greater fluctuations in homicide trends. During periods of declining homicide rates, increases in disadvantage are associated with smaller declines, or even increases. Additionally, where homicide rates increased the most, population out-migration was greatest, consistent with Wilson's (1996) thesis on social and geographic isolation. Conversely, other neighborhoods experienced population turnover that resulted in greater diversity and economic disadvantage. This pattern is consistent with Burgess's (1925) invasion-succession pattern of population mobility. Thus, the increase in violence in South St. Louis during the latter half of the 1990s is consistent with traditional social disorganization models of neighborhood crime (Shaw and McKay, 1942).

Chapter 6: Discussion and Conclusions

Summary of the Research Question

The dissertation examines the relationships between social structure and homicide trends at the neighborhood level in St. Louis, Missouri between 1980 and 2000. Based on prior research and theoretical perspectives, the structural characteristics of urban communities are known to be related to levels of violence, although the intervening mechanisms remain under some debate. The purpose of this dissertation is to determine the extent to which structural features are associated with trajectories of violence. In sum, do changes in social structure explain changes in homicide rates?

In exploring this question, two separate issues are addressed. First, the analysis examines the neighborhood correlates of homicide trajectories. This portion of the analysis is most directly related to the primary research question. However, the second issue examined expands on the growing body of research examining the spatial distribution of crime. This section of the analysis examines the clustering of neighborhood homicide trajectories and whether or not structural changes in neighborhoods can explain this clustering.

The data for the dissertation come from three sources. Incident-level data for homicides were obtained from the St. Louis Homicide Project between 1979 and 1997. Additional homicide data was obtained from Project Safe Neighborhoods (PSN) in St. Louis. These data were geo-coded and mapped to St. Louis census tracts, which are used as a proxy for neighborhoods in the city. Measures of social structure were obtained from the Neighborhood Change Database 1970 – 2000 from Geolytics, Inc. These data come from the 1980, 1990, and 2000 census and were normalized to the 2000 census tract boundaries.

The dissertation uses several analytic strategies to address the research question. First, hierarchical linear models (HLM) were used to determine whether or not changes in social structure are significantly related to within-neighborhood homicide trends. Second, exploratory spatial data analysis (ESDA) techniques were used to examine the spatial structure of homicide trends and neighborhood characteristics. Finally, in a two-stage analysis, neighborhood trends in homicide produced in HLM were imported for spatial regression analysis to explain the clustering of homicide trajectories across St. Louis tracts.

Summary of Findings

The analysis finds that there are significant differences in homicide trends across St. Louis census tracts. Specifically, a few neighborhoods disproportionately contribute to homicide trends in St. Louis and drive the city-wide trend. Communities with higher levels of economic disadvantage experience higher levels of violence, and greater fluctuations over time. Levels of racial and ethnic heterogeneity and residential stability are also related to neighborhood homicide trends. However these findings do not appear consistently throughout the study and are not always in the expected direction.

The changes in community structure exhibit generally weaker and less persistent associations with homicide trends in comparison to the levels. Increases in economic disadvantage were related to smaller declines in violence after 1993 in bivariate models. However, this association is reduced to non-significance when other covariates are controlled for. Increases in residential instability were related to smaller increases in homicide between 1987 and 1993, yet are not significantly related to the trends in other periods. Increases in racial and ethnic heterogeneity were related to greater decreases in violence during the early 1980s, and smaller increases between 1987 and 1993. However, the change in this domain was not significantly associated with homicide trends during the latter 1990s. Finally, changes in the percentage of male youth were marginally related to smaller declines in homicide between 1980 and 1986. While there was a negative relationship in the bivariate model between 1987 and 1993, age structure was not significant when conditioned on other aspects of the community.

The full model of homicide trends in St. Louis neighborhoods explained a substantial portion of the variation in levels of neighborhood homicide rates. However, there were only modest reductions in residual variation for the trend parameters in the model. Therefore, changes in social structure do not provide a powerful explanation for the differences in community trajectories of violence. Still, other factors not included in this analysis are likely to play a role and may be determined in part by the structural characteristics of the neighborhood. Previous research suggests that drug market activity, youth gang activity, incarceration rates, and law enforcement activity may also play significant roles in determining upswings and downswings in violence. Unfortunately, reliable data for these indicators was not available at the census tract level for St. Louis during the study period and are therefore not included in the analysis.

In addition to highlighting the relatively weak explanatory power of structural changes for homicide trends, the full model exhibits some coefficients that are in unexpected directions. From the routine activity and social disorganization perspectives residential instability in the form of renter-occupied housing and multi-unit dwellings would be likely to be related to higher levels of population turnover and less familiarity with neighbors and visitors in those communities. Therefore, the expectation would be that higher levels of instability are associated with greater levels of homicide. The data bear out this expectation for the initial 1980 homicide rate. Extending this logic to the trends in homicide, increases in residential instability were expected to be associated with smaller declines and greater increases in violence. However, the model shows that increases in residential instability are associated with smaller increases in homicide rates between 1987 and 1993.

In addition to the unexpected finding for residential instability, there are unexpected results for the racial and ethnic heterogeneity. According to social disorganization theory, population heterogeneity is expected to have a positive association with crime rates. Conversely, according to Wilson (1987), large changes in social and economic forces combined to geographically and socially isolate urban minorities, and predominantly African-Americans in such a way that population homogeneity is expected to be associated with higher levels of crime and violence. Again, applying this same logic to the study of change, classic social disorganization theory would expect increases in ethnic diversity to be associated with increase in crime rates. Performing the same extension with Wilson's hypothesis, increases in heterogeneity are expected to be associated with the in-migration of middle-class minority families who have moved out of inner-city neighborhoods. Therefore, an increase in diversity would be expected to be related to smaller rather than larger fluctuations in trajectories of violence.

The dissertation finds mixed results for these hypotheses. The level of diversity is positively associated with increase in homicide between 1987 and 1993. This would be consistent with expectations from social disorganization theory. However, increases in ethnic heterogeneity during this period were associated with smaller increases in violence than the sample average. This result is consistent with Wilson's hypothesis rather than that expected from social disorganization. Furthermore, after 1994, communities with more population diversity experienced smaller declines in violence. This combination of results seems inconsistent, but can be explained by considering potential reciprocal effects between crime trends and population mobility in the city.

In the mid-1980s, more diverse neighborhoods were located primarily in North St. Louis city and began experiencing upswings in violence, largely associated with the rise of crack market activity and youth firearm activity. Over the following years, these communities lost substantial proportions of their population to safer areas. Some residents left St. Louis City completely, while others relocated to areas in South St. Louis with lower levels of violence and smaller increases. Thus, as shown in the full model, the initial level of diversity is positively associated with homicide trends, yet the change in diversity is negatively associated with the trend between 1987 and 1993.

By 1994, when violence began to subside throughout the city, the concentration of ethnic diversity has shifted to South St. Louis neighborhoods that had not experienced as large of an increase in homicide rates. Subsequently, these communities did not experience the magnitude of declines observed in the northern half of the city. In fact, some tracts with higher 1994 levels of population heterogeneity in South St. Louis experienced small increases in violence.

These results provide some support for Wilson's social and geographic isolation hypotheses. However, this effect appears to be mainly confined to highly disadvantaged neighborhoods in North St. Louis. The results are also consistent with strain and routine activity theories in these communities. Still, the structural changes occurring in South St. Louis appear to be more consistent with a social disorganization perspective. Therefore, it is plausible that the processes linking social structure and homicide trends operate differently across the northern and southern halves of the city, and drive the relationships observed in different sections of the trend.

Turning to the spatial distribution of homicide trends, the analysis shows a moderate and significant degree of clustering for homicide trends in St. Louis neighborhoods. This result is found consistently throughout the 1980 to 2000 period. Furthermore, the spatial distribution of homicide trends confirms the HLM model results that economically disadvantaged communities in North St. Louis City experienced both the highest levels of homicide and the greatest magnitude of fluctuations in violence. Conversely, southern communities experienced lower levels of homicide and comparatively small fluctuations over time.

In addition to homicide trajectories, measures of structural characteristics in levels also display moderate to strong positive correlation across St. Louis tracts. Economic disadvantage has the greatest degree of clustering in 1980, and declines somewhat during the following twenty years. This is consistent with the diffusion of disadvantage into other areas of the city. Additionally, ethnic heterogeneity begins with only a weak to moderate positive correlation in space. Yet the degree of clustering increases over time due to the out-migration of minority population from North St. Louis coupled with the addition of new immigrant populations in South St. Louis. Residential instability exhibits a relatively stable and strong level of clustering throughout the twenty-year period.

Changes in structural measures show weaker signs of spatial autocorrelation than levels of structure. Both disadvantage and ethnic diversity exhibit clustering throughout the study. The change in disadvantage between 1980 and 1987 was relatively weak, but positive. Yet, after this period, there was a large increase in the concentration of areas that were becoming more disadvantaged. Again, this is consistent with the dispersion of residents from North St. Louis communities into the southern half of the city. Additionally, changes in population heterogeneity also became more concentrated as diversified neighborhoods became clustered on the southeast side of the city. Finally, in contrast to these two aspects of structure, the change in residential instability exhibited no significant spatial autocorrelation during the first two periods of the study, and only weak positive correlation between 1994 and 2000.

OLS regression results replicate the HLM level 2 models for the periods 1980 to 1986, 1987 to 1993, and 1994 to 2000. Broadly, the results are consistent with the trajectory models estimated in HLM. Neighborhoods with higher levels of disadvantage have greater fluctuations in their homicide trends throughout every period. Additionally, increases in racial and ethnic heterogeneity are related to smaller increases in homicide rates during the second period of the study. After 1994, communities with higher levels of residential instability and higher proportions of male youth populations experienced greater than average declines in violence. Furthermore, during this period neighborhoods with increasing levels of disadvantage and higher starting levels of ethnic diversity had smaller than average declines.

Overall, the OLS models explained between 25 and 45 percent of the variation in tract-level homicide trajectories. Moran's *I* statistics for the residuals from these models indicate that the 1980 to 1986 homicide trends continued to exhibit significant positive spatial autocorrelation after controlling for structural covariates. However, for the latter two periods of the study, the structural covariates explain a significant amount of the spatial patterning in homicide trends. Lagrange Multiplier tests for an alternative spatial dependence model of 1980 to 1986 homicide trends were inconclusive with regard to the preferred specification. Tests for both the spatial effects model and spatial disturbance model were significant. Additionally, this model displayed a small but significant degree of heteroskedasticity in the residuals, most likely due to the omission of a key variable. This result is not surprising given the focus on structural explanations of crime trends only, and the low level of explained variation in the model.

Estimation of both spatial effects and spatial disturbance models indicate that both a spatial lag term and spatially correlated error structures were significant. However, the spatial disturbance model fits the data slightly better than the spatial effects model. Additionally, the spatial effects model explicitly incorporates spatially correlated errors. Therefore, if the residual clustering of homicide trends were due to a diffusion effect of homicide rates rather than an omitted variable, one would expect to see a non-significant lambda coefficient in the spatial disturbance model. Thus, the results may cautiously be interpreted to suggest that the residual autocorrelation of homicide trends in the early 1980s was most likely due to the omission of a key explanatory variable.

As with the HLM results, the spatial analysis shows that there was significant population out-migration from North St. Louis neighborhoods that also had high levels of economic disadvantage, predominantly black residents, and larger than average male youth populations. These communities experienced the greatest upswings in violence during the mid-1980s, spurring further population loss. Consistent with evidence from Chicago (Morenoff and Sampson, 1997), many less affluent minority and immigrant residents moved from North to South St. Louis neighborhoods during this period, concentrating on the city's southeast side. For these communities the influx of new residents was coupled with the out-migration of some previous residents, thereby greatly increasing the level of disadvantage, ethnic diversity. The structural changes in residential instability and male youth populations were smaller for these southern neighborhoods as well. These structural changes in South St. Louis were associated with flat or slightly increasing violence during the late 1990s when the remainder of the city was experiencing a decline in homicide rates. Therefore, the evidence of two different processes occurring in St. Louis neighborhoods is supported by the analysis of spatial distributions of homicide trends and structural change.

In North St. Louis, poor, predominantly black neighborhoods were geographically and socially isolated from the remainder of the city through the out-migration of more affluent and ethnically diverse residents. As Wilson (1987) discusses, these communities experienced higher levels of crime and violence. However, these neighborhoods are also more likely to exhibit other social problems such as drug market and gang activity. Furthermore, those law abiding residents remaining in the community were likely to have less contact with other neighbors simply due to the reduced proximity generated by increases in vacant housing. These changes therefore contribute to the routine activity patterns in which there are fewer capable guardians available to intervene and address local problems. The results for these neighborhoods were large increases in homicide rates during the expansion of crack cocaine markets in St. Louis.

While causal direction cannot be formally assessed with these data, the increase in violence among northern neighborhoods was also likely to spur further population out-migration in favor of safer communities, such as those in South St. Louis. Southern tracts were losing population throughout this period as well. However, the influx of residents formerly from North St. Louis generated substantial transformations in the economic and ethnic structure of some tracts. As residents from North St. Louis moved in, in conjunction with other immigrant and minority populations, levels of economic disadvantage and ethnic heterogeneity rose and concentrated on the city's southeast side. These communities enjoyed relatively flat homicide trajectories between 1980 and 1993 in comparison to their northern neighbors. However, by the end of the 1990s when other areas of the city were experiencing large declines in homicide, these southern neighborhoods were experiencing slight upswings in violence. As discussed above, this process is consistent with hypotheses derived from traditional social disorganization theory.

Theoretical Implications

The study of neighborhood structural correlates of crime trends may be couched in several different yet interrelated theoretical perspectives. While the specific intervening processes that produce violent crime differ across these perspectives, each is compatible with at least one of the others, and forms a coherent set of arguments for the social structural origins of homicide rates. The primary perspectives addressed in the analysis include strain theory, routine activities, and social disorganization. However, the dissertation does not represent a full test of any of these perspectives over time since the requisite data pertaining to the social networks, daily activities, motivational attitudes, and cultural strength of neighborhoods are unavailable for St. Louis between 1980 and 2000. Instead, the intervening processes must be assumed at present and are left for future study.

Economic disadvantage is found to be consistently related to homicide trends during this twenty-year period of time. However, the changes in economic disadvantage were only associated with lesser declines in homicide rates between 1994 and 2000. Furthermore, the effect of changes in disadvantage was driven mainly by neighborhoods in South St. Louis that became more disadvantaged during this period.

As a structural measure of strain, economic disadvantage represents the most direct measure of economic success, the outcome of access to legitimate opportunities for success. Higher levels of economic disadvantage are found in neighborhoods in which there are high levels of poverty, unemployment, public assistance payments, joblessness, and low-skilled laborers. Additionally, highly disadvantaged communities have low aggregate levels of educational achievement, income, and access to transportation to and from employment opportunities. Each of these factors represents a barrier that must be overcome to achieve economic success. Where there are higher concentrations of such characteristics then, the strain and frustration of achieving success is likely to be greater (Merton, 1938; Blau and Blau, 1982; Messner and Rosenfeld, 1994). Therefore, the levels and fluctuations in violence are likely to be greater, and the findings provide support for strain theory.

The findings are also consistent with social disorganization theory in that economically disadvantaged neighborhoods have generally undesirable living conditions and fewer opportunities for success. Residents with the resources available to leave the community will generally do so quickly. The ensuing population out-migration is likely to reduce the extent and quality of local relationship networks within the community, thereby reducing the capacity of residents to maintain collective efficacy and generalized social control. This is the outcome of what Wilson (1987) refers to as concentration effects. However, the hypothesis also highlights the potentially reciprocal nature of disadvantaged areas and crime rates.

If disadvantage is an indicator of undesirable living conditions and therefore results in the loss of middle-class and affluent residents, one expects to observe higher levels of crime and other social problems described by Wilson (1987). Yet, a high level of violence in the community is itself an undesirable condition. Thus, as violence increases in the community, safety concerns and the fear of crime become strong motivators for others to leave. Under these circumstances, population out-migration may lead to higher levels of crime which, in turn, lead to additional population loss. In this way, the disadvantaged communities of North St. Louis are consistent with social disorganization expectations in the context of urban decline (McKenzie, 1925; Wilson, 1987). However, these communities also provide support for a reciprocal influence of violence on social structure.

In contrast to North St. Louis census tracts, some neighborhoods in South St. Louis became more disadvantaged as residents from higher crime areas took up residence and more affluent residents moved out. For these areas, structural change took the form of an invasion-succession process, such as that described by Burgess (1925). Poorer and more ethnically diverse populations moved into established communities, prompting many existing residents to leave. As the population turnover continued, levels of disadvantage increased substantially, as did ethnic diversity. Thus, South St. Louis neighborhoods experienced processes consistent with classical social disorganization theory and homicide rates increased slightly in these areas (Shaw and McKay, 1942; Bursik and Grasmick, 1993).

It is important to note that changes in disadvantage were not found to be significantly associated with homicide trends in the most disadvantaged communities of St. Louis. However, when formerly affluent neighborhoods experience substantial increases in disadvantage, homicide rates increased slightly. This result is consistent with the non-linear relationship between violence and disadvantage found in previous research (Krivo and Peterson, 2000; McNulty, 2001). A change in economic disadvantage for the most disadvantaged communities is not expected to produce a significant change in homicide rates. However for more affluent neighborhoods, an economic decline is expected to have a greater influence that increases violence.

These findings provide support for disadvantage hypotheses derived from social disorganization theory when neighborhoods are experiencing turnover, as well as decline. Additionally, the findings suggest several important aspects of urban dynamics. In St. Louis, economic disadvantage is associated with homicide trends in both affluent and disadvantaged neighborhoods. However, the nature of the effect differs depending on the initial level of disadvantage. When levels of disadvantage are high to begin with, homicide trends are magnified in size. However, when levels of disadvantage are low initially, economic decline produces increases in violence.

The significance of disadvantage in this study also supports hypotheses derived from routine activities theory. Specifically, the influence of vacant housing was found to be significantly related to homicide trends, as were the changes in vacant housing. In the bivariate HLM model, changes in vacancies were associated with lesser declines and greater increases in homicide rates between 1980 and 1993. However, after 1994 the increases in vacant housing were associated with greater declines. This apparent inconsistency can be reconciled by again considering reciprocal effects of crime on social structure, as well as the likely effects of drug market activity during these periods, from a routine activity perspective.

High levels of vacant housing are associated with disadvantaged communities, which exhibit the greatest fluctuations in homicide rates. Between 1980 and 1986, neighborhoods with higher levels of vacant housing experienced steeper than average declines in violence. In contrast, where vacant housing increased, population out-migration was greatest, and homicide declines were less steep. Thus, the increase in vacant housing is like to cause disruptions in local relationship networks and collective efficacy. However, increases in vacant housing would also increase the physical distance between residents, as well as providing ideal locations for carrying out illegal or other clandestine activities, such as drug transactions.

Speculating through the lens of routine activities theory, net decreases in population are directly related to housing vacancies. Therefore, where out-migration was greatest, the level of capable guardianship to prevent offenders from engaging in illegal activities was reduced. These communities were therefore primed for the inception and expansion of crack-cocaine markets. The drug market for crack in St. Louis took two predominant forms: open-air selling on the street, and off-street sales in crack houses (Jacobs, 1999). For dealers selling on the street, higher levels of vacant housing represent lower levels of guardianship that would increase the risk of apprehension. The same holds true for dealers selling out of crack houses in two ways. First, vacant houses provide a location to establish a semi-private selling operation that avoids the inherent risks of street-corner selling. Secondly, in areas with extremely high levels of vacant housing, dealers could reduce their risk of apprehension by establishing a crack house near other vacant buildings. This provided an insulating barrier that reduces the risk of other residents observing high levels of customer traffic that would increase the risk of law enforcement attention.

These arguments are speculative at best since the dissertation does not have the necessary data to test the relationships. However, they provide a compelling argument that is supportive of routine activities theory. Disadvantaged neighborhoods experienced greater net population decline, which in turn brought higher levels of vacant housing. As crack-cocaine markets developed in St. Louis, these communities provided the best daily rhythms and tempos for participants in the drug markets. By virtue of their social structure and subsequent routine activity patterns, these tracts were likely to suffer the greatest increases in drug-related violence in St. Louis.

In these same neighborhoods, the increase in homicide was associated with further out-migration of residents to safer parts of the city. After 1993, crack market activity and violent crime began to decline substantially in St. Louis. Yet in those neighborhoods most heavily damaged by violence, residents continued to move out in search of safer locations. Thus, the reversal of drug market activity and the continued loss of population can potentially explain the negative relationship between changes in vacant housing and homicide trends between 1994 and 2000. To the extent that such processes were occurring, the findings lend support to hypotheses derived from routine activities theory.

In addition to economic disadvantage, the relationships between ethnic heterogeneity and homicide trends have important theoretical implications. First, St. Louis is a hyper-segregated city in both racial and economic composition. This fact is most easily observed in the factor loading for percent black with other measures of economic disadvantage (0.809). It is in precisely these communities that homicide rates increased and decreased most dramatically between 1980 and 2000. As discussed previously, McKenzie (1925) hypothesized that those populations least capable of responding to economic, technological, and political changes in the urban system would suffer the greatest dislocations as the system adjusted. It was further assumed that those least capable of responding were those populations least assimilated into the social system. In St. Louis, as in other industrialized rust-belt cities, social and economic changes in the urban system disproportionately affected predominantly black, urban neighborhoods (Wilson, 1987, 1996).

While classical disorganization theory hypothesized that ethnic diversity would be associated with higher crime rates during periods of city growth and expansion, McKenzie and Wilson argue that changes in the urban system are likely to disproportionately influence specific populations so as to concentrate disadvantage among a homogeneous population. The analysis provides support that these processes occurred in St. Louis. However, that does not imply that classical social disorganization processes were not at work in other communities.

As discussed above, South St. Louis neighborhoods had been predominantly white in 1980, with only small percentages of minority or immigrant populations. During the following twenty years, a number of these communities experienced significant turnover in their populations and became much more heterogeneous with respect to race and ethnicity. While there was an overall net decline in population, this cannot account for the transformation that occurred in these communities. Coupled with the turnover in population and increase in diversity, these tracts experienced increases in economic disadvantage due in part to the position of residents moving into the neighborhoods, but also the loss of other affluent residents. These neighborhoods were experiencing similar processes observed during city expansion by Chicago school researchers in the first half of the nineteenth century (Park and Burgess, 1925; Shaw and McKay, 1942). The finding that ethnic heterogeneity is positively associated with homicide trends after 1994 is therefore supportive of hypotheses derived from classical social disorganization theory.

The analysis presented in this study cannot determine the unique contributions of routine activities, strain, and social disorganization processes because the required data is not available for St. Louis during the period of study. Yet the inter-related nature of these theoretical perspectives suggests that some combination of these processes are attributable to the structural changes in local neighborhoods and are related to violent crime trends in the city. Additionally, the implication that violent crime trends have an influence on social structure at the neighborhood level has not been thoroughly explored in the literature. Current theories of neighborhood crime rates generally posit non-recursive models in which crime is the final output of a social process. However, to the extent that crime has a feedback effect on social structure, this represents a mis-specification of theory and the need for a more dynamic view of urban processes. These relationships should be explored in future research, using more detailed longitudinal data.

A further challenge exists for researchers of urban dynamics and crime. In particular, neighborhood level models of crime are generally based on the assumption that the relationships examined are operating in the same causal direction for every location in the system. However, this analysis finds that over time, spatial regimes may coexist within the same city and operate with different types of dynamics. Additionally, the timing of structural and crime rate changes in St. Louis provide compelling evidence that the occurrence of a given process in one location of the city may have an indirect influence on the occurrence of a different process in another area of the city. If such micro-processes operate in different locations of the city and at different times, then our current understanding of the magnitude of relationships between social structure and violent crime will also need to be explored in future research. In short, the results from this analysis provide compelling evidence that neighborhood trajectories of violence and structural change are likely to exhibit more complex spatial and temporal dynamics than are currently understood.

Policy Implications

Violent crime is a perennial issue that policy-makers and urban planners must address with close attention. From an ecological context, increasing levels of violence are not only symptomatic of problems with the health of a community, but can also have detrimental effects on its future health. From a strategic standpoint, the maintenance of ecological balance and carefully controlled change is critical. In cities such as St. Louis, rapid economic and social transformations contributed to an imbalanced system at the end of the twentieth century. Therefore, public policy should work to restore that balance and prevent future imbalances from occurring.

The consistent and long-term association between economic disadvantage and homicide is indicative of the imbalance between the economy and population of the city. St. Louis is not unique in this regard. In cities characterized by the out-migration of blue-collar and semi-skilled employment opportunities and a bifurcation of the residual labor market, significant pockets of economic disadvantage developed during the 1970s and 1980s (Wilson, 1987; Jargowsky, 1997). As communities fall into an economically disadvantaged state, a ripple effect of social consequences follows including population loss, a weakening of collective efficacy, and increases in violence (Sampson and Morenoff, 2006). Although the true nature of the path dependence between disadvantage and violence remains to be seen, a durable feature of disadvantaged communities is a higher level of homicide. Still, public policy may address this issue from in several ways.

Rebuilding the economic base of a city such as St. Louis should be a high priority for city planners and policy makers. Ecologically, the economy of the city should be balanced in such a way so as to provide employment opportunities for a wide range of workers in both skilled and unskilled labor markets. Attracting viable commercial development within the city, and particularly on the north side of the city, would help alleviate the high level of unemployment and joblessness. The development of this commercial base should pay close attention to providing economic opportunities for residents at all skill and education levels. However, such a plan is likely to require significant time to implement effectively. Therefore, other short-term alternatives may be preferable.

In the St. Louis metropolitan region, the majority of employment opportunities are located outside of the city in St. Louis County. As seen in this analysis, a large portion of laborers in disadvantaged communities use public transportation to travel to and from work. As Wilson (1996) notes, for inner-city laborers working in suburban counties, public transit can create a paradox. Using public transportation often requires substantial investments of time and money, both of which are in short supply for the economically disadvantaged. When these investments become too great, workers are more likely to become discouraged and may opt out of the legitimate labor market in favor of more accessible illegitimate means of success. Therefore, another policy option likely to have a greater short-term impact is the improvement of public transportation systems, particularly for employment purposes.

In addition to these policies for improving the economic-social disparity in the city, the control of serious violence may be improved through new law enforcement strategies. In particular, St. Louis initiated several new programs during the late 1990s and more recently, to combat violent crime and provide more responsive service to communities. These programs include Project Safe Neighborhoods, the St. Louis Regional Ceasefire Initiative, Night Watch, Weed and Seed, the Strategic Approaches to Community Safety Initiative (SACSI), and gang outreach programs. Working in conjunction with the U.S. Attorneys Office in the Eastern District of Missouri, the city has implemented a multi-agency strategy to combat both firearms and violence. Whether or not this initiative will result in sustained and long-term reductions in violence is unclear at this point.

An addition to the initiatives described above, St. Louis created a Neighborhood Stabilization Team (NST) under the Department of Public Safety. The mission of NST is to "[Serve] as a catalyst for bringing together the police, elected officials, government agencies, social service organizations, community groups and individuals to identify, permanent solutions to ongoing problems." (NST, 2007).[59] Twenty-six neighborhood stabilization officers are assigned to communities by voting ward and act as a contact person for residents to assist in organizing and coordinating city services for the improvement of neighborhood conditions. Thus, the NST initiative is designed to assist local residents in organizing and improving their quality of life and public safety. However, the effectiveness of the NST is also unknown at this time, and an evaluation of NST is left for future research.

Aside from policies aimed at specific targets, which are reactive in nature, one proactive strategy to improve public safety and quality of life issues is the creation of a multi-agency database for the purpose of monitoring changes in community contexts throughout the city. While law enforcement, the courts, and correctional agencies have started this process in the city, a more comprehensive approach would include data from additional sources. Data from the housing authority, human services, medical and EMS agencies, the department of commerce, as well as other social agencies could be brought together in one system to aid in monitoring the development of the city and constituent neighborhoods. In St. Louis City, a comprehensive information system such as this would

[59] The NST website is accessible at http://stlouis.missouri.org/citygov/nst/.

be of significant use to the Community Development Administration (CDA). The primary responsibility of the CDA is the administration of federal funds from the Community Development Block Grant Program for the development and improvement of housing, the economy, and communities in the city. In conjunction with other city planners, the CDA administers funds according to a 5-year consolidated plan. The current 5-year plan spans the years 2005 to 2009. A comprehensive monitoring system could assist not only in the development of future plans, but also in the administration of funds and services on an annual basis within 5-year plans.

While St. Louis city agencies have implemented policies and strategies for the reduction of violence and improvement of local neighborhoods, there remains much that is unknown about the dynamics of urban development and crime. However, the maintenance of a balanced economic, institutional, and social system is essential for reducing and preventing violence. Future research is needed to explore these dynamics in more detail and generate timely and informed policy decisions.

Strengths and Limitations of the Research

The dissertation explores the spatial and temporal relationships between social structure and homicide rates. To this end, the analysis uses twenty years of annual homicide data, collected at the neighborhood level in St. Louis, Missouri between 1980 and 2000. By studying the growth trajectories of homicide annually over twenty years, the dissertation improves upon previous community research on change that uses multiple cross-sectional data series or shorter annual time-series data.

A second strength of the dissertation is the use of census data that is normalized to a single set of geographic boundaries. Due to population migration over time, census tract boundaries are periodically altered by the Census Bureau in conjunction with local committees. These modifications are necessary for decennial census data collection to prevent tract populations from becoming too large or small. Changes in tract boundaries are problematic in longitudinal studies because individual units are no longer consistent over time and become invalid proxies of the original neighborhood. By normalizing the geographic boundaries of St. Louis census tracts, this research maintains the validity of the neighborhood proxies over the entire period.

A third strength of the dissertation lies in merging two research themes that have been kept relatively separated in the past. In the neighborhood-effects literature, prior research has generally taken three broad approaches: detailing the mechanisms through which social structure is linked to neighborhood outcomes, exploring the changes in communities over time, and describing and explaining the spatial distribution of community outcomes. This research does not address the specific mechanisms linking social structure to homicide trends. However, the analysis brings together the longitudinal study of violence with the spatial distribution of homicide trends. To accomplish this task, a two stage procedure is implemented, in which neighborhood-level homicide trajectories are estimated in a piecewise multi-level model during the first stage. In the second stage HLM parameters are imported into spatial analysis software and the variations across communities are explained as a function of both internal structural changes and proximity to other neighborhoods.

The results of this two-stage procedure highlight neighborhood dynamics that vary over time and across space, and potentially with recursive feedback loops. Thus the analysis provides important insight into the dynamic structural evolution of the city. Furthermore, the findings present new directions for the study of crime trends at the city and the neighborhood-level.

Along with these strengths, the dissertation also has several limitations that should be explained. The most notable limitation is the failure to include measures of many additional contextual variables that are likely to be relevant in the explanation of homicide trends (Rosenfeld, 2004; Levitt, 2004). Drug market activity associated with crack cocaine is known to have a strong positive correlation with violence (Blumstein, 2001, 1995; Cork, 1999; Blumstein and Rosenfeld, 1998). Additionally, there is evidence that targeted law enforcement activity, especially programs targeting firearms, can significantly reduce violent crime (Rosenfeld et al., 2005; Kelling and Sousa, 2001; Braga et al., 2001). Incarceration rates may have a negative association with violence through the incapacitation of violent individuals. Yet, there remains the possibility that incarceration may also have detrimental effects on local relationship networks and neighborhood economics (Rose and Clear, 1998). These data were not available consistently between 1980 and 2000 for St. Louis neighborhoods, and were therefore not included. Additionally, the purpose of this study was not to assess the specific contributions of such non-structural factors. These questions are left for future neighborhood level research.

In addition to the omitted variables discussed above, the dissertation cannot speak to the specific or unique contributions of theoretical processes that link social structure and crime. The data pertaining to local relationship networks, collective efficacy, generalized feelings of strain, daily activity patterns, and systemic social control require detailed survey data collected at the neighborhood level, which has not been done in St. Louis due to logistical and expense-related difficulties.[60] As with including more detailed contextual data, research that explores the intervening mechanisms between structure and crime will need to be addressed in the future.

The third major weakness of the dissertation is strongly related to one of its strengths. The spatial diagnostic tests for the OLS models of homicide trends indicated that there was a small, but statistically significant level of heteroskedasticity present in the residuals. This is a violation of the assumptions made by the model, and made decisions about the appropriate alternative specifications difficult. Additional diagnostic testing could not determine the source of the heteroskedasticity, leaving open the possibility that one or more key variables were omitted from the analysis. However, the two-stage procedure used in this analysis was required because spatially dependent relationships cannot currently be estimated properly in HLM software. Regardless, the analysis presented here has signs of some mis-specification.

Conclusion

For nearly one hundred years, urban researchers have observed strong relationships between measures of social structure and violent crime rates. These observations have produced a large body of research describing the importance of neighborhood-effects in both the origins and social control of violence. Recently,

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[60] Few such data collection efforts exist. For examples see the Project on Human Development in Chicago Neighborhoods (PHDCN: http://www.icpsr.umich.edu/PHDCN/about.html), and Seattle Neighborhoods and Crime Project (SNCP: http://faculty.washington.edu/matsueda/SNCP2.htm).

researchers have started to explore the nature of crime trajectories at the neighborhood level, as well as the geographic distribution of violence in space. However, these two lines of research have generally remained separate areas of study. The analysis presented here brings together both areas, and explores the spatial and temporal dynamics of neighborhood homicide trajectories.

The results show that initial levels and changes in structural covariates are significantly related to major upswings and downturns in homicide trends. However, structural indicators explain far more of the variation in cross-sectional differences than in trends. Additionally, the results show that urban dynamics linking social structure and crime may be more complex than current theories generally propose. Different structural processes are found to be associated with homicide trends in different time periods. These processes operate in different parts of the city, yet appear to be related to one another. Furthermore, the finding that increasing crime rates in one part of the city may have an indirect effect on other parts of the city points to the importance of further study on the reciprocal effects of violent crime on social structure. Overall, the dynamics of violence and neighborhood development in urban contexts appears to be more complex than previously known, and will require future research to fully understand. This dissertation is only one step along the path.

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Appendix A

Table A.1: Paired Samples t-test results for Structural Covariates, 1980 and 1990 (n = 110)

Variable	*Mean Difference*	*t*	*p*
Population	-512.300	-10.586	0.000
Percent Black	4.558	5.211	0.000
Percent Hispanic	-0.029	-0.210	0.834
Population Hetrogeneity	0.050	4.805	0.000
Percent Immigrant	0.421	2.766	0.007
Percent Female-Headed Families	3.358	4.614	0.000
Divorce Rate	1.869	7.690	0.000
Percent Youth (15 - 24)	-4.467	-11.044	0.000
Percent Male Youth (15 - 24)	-1.856	-6.584	0.000
Percent High School Dropouts	-1.361	-0.929	0.355
Percent College Graduate (4-year)	4.623	8.985	0.000
Unemployment Rate	0.423	0.902	0.369
Male Unemployment	0.808	1.292	0.199
Poverty Rate	3.493	4.661	0.000
Average Family Income (1980 Dollars)	766.260	2.651	0.009
Percent Households with Public Assistance	-0.185	-0.389	0.698
Joblessness Rate	-2.514	-3.908	0.001
Percent Workers Using Public Transportation	-4.983	-7.842	0.000
Percent Labor as Service Workers	0.113	0.189	0.850
Percent Same Residence	-2.652	-3.658	0.000
Percent Living in St. Louis 5 Years Ago	-0.188	-0.275	0.784
Percent Owner-Occupied Housing	-0.235	-0.591	0.556
Percent Vacant Housing	3.995	6.027	0.000
Percent Renter-Occupied Housing	-2.260	-3.460	0.001
Percent Multi-Unit Housing	0.627	1.322	0.189

Table A.2: Paired Samples t-test results for Structural Covariates, 1990 and 2000 (n = 110)

Variable	*Mean Difference*	*t*	*p*
Population	-438.010	-8.817	0.000
Percent Black	7.954	6.615	0.000
Percent Hispanic	0.548	3.717	0.000
Population Hetrogeneity	0.058	4.118	0.000
Percent Immigrant	2.197	6.912	0.000
Percent Female-Headed Families	3.527	4.342	0.000
Divorce Rate	1.386	4.236	0.000
Percent Youth (15 - 24)	1.018	1.798	0.075
Percent Male Youth (15 - 24)	0.236	0.972	0.333
Percent High School Dropouts	-5.826	-3.689	0.000
Percent College Graduate (4-year)	2.729	6.058	0.000
Unemployment Rate	1.315	1.665	0.099
Male Unemployment	0.366	0.408	0.684
Poverty Rate	0.965	1.319	0.190
Average Family Income (1980 Dollars)	1683.271	4.772	0.000
Percent Households with Public Assistance	2.231	3.722	0.000
Joblessness Rate	0.238	0.369	0.713
Percent Workers Using Public Transportation	-1.539	-2.260	0.026
Percent Labor as Service Workers	2.153	3.340	0.001
Percent Same Residence	-4.666	-5.617	0.000
Percent Living in St. Louis 5 Years Ago	1.476	2.175	0.032
Percent Owner-Occupied Housing	1.123	2.607	0.010
Percent Vacant Housing	1.753	3.276	0.001
Percent Renter-Occupied Housing	-1.565	-2.981	0.004
Percent Multi-Unit Housing	-2.152	-3.951	0.000

Table A.3: Paired Samples t-test results for Structural Covariates, 1980 and 2000 (n = 110)

Variable	*Mean Difference*	*t*	*p*
Population	-950.31	-11.112	0.000
Percent Black	12.512	6.806	0.000
Percent Hispanic	0.519	3.145	0.002
Population Hetrogeneity	0.107	5.583	0.000
Percent Immigrant	2.619	7.325	0.000
Percent Female-Headed Families	6.884	7.686	0.000
Divorce Rate	3.255	9.707	0.000
Percent Youth (15 - 24)	-3.449	-4.431	0.000
Percent Male Youth (15 - 24)	-1.621	-4.65	0.000
Percent High School Dropouts	-7.187	-5.213	0.000
Percent College Graduate (4-year)	7.354	9.795	0.000
Unemployment Rate	1.737	2.188	0.031
Male Unemployment	1.174	1.246	0.215
Poverty Rate	4.458	4.574	0.000
Average Family Income (1980 Dollars)	2449.531	5.555	0.000
Percent Households with Public Assistance	2.047	2.736	0.007
Joblessness Rate	-2.276	-2.541	0.012
Percent Workers Using Public Transportation	-6.522	-8.981	0.000
Percent Labor as Service Workers	2.265	3.216	0.002
Percent Same Residence	-7.319	-7.495	0.000
Percent Living in St. Louis 5 Years Ago	1.288	1.527	0.130
Percent Owner-Occupied Housing	0.889	1.525	0.130
Percent Vacant Housing	5.748	7.217	0.000
Percent Renter-Occupied Housing	-3.824	-5.125	0.000
Percent Multi-Unit Housing	-1.525	-2.347	0.021

Appendix B

Table B.1: Bivariate HLM Results of Race and Ethnicity Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Population Size*	*Percent Black*	*Ln Percent Hispanic*
1980 Homicide Level, β_{00}	-0.086+	0.047	-0.470***	-0.047
	(0.047)	(0.133)	(0.036)	(0.055)
Variable Level, β_{01}		-0.00003	0.009***	-0.124+
		(0.00003)	(0.001)	(0.069)
1980 – 1986 Trend, β_{10}	-0.032***	-0.049*	-0.025***	-0.031***
	(0.005)	(0.019)	(0.006)	(0.006)
Variable Level, β_{11}		0.000004	-0.0002+	-0.008
		(0.000004)	(0.0001)	(0.008)
Variable Δ, β_{12}		-0.0004	0.001	-0.033**
		(0.0007)	(0.001)	(0.010)
1987 – 1993 Trend, β_{20}	0.043***	0.039*	0.003	0.048***
	(0.005)	(0.016)	(0.005)	(0.005)
Variable Level, β_{21}		-0.000001	0.001***	-0.009
		(0.000004)	(0.0001)	(0.006)
Variable Δ, β_{22}		-0.0008	0.003***	-0.038*
		(0.0007)	(0.001)	(0.015)
1994 – 2000 Trend, β_{30}	-0.046***	-0.089***	-0.027***	-0.051***
	(0.006)	(0.016)	(0.007)	(0.007)
Variable Level, β_{31}		0.00001*	-0.0005***	0.013
		(0.000004)	(0.0001)	(0.008)
Variable Δ, β_{32}		0.001+	-0.001*	0.002
		(0.0007)	(0.0007)	(0.009)
Random Effects	*Variance*	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.2217***	0.0822***	0.2155***
1980 – 1986 Trend, r_1	0.0019***	0.0020***	0.0019***	0.0020***
1987 – 1993 Trend, r_2	0.0016***	0.0016***	0.0010***	0.0014***
1994 – 2000 Trend, r_3	0.0026***	0.0026***	0.0021***	0.0024***
Level 1 Error, e	0.0478	0.0478	0.0478	0.0478

+ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Table B.2: Bivariate HLM Results of Race and Ethnicity Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Ln Population Heterogeneity*	*Ln Percent Immigrant*
1980 Homicide Level, β_{00}	-0.086+	0.115	-0.093+
	(0.047)	(0.106)	(0.050)
Variable Level, β_{01}		0.101+	-0.029
		(0.052)	(0.068)
1980 – 1986 Trend, β_{10}	-0.032***	-0.059***	-0.034***
	(0.005)	(0.016)	(0.006)
Variable Level, β_{11}		-0.015*	-0.012
		(0.007)_	(0.011)
Variable Δ, β_{12}		-0.025+	-0.005
		(0.013)	(0.010)
1987 – 1993 Trend, β_{20}	0.043***	0.067***	0.044***
	(0.005)	(0.011)	(0.008)
Variable Level, β_{21}		0.012*	-0.006
		(0.005)	(0.007)
Variable Δ, β_{22}		-0.010	-0.005
		(0.018)	(0.017)
1994 – 2000 Trend, β_{30}	-0.046***	-0.068***	-0.043***
	(0.006)	(0.014)	(0.009)
Variable Level, β_{31}		-0.014*	-0.0003
		(0.007)	(0.008)
Variable Δ, β_{32}		-0.015	-0.007
		(0.014)	(0.010)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.2127***	0.2225***
1980 – 1986 Trend, r_1	0.0019***	0.0019***	0.0019***
1987 – 1993 Trend, r_2	0.0016***	0.0015***	0.0016***
1994 – 2000 Trend, r_3	0.0026***	0.0028***	0.0027***
Level 1 Error, e	0.0478	0.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Table B.3: Bivariate HLM Results of Family Structure Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Female-Headed Families*	*Divorce Rate*
1980 Homicide Level, β_{00}	-0.086+	-0.545***	-0.141
	(0.047)	(0.059)	(0.191)
Variable Level, β_{01}		0.027***	0.006
		(0.003)	(0.020)
1980 – 1986 Trend, β_{10}	-0.032***	-0.022*	-0.007
	(0.005)	(0.009)	(0.025)
Variable Level, β_{11}		-0.0007	-0.002
		(0.0005)	(0.002)
Variable Δ, β_{12}		0.001	-0.009**
		(0.001)	(0.003)
1987 – 1993 Trend, β_{20}	0.043***	0.0005	0.021
	(0.005)	(0.008)	(0.020)
Variable Level, β_{21}		0.002***	0.002
		(0.0003)	(0.002)
Variable Δ, β_{22}		0.002+	-0.0002
		(0.001)	(0.004)
1994 – 2000 Trend, β_{30}	-0.046***	-0.015	-0.018
	(0.006)	(0.010)	(0.026)
Variable Level, β_{31}		-0.002**	-0.002
		(0.0005)	(0.002)
Variable Δ, β_{32}		-0.001	0.002
		(0.001)	(0.003)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.1136***	0.2214***
1980 – 1986 Trend, r_1	0.0019***	0.0019***	0.0019***
1987 – 1993 Trend, r_2	0.0016***	0.0010***	0.0016***
1994 – 2000 Trend, r_3	0.0026***	0.0022***	0.0027***
Level 1 Error, e	0.0478	0.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Table B.4: Bivariate HLM Results of Age Structure Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Youth 15 - 24*	*Male Youth 15 - 24*
1980 Homicide Level, β_{00}	-0.086+	-0.845***	-0.746***
	(0.047)	(0.213)	(0.215)
Variable Level, β_{01}		0.040***	0.075**
		(0.011)	(0.023)
1980 – 1986 Trend, β_{10}	-0.032***	-0.002	-0.010
	(0.005)	(0.026)	(0.028)
Variable Level, β_{11}		-0.001	-0.002
		(0.001)	(0.003)
Variable Δ, β_{12}		0.004	0.005
		(0.003)	(0.003)
1987 – 1993 Trend, β_{20}	0.043***	0.019	0.016
	(0.005)	(0.013)	(0.014)
Variable Level, β_{21}		0.001	0.003
		(0.001)	(0.002)
Variable Δ, β_{22}		-0.004***	-0.010**
		(0.001)	(0.003)
1994 – 2000 Trend, β_{30}	-0.046***	-0.026*	-0.018
	(0.006)	(0.012)	(0.015)
Variable Level, β_{31}		-0.001*	-0.004+
		(0.0007)	(0.002)
Variable Δ, β_{32}		-0.0004	-0.005
		(0.001)	(0.003)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.1885***	0.1974***
1980 – 1986 Trend, r_1	0.0019***	0.0018***	0.0018***
1987 – 1993 Trend, r_2	0.0016***	0.0015***	0.0015***
1994 – 2000 Trend, r_3	0.0026***	0.0025***	0.0024***
Level 1 Error, e	0.0478	.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Table B.5: Bivariate HLM Results of Education Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*High-School Dropout Rate*	*Ln College Graduates*
1980 Homicide Level, β_{00}	-0.086+	-0.150+	0.536***
	(0.047)	(0.079)	(0.117)
Variable Level, β_{01}		0.003	-0.304***
		(0.003)	(0.057)
1980 – 1986 Trend, β_{10}	-0.032***	-0.030**	-0.056***
	(0.005)	(0.010)	(0.015)
Variable Level, β_{11}		-0.0001	0.013+
		(0.0005)	(0.007)
Variable Δ, β_{12}		0.0001	-0.006
		(0.0006)	(0.014)
1987 – 1993 Trend, β_{20}	0.043***	0.029***	0.092***
	(0.005)	(0.007)	(0.020)
Variable Level, β_{21}		0.0004	-0.022**
		(0.0003)	(0.008)
Variable Δ, β_{22}		-0.003**	0.011
		(0.0006)	(0.014)
1994 – 2000 Trend, β_{30}	-0.046***	-0.051***	-0.049*
	(0.006)	(0.010)	(0.022)
Variable Level, β_{31}		0.001	0.003
		(0.001)	(0.008)
Variable Δ, β_{32}		0.001**	-0.056**
		(0.0004)	(0.018)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.2188***	0.1869***
1980 – 1986 Trend, r_1	0.0019***	0.0019***	0.0019***
1987 – 1993 Trend, r_2	0.0016***	0.0014***	0.0015***
1994 – 2000 Trend, r_3	0.0026***	0.0025***	0.0026***
Level 1 Error, *e*	0.0478	0.0478	0.0478

+ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Table B.6: Bivariate HLM Results of Economic Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Total Unemployment*	*Male Unemployment*
1980 Homicide Level, β_{00}	-0.086+	-0.742***	-0.660***
	(0.047)	(0.065)	(0.066)
Variable Level, β_{01}		0.056***	0.044***
		(0.005)	(0.004)
1980 – 1986 Trend, β_{10}	-0.032***	-0.002	-0.012
	(0.005)	(0.010)	(0.009)
Variable Level, β_{11}		-0.003**	-0.002*
		(0.0008)	(0.0007)
Variable Δ, β_{12}		0.003*	0.003**
		(0.001)	(0.001)
1987 – 1993 Trend, β_{20}	0.043***	0.010	0.017*
	(0.005)	(0.008)	(0.007)
Variable Level, β_{21}		0.003***	0.002***
		(0.0006)	(0.0005)
Variable Δ, β_{22}		0.002	0.0006
		(0.002)	(0.002)
1994 – 2000 Trend, β_{30}	-0.046***	-0.030**	-0.034***
	(0.006)	(0.010)	(0.009)
Variable Level, β_{31}		-0.001*	-0.0009+
		(0.0006)	(0.0005)
Variable Δ, β_{32}		0.0004	0.0003
		(0.001)	(0.001)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.0719***	0.0861***
1980 – 1986 Trend, r_1	0.0019***	0.0015***	0.0018***
1987 – 1993 Trend, r_2	0.0016***	0.0013***	0.0013***
1994 – 2000 Trend, r_3	0.0026***	0.0024***	0.0025***
Level 1 Error, e	0.0478	0.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Table B.7: Bivariate HLM Results of Economic Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Poverty Rate*	*Average Family Income*
1980 Homicide Level, β_{00}	-0.086+	-0.674***	0.622*
	(0.047)	(0.049)	(0.283)
Variable Level, β_{01}		0.027***	-0.00004*
		(0.002)	(0.00002)
1980 – 1986 Trend, β_{10}	-0.032***	-0.013	-0.055**
	(0.005)	(0.008)	(0.020)
Variable Level, β_{11}		-0.001*	0.000001
		(0.0004)	(0.000001)
Variable Δ, β_{12}		0.002	-0.000003
		(0.001)	(0.000002)
1987 – 1993 Trend, β_{20}	0.043***	0.004	0.094***
	(0.005)	(0.007)	(0.015)
Variable Level, β_{21}		0.002***	-0.000003**
		(0.0003)	(0.000001)
Variable Δ, β_{22}		0.001	0.000001
		(0.001)	(0.000002)
1994 – 2000 Trend, β_{30}	-0.046***	-0.015	-0.073***
	(0.006)	(0.010)	(0.019)
Variable Level, β_{31}		-0.001**	0.000001
		(0.0004)	(0.000001)
Variable Δ, β_{32}		-0.0005	-0.000001
		(0.001)	(0.000002)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.0671***	0.1684***
1980 – 1986 Trend, r_1	0.0019***	0.0016***	0.0019***
1987 – 1993 Trend, r_2	0.0016***	0.0012***	0.0013***
1994 – 2000 Trend, r_3	0.0026***	0.0023***	0.0025***
Level 1 Error, e	0.0478	0.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Table B.8: Bivariate HLM Results of Economic Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Public Assistance*	*Total Joblessness*	*Male Joblessness*
1980 Homicide Level, β_{00}	-0.086+	-0.613***	-1.741***	-1.390***
	(0.047)	(0.045)	(0.336)	(0.151)
Variable Level, β_{01}		0.034***	0.033***	0.031***
		(0.002)	(0.007)	(0.003)
1980 – 1986 Trend, β_{10}	-0.032***	-0.012+	0.080*	0.030
	(0.005)	(0.007)	(0.038)	(0.021)
Variable Level, β_{11}		-0.001**	-0.002**	-0.001**
		(0.0005)	(0.0008)	(0.0005)
Variable Δ, β_{12}		0.002+	0.002	0.003*
		(0.001)	(0.001)	(0.001)
1987 – 1993 Trend, β_{20}	0.043***	0.007	-0.031	-0.014
	(0.005)	(0.007)	(0.028)	(0.017)
Variable Level, β_{21}		0.002***	0.002**	0.001***
		(0.0005)	(0.0006)	(0.0004)
Variable Δ, β_{22}		0.004**	0.0009	-0.0007
		(0.001)	(0.001)	(0.001)
1994 – 2000 Trend, β_{30}	-0.046***	-0.026***	0.008	0.013
	(0.006)	(0.008)	(0.029)	(0.021)
Variable Level, β_{31}		-0.001**	-0.001+	-0.001**
		(0.0004)	(0.0006)	(0.0004)
Variable Δ, β_{32}		0.002	-0.0008	0.0005
		(0.001)	(0.001)	(0.0009)
Random Effects	***Variance***	***Variance***	***Variance***	***Variance***
Initial Homicide Rate, r_0	0.2212***	0.0669***	0.1450***	0.0996***
1980 – 1986 Trend, r_1	0.0019***	0.0017***	0.0017***	0.0017***
1987 – 1993 Trend, r_2	0.0016***	0.0012***	0.0014***	0.0013***
1994 – 2000 Trend, r_3	0.0026***	0.0023***	0.0023***	0.0022***
Level 1 Error, e	0.0478	0.0478	0.0478	0.0478

+ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Table B.9: Bivariate HLM Results of Economic Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Public Transportation*	*Service Workers*
1980 Homicide Level, β_{00}	-0.086+	-0.935***	-0.951***
	(0.047)	(0.067)	(0.090)
Variable Level, β_{01}		0.043***	0.040***
		(0.003)	(0.004)
1980 – 1986 Trend, β_{10}	-0.032***	0.009	-0.011
	(0.005)	(0.012)	(0.013)
Variable Level, β_{11}		-0.002**	-0.0009
		(0.0006)	(0.0006)
Variable Δ, β_{12}		0.003***	0.0009
		(0.0009)	(0.001)
1987 – 1993 Trend, β_{20}	0.043***	0.011	-0.009
	(0.005)	(0.008)	(0.016)
Variable Level, β_{21}		0.002***	0.002**
		(0.0004)	(0.0007)
Variable Δ, β_{22}		0.002	0.002
		(0.002)	(0.002)
1994 – 2000 Trend, β_{30}	-0.046***	-0.009	-0.047*
	(0.006)	(0.009)	(0.021)
Variable Level, β_{31}		-0.002***	-0.0002
		(0.0006)	(0.0009)
Variable Δ, β_{32}		0.003*	0.004***
		(0.001)	(0.001)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.0664***	0.1003***
1980 – 1986 Trend, r_1	0.0019***	0.0017***	0.0019***
1987 – 1993 Trend, r_2	0.0016***	0.0012***	0.0013***
1994 – 2000 Trend, r_3	0.0026***	0.0018***	0.0023***
Level 1 Error, e	0.0478	0.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Table B.10: Bivariate HLM Results of Mobility Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Same Residence*	*Living in St. Louis 5 Years Ago*
1980 Homicide Level, β_{00}	-0.086+	-0.210	-0.354*
	(0.047)	(0.206)	(0.162)
Variable Level, β_{01}		0.002	0.010+
		(0.004)	(0.006)
1980 – 1986 Trend, β_{10}	-0.032***	-0.032	-0.040*
	(0.005)	(0.029)	(0.020)
Variable Level, β_{11}		0.00001	0.0003
		(0.0005)	(0.0007)
Variable Δ, β_{12}		0.00003	0.0006
		(0.0008)	(0.001)
1987 – 1993 Trend, β_{20}	0.043***	0.057**	-0.030*
	(0.005)	(0.020)	(0.012)
Variable Level, β_{21}		-0.0002	0.003***
		(0.0004)	(0.0004)
Variable Δ, β_{22}		0.002	0.001
		(0.001)	(0.002)
1994 – 2000 Trend, β_{30}	-0.046***	-0.096**	-0.010
	(0.006)	(0.027)	(0.024)
Variable Level, β_{31}		0.001+	-0.001
		(0.0005)	(0.001)
Variable Δ, β_{32}		0.0001	0.002+
		(0.0009)	(0.001)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.2234***	0.2138***
1980 – 1986 Trend, r_1	0.0019***	0.0019***	0.0020***
1987 – 1993 Trend, r_2	0.0016***	0.0016***	0.0012***
1994 – 2000 Trend, r_3	0.0026***	0.0025***	0.0024***
Level 1 Error, e	0.0478	0.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Table B.11: Bivariate HLM Results of Housing Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Owner-Occupied Housing*	*Vacant Housing*
1980 Homicide Level, β_{00}	-0.086+	0.413***	-0.496***
	(0.047)	(0.102)	(0.067)
Variable Level, β_{01}		-0.011***	0.035***
		(0.002)	(0.006)
1980 – 1986 Trend, β_{10}	-0.032***	-0.056***	-0.022*
	(0.005)	(0.015)	(0.009)
Variable Level, β_{11}		0.0005+	-0.001+
		(0.0003)	(0.0007)
Variable Δ, β_{12}		0.0004	0.003**
		(0.002)	(0.001)
1987 – 1993 Trend, β_{20}	0.043***	0.063***	-0.001
	(0.005)	(0.011)	(0.007)
Variable Level, β_{21}		-0.0005*	0.003***
		(0.0002)	(0.0005)
Variable Δ, β_{22}		0.002	0.004***
		(0.002)	(0.001)
1994 – 2000 Trend, β_{30}	-0.046***	-0.085***	-0.013
	(0.006)	(0.014)	(0.009)
Variable Level, β_{31}		0.0009***	-0.002***
		(0.0002)	(0.0006)
Variable Δ, β_{32}		0.004+	-0.006***
		(0.002)	(0.001)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.1670***	0.1202***
1980 – 1986 Trend, r_1	0.0019***	0.0018***	0.0017***
1987 – 1993 Trend, r_2	0.0016***	0.0015***	0.0012***
1994 – 2000 Trend, r_3	0.0026***	0.0020***	0.0019***
Level 1 Error, e	0.0478	0.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Table B.12: Bivariate HLM Results of Housing Effects on Log Homicide Rates, Robust Standard Errors in Parentheses

Fixed Effects	*Unconditional Model*	*Renter-Occupied Housing*	*Multi-Unit Housing*
1980 Homicide Level, β_{00}	-0.086+	-0.489***	-0.375***
	(0.047)	(0.115)	(0.082)
Variable Level, β_{01}		0.009***	0.008***
		(0.002)	(0.002)
1980 – 1986 Trend, β_{10}	-0.032***	-0.010	-0.013
	(0.005)	(0.017)	(0.010)
Variable Level, β_{11}		-0.0005	-0.0005
		(0.0004)	(0.0003)
Variable Δ, β_{12}		-0.002	-0.002
		(0.001)	(0.001)
1987 – 1993 Trend, β_{20}	0.043***	0.028*	0.037***
	(0.005)	(0.013)	(0.009)
Variable Level, β_{21}		0.0003	0.0002
		(0.0003)	(0.0002)
Variable Δ, β_{22}		-0.002	-0.001
		(0.001)	(0.002)
1994 – 2000 Trend, β_{30}	-0.046***	0.0002	-0.016+
	(0.006)	(0.013)	(0.009)
Variable Level, β_{31}		-0.001***	-0.0008***
		(0.0003)	(0.0002)
Variable Δ, β_{32}		-0.002	-0.001
		(0.002)	(0.002)
Random Effects	*Variance*	*Variance*	*Variance*
Initial Homicide Rate, r_0	0.2212***	0.1964***	0.1949***
1980 – 1986 Trend, r_1	0.0019***	0.0018***	0.0018***
1987 – 1993 Trend, r_2	0.0016***	0.0015***	0.0017***
1994 – 2000 Trend, r_3	0.0026***	0.0024***	0.0023***
Level 1 Error, e	0.0478	0.0478	0.0478

+ p < .10 , * p < .05 , ** p < .01 , *** p < .001

Appendix C

Table C.1:. Correlation Matrix of Indicators of Disadvantage and Instability in St. Louis Census Tracts, 1980 - 2000 (n = 110)

1980 Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Percent Black	1																
2. Percent Female Headed Families	.768***	1															
3. Unemployment	.798***	.782***	1														
4. Poverty Rate	.766***	.871***	.821***	1													
5. Ln. Average Family Income	-.585***	-.762***	-.754***	-.798***	1												
6. Percent Public Assistance Households	.845***	.888***	.893***	.901***	-.788***	1											
7. Male Joblessness	.722***	.648***	.782***	.773***	-.695***	.769***	1										
8. Percent Labor Using Public Transpotation	.806***	.742***	.740***	.807***	-.665***	.839***	.743***	1									
9. Percent Labor as Service Workers	.864***	.730***	.797***	.779***	-.693***	.842***	.738***	.773***	1								
10. Vacant Housing	.408***	.542***	.564***	.691***	-.436***	.606***	.445***	.549***	.448***	1							
11. Ln Percent College Graduates	-.357***	-.415***	-.605***	-.415***	.643***	-.541***	-.490***	-.268**	-.522***	-.159	1						
12. Percent Owner-Occupied Housing	-.262**	-.473***	-.256**	-.535***	.395***	-.414***	-.359***	-.560***	-.268**	-.520***	-.102	1					
13. Percent Renter-Occupied Housing	.176	.361***	.117	.386***	-.315**	.276**	.270**	.459***	.172	.269**	.160	-.960***	1				
14. Percent Multi-Unit Housing	.123	.255**	.016	.296**	-.079	.190*	.150	.390***	.057	.455***	.338***	-.880***	.839***	1			
15. Ln Percent Hispanic	-.316**	-.179	-.252**	-.113	.107	-.247**	-.151	-.244*	-.206*	-.004	.101	.090	-.100	-.085	1		
16. Ln Percent Immigrant	-.219*	-.167	-.221*	-.102	.215*	-.220*	-.254**	-.134	-.246*	.116	.411***	-.181	.165	.289**	.037	1	
17. Ln Population Heterogeneity	.094	.170	.021	.245**	.004	.061	.065	.113	.031	.351***	.230*	-.357***	.313**	.472***	.153	.196*	1

1990 Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Percent Black	1																
2. Percent Female Headed Families	.685***	1															
3. Unemployment	.742***	.750***	1														
4. Poverty Rate	.733***	.869***	.856***	1													
5. Ln. Average Family Income	-.596***	-.750***	-.781***	-.813***	1												
6. Percent Public Assistance Households	.793***	.821***	.873***	.911***	-.811***	1											
7. Male Joblessness	.737***	.632***	.729***	.758***	-.708***	.775***	1										
8. Percent Labor Using Public Transpotation	.825***	.719***	.745***	.790***	-.749***	.840***	.810***	1									
9. Percent Labor as Service Workers	.777***	.613***	.780***	.737***	-.757***	.798***	.747***	.757***	1								
10. Vacant Housing	.534***	.772***	.644***	.627***	-.703***	.752***	.608***	.697***	.530***	1							
11. Ln Percent College Graduates	-.462***	-.406***	-.585***	-.511***	.707***	-.583***	-.648***	-.590***	-.740***	-.330***	1						
12. Percent Owner-Occupied Housing	-.256**	-.488***	-.332***	-.544***	.364***	-.415***	-.352***	-.431***	-.148	-.730***	-.096	1					
13. Percent Renter-Occupied Housing	.141	.326**	.187*	.378***	-.196*	.248**	.213*	.287**	.003	.535***	.224*	-.962***	1				
14. Percent Multi-Unit Housing	.108	.254**	.118	.344***	-.086	.191*	.214*	.233*	-.044	.530***	.254**	-.909***	.912***	1			
15. Ln Percent Hispanic	-.618***	-.318**	-.445***	-.346***	.291**	-.451***	-.517***	-.507***	-.493***	-.135	.368***	-.060	.125	.104	1		
16. Ln Percent Immigrant	-.361***	-.156	-.269**	-.132	.265**	-.315**	-.290**	-.282**	-.393***	-.066	.469***	-.304**	.412***	.347***	.424***	1	
17. Ln Population Heterogeneity	-.165	.193*	-.104	.117	.080	-.048	-.176	-.096	-.287**	.336***	.365***	-.463***	.452***	.477***	.440***	.493***	1

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

Table C.1: Correlation Matrix of Indicators of Disadvantage and Instability in St. Louis Census Tracts, 1980 - 2000 (n = 110) Continued

2000	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Variable																	
1. Percent Black	1																
2. Percent Female Headed Families	.675***	1															
3. Unemployment	.588***	.542***	1														
4. Poverty Rate	.681***	.803***	.731***	1													
5. Ln. Average Family Income	-.535***	-.692***	-.556***	-.709***	1												
6. Percent Public Assistance Households	.741***	.813***	.610***	.829***	-.705***	1											
7. Male Joblessness	.722***	.512***	.736***	.678***	-.575***	.681***	1										
8. Percent Labor Using Public Transpotation	.764***	.613***	.587***	.634***	-.518***	.681***	.681***	1									
9. Percent Labor as Service Workers	.626***	.521***	.545***	.606***	-.662***	.694***	.612***	.573***	1								
10. Vacant Housing	.714***	.753***	.599***	.774***	-.660***	.804***	.633***	.671***	.637***	1							
11. Ln Percent College Graduates	-.587***	-.495***	-.507***	-.581***	.747***	-.678***	-.650***	-.505***	-.733***	-.556***	1						
12. Percent Owner-Occupied Housing	-.278**	-.564***	-.317**	-.593***	.319*	-.433***	-.301**	-.439***	-.099	-.525***	-.099	1					
13. Percent Renter-Occupied Housing	.089	.358***	.138	.398***	-.121	.206*	.122	.286**	-.108	.242*	.212*	-.947***	1				
14. Percent Multi-Unit Housing	.067	.315*	.125	.359***	-.030	.108	.111	.226*	-.185	.230*	.270**	-.894***	.925***	1			
15. Ln Percent Hispanic	-.645***	-.379***	-.447***	-.379***	.235*	-.338***	-.448***	-.483***	-.314**	-.377***	.317**	.015	.108	.034	1		
16. Ln Percent Immigrant	-.474***	-.281**	-.139	-.156	.245*	-.267**	-.316**	-.212*	-.281**	-.311**	.343***	-.127	.251**	.255**	.425***	1	
17. Ln Population Heterogeneity	-.441***	-.062	-.127	-.057	.211*	-.187	-.384***	-.289**	-.389***	-.150	.470***	-.318**	.419***	.387***	.479***	.516***	1

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

Appendix D

Table D.1. Moran's I Statistics for Homicide Trends and Levels of Social Structure, 1980 - 2000 (n = 110)

Variable	*1980*	*1986*	*1994*	*2000*
Initial Homicide Rates	.451***	.347***	.441***	
Homicide Trend	.264***	.323***	.299***	
Population	.158**	.177**	.232**	.311***
Percent Black	.823***	.857***	.866***	.843***
Percent Hispanic	.131*	.407***	.528***	.430***
Population Heterogeneity	.576***	.639***	.662***	.634***
Percent Immigrant	.082	.350***	.424***	.441***
Percent Female-Headed Families	.584***	.550***	.504***	.446***
Divorce Rate	.241***	.323***	.220**	.019
Percent Youth (15-24)	.116*	.247***	.251***.	.185**
Percent Male Youth (15-24)	.198**	.188**	.178**	.126*
Percent High School Dropouts	.350***	.226**	.135*	.081
Percent College Graduate (4-year)	.353***	.449***	.499***	.474***
Unemployment Rate	.576***	.557***	.584***	.443***
Male Unemployment	.540***	.596***	.585***	.373***
Poverty Rate	.722***	.721***	.655***	.561***
Average Family Income (1980 Dollars)	.518***	.497***	.469***	.388***
Percent Households with Public Assistance	.659***	.659***	.622***	.545***
Joblessness Rate	.386***	.509***	.597***	.643***
Male Joblessness Rate	.501***	.662***	.687***	.629***
Percent Workers Using Public Transportation	.657***	.688***	.700***	.604***
Percent Labor as Service Workers	.602***	.571***	.542***	.413***
Percent Same Residence	.302***	.450***	.514***	.428***
Percent Living in St. Louis 5 Years Ago	.174**	.334***	.389***	.349***
Percent Owner-Occupied Housing	.701***	.691***	.667***	.633***
Percent Vacant Housing	.561***	.684***	.698***	.656***
Percent Renter-Occupied Housing	.570***	.590***	.565***	.514***
Percent Multi-Unit Housing	.539***	.568***	.575***	.566***

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

Table D.2. Moran's I Statistics for Changes in Social Structure, 1980 - 2000 (n = 110)

Variable	*1980 - 1986*	*1987 - 1993*	*1994 - 2000*
Homicide Trend	.264***	.323***	.299***
Population	.150**	.377***	.401***
Percent Black	.386***	.663***	.709***
Percent Hispanic	.146**	.201**	.096*
Population Heterogeneity	.524***	.705***	.500***
Percent Immigrant	.125*	.211**	.258***
Percent Female-Headed Families	.116*	.358***	.188**
Divorce Rate	.110*	.146**	.070
Percent Youth (15-24)	.051	.063	.055
Percent Male Youth (15-24)	.089*	.012	-.079
Percent High School Dropouts	.013	.285***	.050
Percent College Graduate (4-year)	.060	.135*	-.097*
Unemployment Rate	-.121*	.073	.012
Male Unemployment	-.038	.051	-.065
Poverty Rate	-.085	.123*	.197**
Average Family Income (1980 Dollars)	.125*	.168**	.093*
Percent Households with Public Assistance	.073	.318***	.295***
Joblessness Rate	.196**	.510***	.250***
Male Joblessness Rate	.152**	.300***	-.021
Percent Workers Using Public Transportation	.184**	.181***	.106*
Percent Labor as Service Workers	.092*	.270***	.040
Percent Same Residence	.012	.015	.030
Percent Living in St. Louis 5 Years Ago	-.048	.102*	.083
Percent Owner-Occupied Housing	-.013	.193**	.151**
Percent Vacant Housing	.211**	.349***	.226***
Percent Renter-Occupied Housing	.195**	.271***	.140*
Percent Multi-Unit Housing	-.011	.089*	.192**

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