THE EFFECTS OF URBAN RESIDENTIAL ENVIRONMENTS ON MENTAL WELL BEING: A MULTILEVEL ANALYSIS OF NEIGHBORHOOD STABILITY, MIDDLE INCOME COMPOSITION AND DEPRESSION IN DETROIT

by

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DEDICATION

I dedicate this dissertation to my mother, Shirley Morrison Coombe, and my daughter, Paloma Paez-Coombe.

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CHAPTER 1.

INTRODUCTION

Residential stability has long been considered a core structural characteristic of neighborhoods that is central to the well being of individual residents and the community itself (Faris and Dunham 1939; Shaw and McKay 1942). Residentially stable neighborhoods have a high proportion of residents who have lived in the neighborhood for over five years, whereas residentially mobile or unstable neighborhoods have experienced a high turnover in population during that time period. Stable neighborhoods can be beneficial to health by enabling residents to develop relationships and networks that provide economic and social support (Israel and Rounds 1987), facilitate the development of formal and informal organization (Cottrell 1977; Parker, Lichtenstein, Schulz, Israel, Schork, and Steinman 2001), and enable the accumulation of wealth through homeownership, employment, and local investment (Oliver and Shapiro 1995). Everyday interactions with neighbors can provide consistency and coherency, a sense of belonging and continuity, and access to psychological, social, and material resources that can be drawn upon during times of stress (Boardman 2004; Lin, Ye, and Ensel 1999).

In addition to benefits to individual residents, residential stability can generate collective structural resources that contribute to the economic standing of the neighborhood and may be more enduring than the individuals who live there. These collective resources include economic structures such as employment opportunities, lending, property values, and owner-occupancy; social networks and community integration; public services and infrastructure such as schools and safety; the physical and built environments, including housing stock; and political representation and influence.

However, a growing body of research suggests that the effects of neighborhood residential stability on health depend on the socioeconomic status and composition of the neighborhood (Boardman 2004; Ross, Reynolds, and Geis 2000). It is thought that in more affluent neighborhoods, stability has many of the beneficial effects described above due to the quality and quantity of resources available to residents and the neighborhood. The "advantages of advantaged neighbors" (Jencks and Mayer 1990, p.113) accumulate in part through residence in stable neighborhoods rich in health-enhancing resources (Ross and Wu 1996; Williams and Collins 2001).

Residential stability may not confer the same advantages in neighborhoods under economic stress as it does in more affluent or economically mixed neighborhoods (Mullings and Wali 2001; Schulz, Israel, Zenk, Parker, Lichtenstein, Shellman-Weir, and Klem 2006). The lack or loss of middle income and affluent households can erode both neighborhood economic standing and residents' personal resources through declining property values, crime, inferior schools, reduced access to employment, disinvestment in public services, and fewer amenities. Residents of such neighborhoods may not have the resources to protect themselves from fire or crime in the absence of public infrastructure, maintain aging homes, or sustain political organization and influence over decisions affecting their community.

In such circumstances, residential stability may be detrimental to residents' physical and mental health through daily exposure to chronic stress in the physical, economic, and social environments in which they live. Faced with persistent stressors over which they have little or no control, residents may experience powerlessness, hopelessness, and reduced social network resources that increase their susceptibility to depression.

There is now a small but consistent body of evidence suggesting that the meaning of residential stability for health is contingent on neighborhood economic status, in particular the proportion of either poor or affluent residents (Ross, Reynolds, and Geis 2000). In addition, there has been substantial discussion in the urban planning arena on the importance of middle income residents for regenerating inner city communities (Booza, Cutsinger, and Galster 2006; Burns 2006). However, there has been no research to date on the joint effects of neighborhood stability and neighborhood middle income composition on residents' physical or mental health. An "adequate" proportion of middle income residents may be particularly important in economically disinvested cities that have lost most of their affluent and middle class residents—groups that previously contributed to the local economic, organizational, and political foundation of the community (Quercia and Galster 1997).

Many urban areas in the U.S. are characterized by racial as well as economic segregation (Jargowsky 1997b; Massey and Denton 1993; Schulz, Williams, Israel, and Lempert 2002). Racial residential segregation has been and continues to be a defining force in the inequitable distribution of resources within and between regions, residential neighborhoods, racial and ethnic groups, and individuals. The complex intertwining of race and class are manifested most saliently in the spatial distribution of people and resources in US cities. Examining the relationship between residential environments and mental health in one of the most economically and racially segregated cities in the country may help us to understand more about the pathways through which racial inequality shapes health.

This dissertation investigates the following questions: Is living in a stable neighborhood beneficial to mental health in an economically disinvested city? Is stability only beneficial when there is an adequate proportion of middle income residents, but detrimental when there are relatively few middle income residents, regardless of one's own income? Is the effect of stable neighborhoods on mental health the same regardless of the racial composition of the neighborhood? What are the pathways through which neighborhood stability and middle income jointly affect depression? Are stable neighborhoods with few middle income residents detrimental to mental health in part because of the financial vulnerability experienced by residents? Does social support account for the beneficial effect of stability in neighborhoods with higher proportion middle income residents?

I use multilevel modeling to examine these questions in three neighborhoods of Detroit, Michigan, and suggest future research, interventions, and policies to improve the mental health of neighborhood residents.

CHAPTER 2.

BACKGROUND AND SETTING

Over the past fifty years there has been a dramatic change in the physical, social, and economic landscape of industrial cities across the United States. Economic restructuring combined with racially discriminatory policies and practices have resulted in a massive and unequal redistribution of economic resources and population from the core cities to surrounding metropolitan areas (Jargowsky 1997a; Massey and Denton 1993; Wilson 1987). As a result, concentrated poverty, that is, areas in which the poverty rate is forty percent or higher, rose dramatically between 1970 and 1990 in inner cities and is rising again after a brief decline during the relatively prosperous 1990s (Jargowsky 2003). Race-based residential segregation and hyper-segregation continue to rise within cities where the minority population is large (Sethi and Somanathan 2004).

Understanding and addressing the effects of concentrated advantage and disadvantage is crucial to eliminating racial inequities in health. Economic and racial residential segregation are fundamental causes of physical and mental health that structure the distribution of health related resources and risks at the individual, neighborhood, community levels and beyond (Link and Phelan 1995; Schulz, Williams, Israel, and Lempert 2002; Williams and Collins 2001).

The effects of these macro-level conditions on poor neighborhoods in core cities whose residents are largely African American and ethnic minorities, have been well documented (Morenoff and Tienda 1997; Schulz, Williams, Israel, and Lempert 2002; Sugrue 1996; Wilson 1987). Economically disinvested neighborhoods have a disproportionate burden of physical stressors that adversely affect health, such as air pollution, toxic waste, and deteriorating housing stock (Galea, Ahern, Rudenstine, Wallace, and Vlahov 2005; Gee and Payne-Sturges 2004). Critical resources essential to economic well being, such as employment opportunities, quality education, and transportation are diminished (Schulz, Williams, Israel, and Lempert 2002). Access to basic resources for promoting good health is limited, such as nutritious and affordable food, quality health care, and safe places for exercise and recreation (Zenk, Schulz, Israel, James, Bao, and Wilson 2005). Disinvestment in basic public services, such as police and fire protection and refuse collection, contributes to unsafe environments that are detrimental to both physical and psychological well being (Wallace and Wallace 1990).

Daily exposure to such stressful neighborhood conditions have been consistently linked to a range of mental health outcomes (Galea, Bresnahan, and Susser 2005; Ross 2000; Schulz, Williams, Israel, Becker, Parker, James, and Jackson 2000; Truong and Ma 2006). Environmental stressors may heighten residents' distress and feelings of powerlessness, increase social strain, and reduce access to salutary material and social resources that might buffer the effects of neighborhood disadvantage.

Economically strained and racially segregated communities have historically developed and relied on shared economic and social resources to “mitigate, resist, and undo” such challenges (Geronimus 2000, p.867; Stack 1974). Even within the extreme economic and political constraints imposed by racial segregation and other forms of discrimination, urban African American neighborhoods within and between cities historically had an economic and educational infrastructure that provided ladders of opportunity through interconnections across class and place (Blackwell, Kwoh, and Pastor 2002; Fullilove 2004; Wilson 1987).

However, over the past 50 years, core urban areas have experienced extreme loss of jobs, housing, infrastructure, and population due to deindustrialization and other aspects of economic restructuring, combined with racially discriminatory policies and practices. In the process, core urban neighborhoods have lost much of the middle class that is essential to local economic, institutional, and political life (Farley, Danziger, and Holzer 2000; Massey 1996). Out-migration of middle and upper income households has lead to loss of local businesses and reduced property values, resulting in a dramatic reduction in the city’s tax base. Combined with loss of population for determining political representation, this leaves inner-city residents with weakened political power to attract public resources from state legislators to their neighborhoods (Quercia and Galster 1997).

Organizational and social networks that provide essential material and social support (Stack 1974) have been overextended, disrupted, or depleted by loss of economic resources concurrent with increased stressors (Mullings and Wali 2001; Wallace, Fullilove, and Wallace 1992). The compounding effects of the day-to-day stress of living in an economically disinvested community combined with increasing isolation from higher resourced social, economic, and political networks may lead to chronic and acute financial vulnerability, having an injurious effect on mental health (Elliott 2000; Leventhal and Brooks-Gunn 2003).

Detroit, Michigan

Detroit has a rich history as a vibrant and prosperous city with a strong blue collar middle class, a high rate of homeownership, and over a hundred distinct historic neighborhoods (Farley, Danziger, and Holzer 2000; Sugrue 1996). However, between 1950 and 2000 Detroit lost approximately 350,000 jobs and nearly half its population, from 1.8 million to 950,000 (Farley, Danziger, and Holzer 2000). As whites fled the city for newer, more prosperous suburbs, African Americans were confined by racially discriminatory policies and practices and violence to older, lower resource residential neighborhoods (Farley, Danziger, and Holzer 2000; Schulz, Williams, Israel, and Lempert 2002). In fifty years the racial composition went from 16.2% to 81.2% African American (see Figures 2.1 and 2.2 to compare 1970 to 2000) primarily due to the flight of whites from the city (Farley, Danziger, and Holzer 2000).

Shifts in the economic structure combined with racial residential segregation contributed to substantial increases in poverty and concentrated poverty within Detroit, and substantial concentration of wealth and economic resources in the surrounding suburbs (Jargowsky 1997b; Massey and Denton 1993; Schulz, Williams, Israel, and Lempert

2002). The Detroit metropolitan area is one of the most extreme examples in the U.S. of racial residential segregation and the spatial concentration of wealth and poverty (Farley, Danziger, and Holzer 2000; Schulz, Williams, Israel, and Lempert 2002; Sugrue 1996).

These changes have had a profound impact on the structure of residential neighborhoods in Detroit. In the 1990s nearly every neighborhood in the city lost residents, resulting in declining property values for those who remained and a substantially reduced tax base. There has been an exponential growth in neighborhood poverty, as mixed income neighborhoods have lost most of their middle income residents. In 2000, 72% of inhabited census tracts in Detroit had at least 20% of residents living in poverty (Schulz, Williams, Israel, and Lempert 2002). Figures 2.3 and 2.4 compare poverty in 1970 and 2000.

In spite of severe loss of population, Detroit has a high rate of neighborhood residential stability. That is, among those who were currently living in Detroit in 2000, 60% of residents were living in the same house as five years previous, and an additional 32% lived in a different house but within the same county. In addition, 55% of Detroit residents own their own homes.

In this context of economic and social change, this study will examine the effects of neighborhood residential environments on the mental health of residents of three areas of Detroit. I will explore whether people in stable neighborhoods have lower rates of depression than those in unstable neighborhoods, and whether this varies depending on the proportion of middle income people living in the neighborhood. First, I will review the literature that informs this investigation.

Figure 2.1 Map of Percent African American, Detroit 1970

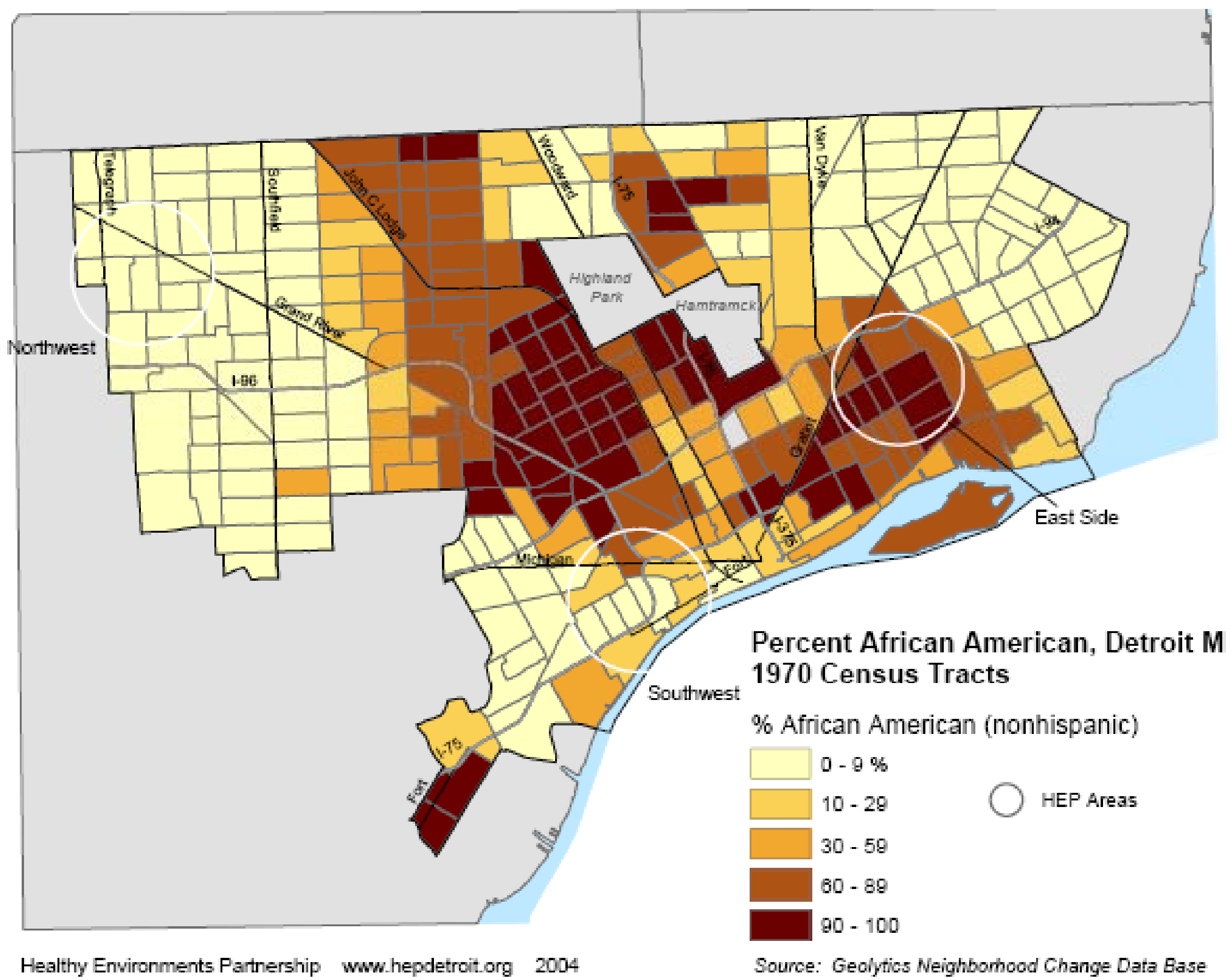


Figure 2.2 Map of Percent African American, Detroit, MI 2000

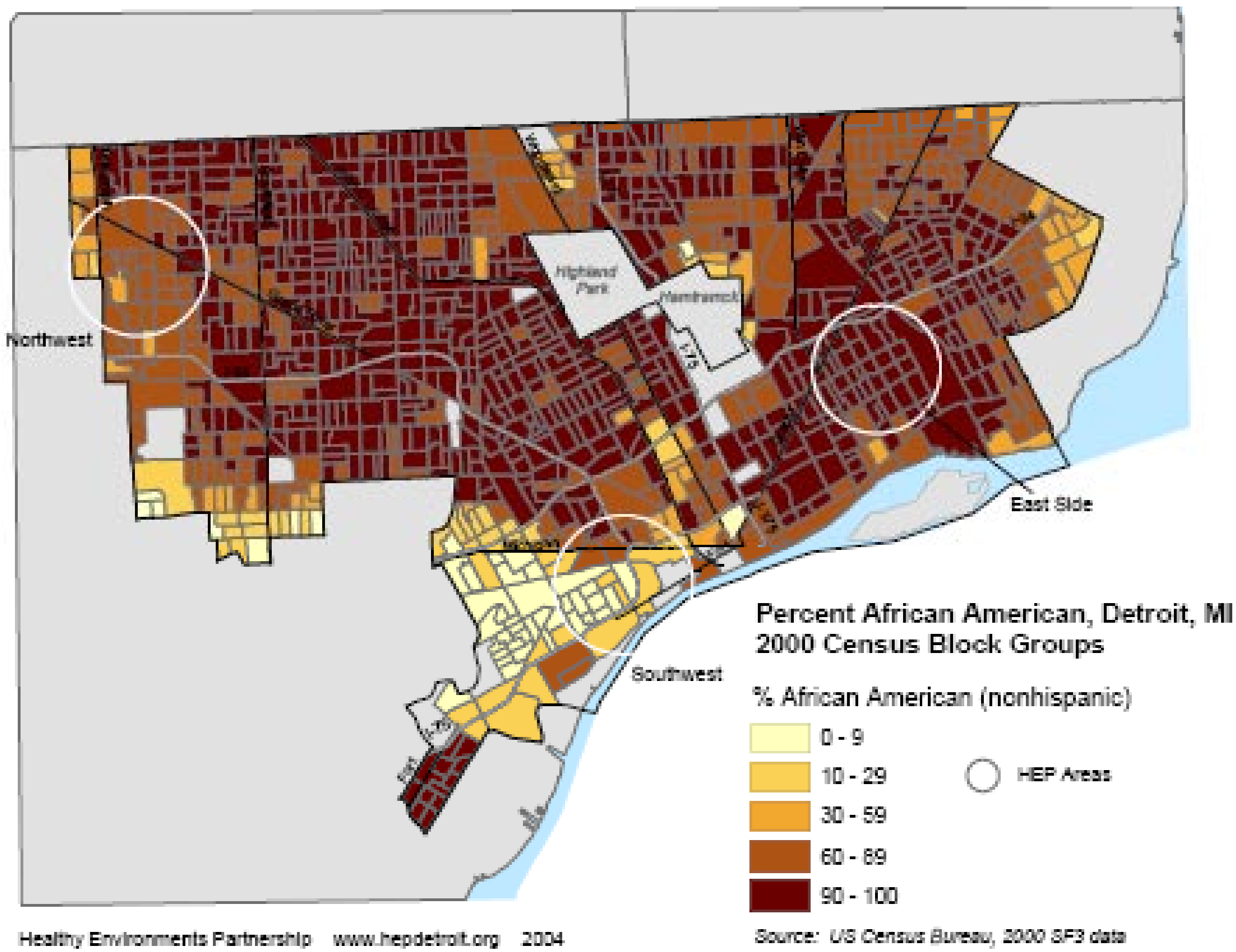


Figure 2.3 1970: Percent Poverty in Detroit, MI

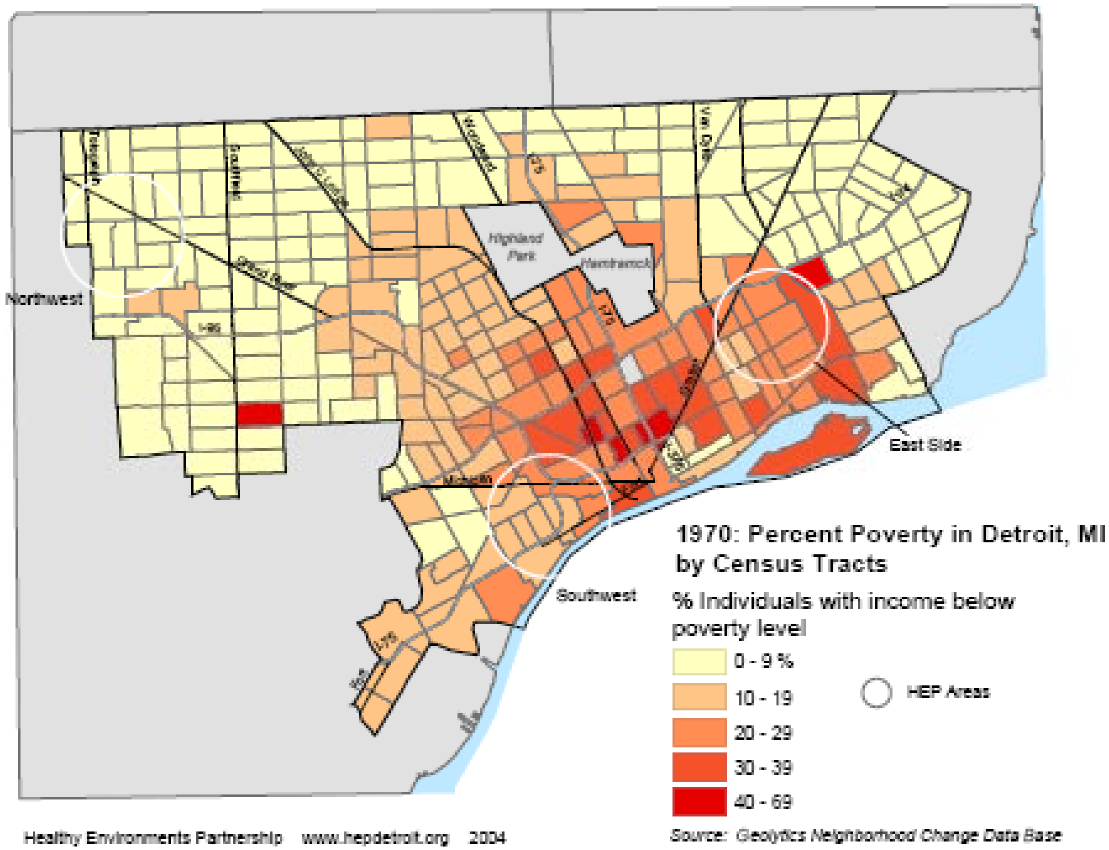
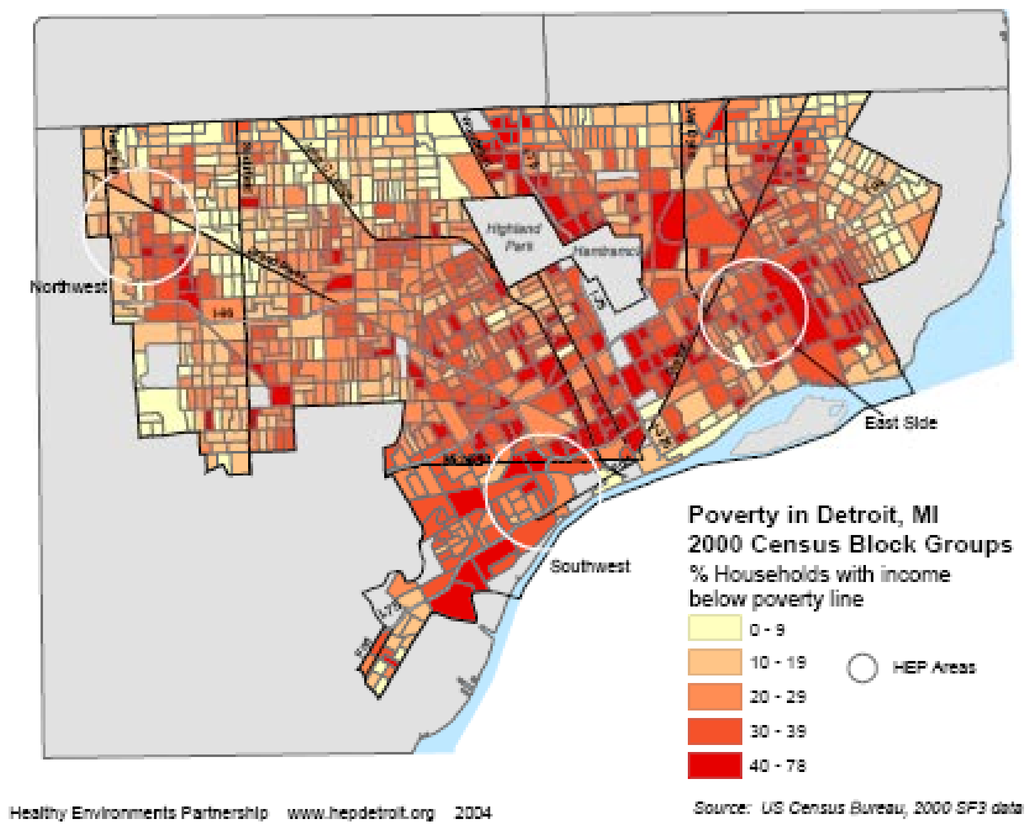


Figure 2.4 Poverty in Detroit, MI 2000



CHAPTER 3.

LITERATURE REVIEW

Overview

There is a substantial and growing body of research on the relationship between neighborhood context and mental and physical health. In particular, there is consistent evidence that community socioeconomic context affects the health of individual residents over and above their own economic position (Robert 1999). In recent years there have been at least seven published reviews of the literature on neighborhood context and health (Ellen, Mijanovich, and Dillman 2001; Flournoy and Yen 2004; Leventhal and Brooks-Gunn 2000; Pickett and Pearl 2001; Robert 1999; Sampson, Morenoff, and Gannon-Rowley 2002; Truong and Ma 2006), and several others on specific aspects of neighborhood context and health (Evans 2003a; Evans 2003b).

The primary focus of this investigation is the joint effects of two structural aspects of neighborhoods, residential stability and middle income composition, on the mental well being of residents in economically disinvested urban communities in Detroit, Michigan. For this dissertation, I reviewed the published literature through 2006 on the effects of neighborhood residential environments on health in three domains: residential stability and health, neighborhood income composition and health, and neighborhood socioeconomic structure and mental health. (Summaries of the literature in each domain are in Tables 3.1 – 3.3 located at the end of this chapter.)

I included all studies of health that had neighborhood level measures of residential stability and income, regardless of health outcome (Table 3.1, N = 8). Only three of these examined mental health. In my review of the second domain, neighborhood income composition, I included all studies with measures of neighborhood affluence or income heterogeneity (Table 3.2, N = 8). The substantial literature on socioeconomic context that considers only neighborhood disadvantage and not affluence was excluded. In addition, because income inequality captures an aspect of income structure conceptually related to my main research question, I included empirical studies of income inequality at the within-city level, of which I found only three. One of those compared measures of income composition (poverty and affluence) to measures of inequality in relation to self-rated health. Only two of the studies in the income composition domain examined mental health outcomes.

In the third domain, I included empirical studies of the effects of neighborhood socioeconomic structure on mental health. I limited inclusion to the types of psychological distress and disorder that may be sensitive to the effects of living in urban neighborhoods and that are most commonly experienced, such as depression and anxiety (Table 3.3, N = 15). Externalizing aspects of mental health, such as crime, delinquency, child maltreatment, and violent behavior, are excluded from this review.

Within the literature identified in the three domains just described, I further identified those studies that included measures of neighborhood racial and ethnic composition to examine whether neighborhood structural characteristics may in part explain racial and ethnic disparities in health. I also identified throughout the review those studies that included measures of financial stress or social resources as potential mechanisms through which neighborhood structure may affect health.

I have used these three conceptual domains to organize my review of the literature, however, they are not mutually exclusive. I located a total of 24 published studies that met my inclusion criteria. Of these, several are included in two domains, and only one is included in all three areas (Kubzansky, Subramanian, Kawachi, Fay, Soobader, and Berkman 2005). I will discuss the literature by domains, followed by a discussion of those studies that included racial composition, financial stress, and social resources. I then discuss gaps in the literature and the potential contributions of this dissertation to understanding the effects of neighborhood residential environments on mental health.

A. Residential stability

Residential stability and mobility are two ends of a continuum that characterizes the extent of flux of people into and out of a residential neighborhood (Ross, Reynolds, and Geis 2000). Residential stability refers to the proportion of neighborhood residents who lived in the same residence five years previously. Traditionally residential stability has been considered beneficial to the health of communities and those who live in them (Faris and Dunham 1939; Shaw and McKay 1942). There is a long line of research dating to the

Chicago School studies of urban crime and delinquency that suggests that residential mobility, socioeconomic disadvantage, and racial/ethnic heterogeneity jointly contribute to social disorganization. This remains a durable concept in the contemporary social ecological literature (Brooks-Gunn, Duncan, and Aber 1997a; Brooks-Gunn, Duncan, and Aber 1997b; Kawachi and Berkman 2000; Morenoff, Sampson, and Raudenbush 2001).

In my review of the literature on neighborhood context and health, I identified nine empirical studies that examined residential stability, all of which used multilevel analysis (See Appendices 3.1 - 3.3 for summary tables of all studies). Five of these included stability, poverty, and immigrant or racial concentration (Browning and Cagney 2003; Browning and Cagney 2002; Browning, Cagney, and Wen 2003; Kubzansky et al. 2005; Silver, Mulvey, and Swanson 2002). All defined neighborhood at the level of census tract or clusters of tracts. Unlike earlier work, however, these studies investigated whether the effect of neighborhood residential stability on residents' health differs depending on characteristics of the neighborhood.

Kubzansky and colleagues found that living in a poor neighborhood (percent poverty in census tract) was associated with higher depressive symptoms among older adults in New Haven. Percent affluence, measured as percentage of individuals with 1980 income greater than $75,000, was marginally significant ($p \geq .10$); however, residential stability was not significant after taking into account individual level factors (Kubzansky et al. 2005). Using individual level data from a random multistage probability study of the

Detroit metropolitan area, Boardman found that the negative impact of stress on health was stronger among residents of relatively unstable neighborhoods, and that neighborhood variation in stress levels accounted for a significant proportion of differences in overall physical health (Boardman 2004).

In a study using data from a statewide representative sample linked to census data, Ross found that reported symptoms of depressed mood were higher among residents of socioeconomically disadvantaged neighborhoods in Illinois net of individual characteristics (see Table 1) (Ross 2000). In a subsequent analysis of the same data, Ross and colleagues found different effects of neighborhood disadvantage on mental health depending on residential stability (Ross, Reynolds, and Geis 2000). Under conditions of low poverty, residents of stable neighborhoods had lower depression than residents of more mobile neighborhoods. However, under conditions of high poverty, residents of stable neighborhoods had higher levels of depression than residents of more mobile neighborhoods. These findings indicate that the effects of residential stability depend on the neighborhood level of poverty.

Extending this work to other mental health outcomes using data from the first wave of the Epidemiological Catchment Area (ECA) study, Silver and colleagues found that major depression and substance abuse disorder were more prevalent in disadvantaged and residentially unstable neighborhoods in five locations across the United States: New Haven, Baltimore, Durham, and Los Angeles (Silver, Mulvey, and Swanson 2002).

Four studies in this review report separate analyses of data from the Project on Human Development in Chicago Neighborhoods Community Survey (PHDCN-CS) (Browning and Cagney 2003; Browning and Cagney 2002; Browning, Cagney, and Wen 2003; Cagney and Browning 2004; Wen, Browning, and Cagney 2003). The survey is a probability sample of 8,782 residents of Chicago clustered into 343 "neighborhoods" of about 8,000 people each. The investigators examined concentrated disadvantage, residential stability, immigrant concentration, as well as collective efficacy in relation to physical health outcomes. In the first of these analyses, they found no significant effect of concentrated disadvantage or residential stability on self-rated health, although neighborhood collective efficacy had a positive effect on health (Browning and Cagney 2002). In a subsequent study of asthma rates, the investigators added neighborhood disorder as measured by a factor score of aggregated survey responses (Cagney and Browning 2004). Findings indicated that residential stability was protective of respiratory health only when levels of collective efficacy were controlled.

In two other analyses, the same investigators included concentrated affluence, measured as the percentage of households with incomes $50,000 or over in 1990[1] (Browning and Cagney 2003; Browning, Cagney, and Wen 2003). This approach assesses concentrations in both the upper and lower tails of the income distribution. Both studies found that affluence was a stronger predictor of health than poverty. Moreover, they tested the interaction between affluence and stability and found that in low affluence communities, residential stability was negatively associated with health (Browning and

[1] $50,000 represents 170% of the 1990 national median income, and is equivalent to $66,000 in 2000 dollars.

Cagney 2003). This is consistent with the previously described studies that found that residential stability has different effects on health depending on the economic status of the neighborhood. Browning and colleagues also found that neighborhood affluence accounted for a substantial portion of the health disparity between African Americans and Whites.

The above investigations all used multilevel analysis. All but one of these studies (Ross, Reynolds, and Geis 2000) used a stability measure that combined two highly correlated factors, percent residents living five years or more in the same residence and percent homeownership. While there is substantial evidence that homeownership is associated with better health compared to renting (Hiscock, Macintyre, Kearns, and Ellaway 2003), homeownership is conceptually different than stability and may be more accurately a measure of wealth (assets) than a proxy for stability.

This small but consistent body of evidence suggests that neighborhood residential stability has a beneficial effect on health only in more economically advantaged communities, when measured at the tract level across region (Detroit metropolitan area), state (Illinois), and country (four cities). The citywide studies of Chicago defined neighborhoods by neighborhood clusters of tracts (NCs) comprised of approximately 8,000 people each. All of the investigators speculated that social disorder is the primary mechanism by which neighborhood economic disadvantage negatively influences health, and that residential stability affects neighborhoods differentially in part because residents in low income neighborhoods feel powerless to escape stressful and dangerous environments. However, the finding that affluence modifies the effect of stability suggests that there may be other pathways by which stability and income composition influence health, such as the collective availability of salutogenic resources. Further examination may help to clarify the pathways connecting stability and income composition to health, and whether similar results would be found in smaller geographic areas.

B. Income Composition

Income composition refers to the relative share of each income level in a population, expressed as a percentage of the overall income of that population. While there is substantial evidence that neighborhood income levels exert an influence on health net of individual socioeconomic resources (Robert 1999), little is known about how different aspects of neighborhood income composition affect health. Until recently, neighborhood effects research has focused primarily on one dimension of neighborhood income structure, poverty and related aspects of socioeconomic disadvantage. There is, however, an emerging interest in exploring the health effects of the proportion of residents in the upper end of the income distribution. This review will focus on studies that include poverty and measures of middle and upper levels of income composition, usually referred to as “affluence” and variously defined. Because prevalence of poverty is widely considered to be a core measure of disadvantage in neighborhoods (Jargowsky 2003; Krieger, Williams, and Moss 1997; U.S. Census Bureau 1995), I will not review the many studies using only composite measures of neighborhood socioeconomic disadvantage. I located only six published studies meeting these criteria, four of which are separate analyses by Browning, Cagney, and Wen of data from the Chicago Neighborhoods Study cited above.

I also considered for inclusion two additional dimensions of economic differentiation that are largely unexamined at the local level but which may be consequential to health: income inequality and economic segregation. Income inequality is typically a *within* area measure while segregation is a *between* area measure of economic structure. For example, income inequality describes the economic distribution within an area, such as within a city, while segregation refers to the spatial separation of classes between areas, such as between cities. Although income inequality has been the subject of much research and debate, an exhaustive literature review published in 2004 found little research at the city or neighborhood level, and mixed evidence for direct health effects among states (Lynch, Davey Smith, Harper, Hillemeier, Ross, Kaplan, and Wolfson 2004). Economic segregation, the spatial segregation of households by income or social class, has been largely studied at the level of metropolitan area (Jargowsky 1996; Waitzman and Smith 1998).

There has been relatively little investigation at the local level of these two aspects of income structure, considering the enormous economic restructuring of the past 30 years and the substantial rise in concentrated poverty and economic segregation in the US (Jargowsky 1996; Jargowsky 2003). However, I located two neighborhood level studies that I include in this review.

In summary, due to the scope of this investigation, I have restricted this literature review to studies that include measures of both affluence and poverty, and studies of income inequality or economic segregation at the neighborhood level. Table 2 summarizes the literature described in the following section (N = 8).

One of the earlier studies to look at the simultaneous effects of neighborhood economic affluence and disadvantage on health found that the percentage of families earning $30,000 or more in 1980 (180% of the national median income) and the percentage of unemployed persons predicted chronic conditions independent of individual and family SES (Robert 1998). Data were from a nationally representative study linked to census area data, although the author did not specify which census area was used. Neighborhood effects were not significant for all predictors and outcomes; nevertheless this research suggested the importance of considering both ends of the income distribution.

The most extensive examination of affluence (four of the six studies located) has been conducted by Browning, Cagney, Wen and colleagues using data from the Chicago Neighborhood Survey (PHDCN-CS), described earlier. In all studies they measured affluence as the percentage of households with incomes $50,000 or over in 1990. This is equal to 170% of the 1990 national median of $30,000, and when adjusted for the Consumer Price Index is equivalent to $66,000 in 2000 (for comparison to studies using 2000 census data).

Three of these studies included residential stability and were reviewed in the previous section (Browning and Cagney 2003; Browning, Cagney, and Wen 2003; Wen, Browning, and Cagney 2003). All found evidence that affluence at the neighborhood cluster level was a significant predictor of health, and that neighborhood affluence accounted for a substantial portion of the racial disparity in health in this sample.

In one study, Wen and colleagues used three different measures to comparatively evaluate the effects of neighborhood economic structure on health: concentrated affluence, concentrated poverty, and income inequality as measured by the Gini coefficient (Wen, Browning, and Cagney 2003). They found that affluence but not poverty or income inequality had significant contextual effects on health. Further, they found that a composite measure of social resources partially explained the effect of affluence and exerted an independent effect on individual health, suggesting that the presence of affluent residents is essential to neighborhood social organization. This interpretation is consistent with findings of Galea and Ahern that wider distribution of educational levels at the neighborhood level, using the Gini coefficient of education inequality, was associated with some indicators of better short-term health (Galea and Ahern 2005).

Wen and colleagues extended this work further in a study of the effects of advantageous social environment, measured by community economic structure and social processes, on mortality of seriously ill elderly in Chicago (Wen, Cagney, and Christakis 2005). They found that advantageous socioeconomic context and collective efficacy contributed to lower mortality risk. Social support did not affect mortality; however, social network density was detrimental to health.

For this review I found only two empirical studies of neighborhood income inequality and health. Both demonstrated that neighborhood-level income inequality was associated with worse health outcomes. A study in New York City found that income inequality by community district was significantly associated with fatal drug overdose independent of individual and neighborhood level factors (Galea, Ahern, Vlahov, Coffin, Fuller, Leon, and Tardiff 2003). Two different measures of income distribution were used, Gini coefficient and percent of total income earned by the lowest earning 70% of households. A Canadian study using data from the National Population Health Study compared two aspects of economic structure, five measures of income inequality, and neighborhood income levels using median share (quintiles based on median income) (Hou and Myles 2005). They found that the association between average neighborhood health and income inequality is partly due to contextual effects associated with high and low inequality neighborhoods. This suggests that high neighborhood inequality is a proxy for concentrations of both disadvantaged and advantaged groups. However, the inequality measures do not capture *how* neighborhoods differ.

In my review of the literature in the residential stability domain, I found only four published studies that examined the interaction between neighborhood residential stability and income composition (Browning and Cagney 2003; Browning, Cagney, and Wen 2003; Kubzansky et al. 2005; Ross, Reynolds, and Geis 2000). Of these only Ross and colleagues did not include a measure of affluence. All four found that neighborhood income modifies the effect of residential stability on health, such that in neighborhoods with high economic advantage, stability has a beneficial effect on health, while in neighborhoods of low economic advantage, stability is detrimental to health. None of the affluence measures included middle income.

This small body of evidence supports the notion that different aspects of neighborhood economic structure have differing contextual effects on population health and may partially explain why health effects vary across neighborhoods. The findings regarding affluence imply that what matters is not simply the percent of one's neighbors who are "not poor," but also the percent of those who are high income. Racial and economic segregation are integrally related, and the finding in two studies that affluence accounted for a substantial portion of racial disparities is an area for further investigation. Understanding *how* the distribution of income both within and between residential neighborhoods affects health may help us understand racial inequalities in health. With the exception of drug overdose, none of these studies investigated mental health outcomes.

C. Mental Health and Neighborhood Socioeconomic Context

Until recently, most of the current generation of empirical work on neighborhood effects has examined physical health outcomes. While there is a long line of research on the effects of neighborhood disadvantage and disorder on delinquency and crime (Faris and Dunham 1939), studies examining other aspects of neighborhood structure are only recently being published. A review of the literature in 2001 (Pickett and Pearl 2001) found only one of the 25 reviewed studies to investigate mental health outcomes (Reijneveld 1998). A recent chapter on mental health in cities cited six studies that examined spatial characteristics of urban areas and mental health (Freudenberg, Galea, and Vlahov 2006), all of which found an association between neighborhood characteristics and mental health except one (Reijneveld 1998). A review article on the built environment and mental health included five studies on neighborhood physical and social quality and found consistent evidence of association with mental health outcomes (Evans 2003a), and I have included in this review two studies on the built environment that found some associations between neighborhood housing conditions and depression (Galea et al. 2005; Weich, Blanchard, Prince, Burton, Erens, and Sproston 2002). The literature is growing rapidly, however, and a recent systematic review of the literature on neighborhoods and mental health identified 29 studies for inclusion (Truong and Ma 2006). All but two found statistically significant associations between mental health and at least one measure of neighborhood characteristics.

For this dissertation, I reviewed the adult mental health literature that had a substantial focus on neighborhood structural factors other than, or in addition to, poverty, including: race, ethnicity, income composition or distribution, financial stress, or social resources and processes. I identified thirteen published articles on neighborhood structural factors and mental health relevant to the current investigation, five of which are already described in the previous two domains (see Table 3). Only one of the mental health studies included a measure of affluence and none included a measure of the proportion of middle income residents. All but one study found a significant association between at least one neighborhood characteristic and mental health, and that study did not include neighborhood poverty as a measure (Henderson, Diez-Roux, Jacobs, Kiefe, and West 2005). In contrast to the literature in the other two domains in this review, only half of the mental health studies used multilevel modeling to account for the hierarchical structure of the data.

Twelve of the included studies examined indicators of depression or depressive symptoms, most using the Center for Epidemiologic Studies Depression Scale (CES-D), a widely used measure of depressive symptoms (Radloff 1977). Only two of the studies measured diagnosable major depressive disorder (Cutrona, Russell, Brown, Clark, and Gardner 2005; Silver, Mulvey, and Swanson 2002). All studies of depression found a neighborhood effect over and above individual factors. Kubzansky and colleagues found that living in a poor neighborhood (percent poverty in census tract) was associated with higher depressive symptoms among older adults in New Haven (Kubzansky et al. 2005). Affluence defined as percent individuals with 1980 income over $75,000 was marginally significant ($p \geq .10$) and residential stability was not significant after taking into account individual level factors. Silver and colleagues (2002) and Ross and colleagues (2000) found significant effects of tract level residential stability on mental health and were discussed above. Silver and colleagues examined several mental disorders, including major depression, schizophrenia and substance abuse, and found that depression was more prevalent in economically disadvantaged and residentially mobile neighborhoods. Similarly, Ross and colleagues found that residents of poor stable neighborhoods have higher levels of psychological distress than residents of poor mobile neighborhoods, and that stability was associated with neighborhood disorder in poor stable neighborhoods.

Cutrona and colleagues found that rates of diagnosable depression (measured by the CIDI) were significantly higher among women living in neighborhoods characterized by high poverty and social disorder compared to women living in neighborhoods with low poverty and disorder (Cutrona et al. 2005). However, this association was not significant two years later in this longitudinal study.

In a large study of census tract neighborhoods in 25 metropolitan areas in Canada, Matheson and colleagues used factor analysis to identify two composite measures of neighborhood chronic stress—residential instability and material deprivation—and two measures of population structure—ethnic diversity and dependency. Controlling for neighborhood diversity and dependency and individual factors, neighborhood stability and deprivation were significantly associated with depression (Matheson, Moineddin, Dunn, Creatore, Gozdyra, and Glazier 2006).

In a study of Baltimore residents at the block group level, Caughy and colleagues stratified their sample by racial and economic composition to examine the relationship between social capital, neighborhood impoverishment, and child mental health (Caughy, O'Campo, and Muntaner 2003). Using parental attachment to community as an indicator of social capital, the investigators found that children of parents who knew few neighbors had fewer internalizing problems in poor neighborhoods compared to children of parents who knew many neighbors. The reverse was true in more advantaged neighborhoods, consistent with the social isolation theory supported by the work of Ross and colleagues (2000). Although the outcome was child as opposed to adult mental health, it makes an important contribution to this literature review because it tests social isolation theory, that social ties may be detrimental to health in neighborhoods of concentrated poverty (Wilson 1996). The sample was comprised of African American families in high poverty neighborhoods.

An experimental study, Moving to Opportunity, found that parents in families who were moved from concentrated public housing to low poverty neighborhoods experienced less distress than those who remained in high poverty neighborhoods (Leventhal and Brooks-Gunn 2003). Elliott stratified data from a telephone survey of adults into lower or higher SES neighborhoods (defined by zip code) in an examination of the stress process framework (Elliott 2000). Both social support and financial strain mediated the relationship between SES and mental health, and social support was only protective in higher SES neighborhoods.

Only one study (Henderson et al. 2005) failed to find a significant association between neighborhood disadvantage and mental health. In that study, investigators examined the association between neighborhood socioeconomic characteristics and ethnic density and depressive symptoms using data from the four city CARDIA study. The inability to use multilevel modeling and the selection of measures may have been inadequate to detect the effects of income distribution. This was the only study in the mental health portion of this review that did not include percent poverty as a neighborhood measure.

A number of studies included measures of neighborhood racial and ethnic composition and found no association with mental health controlling for individual level factors (Elliott 2000; Goldsmith, Holzer III, and Manderscheid 1998; Kubzansky et al. 2005; Leventhal and Brooks-Gunn 2003; Silver, Mulvey, and Swanson 2002). Three studies specifically examined the effects of racial or ethnic concentration. Using data from the Detroit Area Study (described under Boardman above), Schulz and colleagues split their sample by high-low poverty area and included race as a variable in the multivariate model to examine the effects of neighborhood poverty, racial segregation, and individual experiences of unfair treatment on psychological distress (Schulz et al. 2000). They found that both psychological distress and life satisfaction were significantly associated with unfair treatment and neighborhood percent poverty. However, once differentials in poverty and unfair treatment were accounted for, racial differences in psychological distress and life satisfaction were eliminated or reversed. This study provides further evidence of the complex relationship between the role of race and class in neighborhoods structured by racial segregation (Browning and Cagney 2003; Browning, Cagney, and Wen 2003; Schulz, Williams, Israel, and Lempert 2002; Williams and Collins 2001).

Henderson and colleagues stratified their sample by race and gender to examine the effects of neighborhood economic and racial composition on depressive symptoms. Weak associations between racial composition and depressive symptoms largely disappeared after controlling for individual and neighborhood socioeconomic characteristics (Henderson et al. 2005).

Consistent with other findings, a study of neighborhood ethnic composition, poverty, and depressive symptoms in a sample of older Mexican Americans found that neighborhood poverty was positively associated with depression (Ostir, Eschbach, Markides, and Goodwin 2003). However, the study also found that Mexican American concentration was associated with a decrease in depressive symptoms, indicating that in some areas ethnic concentration may have a protective effect on mental health.

In this domain of the literature review I found a growing body of investigation into the relationship of neighborhood structural factors and mental health. Only half of the studies used multilevel methods for analysis and only two defined neighborhood at the block group level. As in the two previously discussed domains, there is evidence that neighborhood factors interact in complex ways, such that structural characteristics such as stability or racial composition may affect mental health differently in different types of neighborhoods. A number of the studies went beyond establishing associations to explore pathways by which neighborhood socioeconomic structure influences health. However, this work is dominated by the social disorder/social isolation theory. While most of the studies examined depressive symptoms, only two used a measure of diagnosable depressive disorder. All of the studies found that individual factors made the most substantial contribution to mental health; however, in most studies modest neighborhood effects of neighborhood economic structure remained after controlling for individual characteristics.

Summary of the Literature and Need for Further Research

The published research to date suggests that structural characteristics of neighborhoods interact in important ways for residents' health. Residential stability may be detrimental to health in economically disadvantaged communities by constraining mobility and exposing residents to stressful social and physical environments from which they cannot easily leave. There is a small but consistent body of evidence that the effect of neighborhood economic disadvantage on health is partially mediated by social and physical disorder, collective efficacy, and sense of community. However, the several studies that include measures of social ties, including network density and social support, have either found insufficient evidence of mediation, or have found that the effects differ depending on the degree of neighborhood impoverishment. Social isolation may be protective in impoverished neighborhoods (Caughy, O'Campo, and Muntaner 2003), while social ties may be protective in neighborhoods with higher socioeconomic status (Elliott 2000). However, the emphasis on social relations and processes as the primary pathway between neighborhood stability and health continues to dominate research. I found little examination of the role of collective economic resources (property values, public services, amenities) and the resultant financial vulnerability or security of neighborhood residents.

Further, other aspects of the income distribution within a neighborhood besides socioeconomic disadvantage appear to be consequential to health. In particular, the presence of affluent residents may provide important social, political, and material resources that are more predictive of health than the prevalence of poverty. No studies examined percent middle income or included middle income residents in the measure of affluence. I found only one study that explored the pathways through which affluence affects health (Wen, Browning, and Cagney 2003). While that study included measures of health-enhancing services and a composite measure of social resources, there is a need to investigate the role of collective material resources as a pathway between neighborhood stability, advantage and health, particularly in lower income neighborhoods.

This body of literature has added to our understanding of the neighborhood economic advantage. However, I found no studies that examined the effects of the proportion of middle income residents, as distinct from those who are affluent, on the stability-health relationship, particularly in primarily low income urban centers. In spite of references to loss of middle income residents from inner cities, there were no studies of the effects of change in neighborhood income composition on health.

The recognition that neighborhood context has an effect on mental as well as physical health opens new avenues for exploring how neighborhoods affect psychological well being and disease. Little is known, however, regarding what aspects of mental health are influenced by particular contexts, and at what level "neighborhood" matters. While most of the mental health studies examined depressive symptoms, the two studies that used measures of diagnosable major depressive disorder also found significant neighborhood effects, warranting further study of depression. All but two of the studies defined neighborhood at the tract level or larger. However, the findings of neighborhood effects at the block group level suggest that smaller geographic areas are important for at least some mental health outcomes (Caughy, O'Campo, and Muntaner 2003; Cutrona et al. 2005).

Finally, the literature reviewed here provides evidence that most, if any, effects of neighborhood racial composition on health disappear when controlling for individual characteristics. Including measures of racial composition when investigating the effects of neighborhood residential and economic conditions on health is essential to understanding how racial sorting into communities of advantage or disadvantage has contributed to racial health inequalities.

Table 3.1 Summary of Empirical Studies of Neighborhood Residential Stability and Health

Authors • Method of Analysis – Neighborhood Definition	Health Outcomes	Neighborhood Structural Variables	Main Findings
Kubzansky *et al.* (2005) • Multilevel linear regression – Tract	Depressive symptoms (CES-D)	% poverty % Black residents % > 5 years living in same home % over age 65 % individuals with income > $75,000 Service environment (Yellow Pages)	Living in poor neighborhood was associated with higher levels of depressive symptoms in older adults. Higher proportion elderly associated with better mental health. No significant association with affluence, residential stability, racial heterogeneity
Matheson *et al.* (2005) • Hierarchical logistic regression – Census block group clusters	Depression (CES-D 4+ symptoms)	4 neighborhood chronic stress factor scores: Residential instability (7 census variables) Material deprivation (6 variables) Dependency (3 age structure variables) Ethnic diversity (immigrants and minorities)	Neighborhood instability and material deprivation predict depression. Neighborhood dependency and ethnic diversity do not predict depression
Boardman (2004) (Detroit Area Study 95) • Multilevel linear modeling – Tract	Overall physical health	Residential stability: • % ownership • % in same residence 5 yrs earlier	No main effect of stability on health Stability moderates the effect of stress: negative effect of stress on physical health is stronger in unstable neighborhoods. Neighborhood variations in health are mediated by individual sociodemographic characteristics. Neighborhood variation in stress levels partially accounts for neighborhood variation in health status. High stability buffers effects of high stress.

Authors • Method of Analysis – Neighborhood Definition	Health Outcomes	Neighborhood Structural Variables	Main Findings
Cagney & Browning (2004) • Multilevel logistic regression – Clusters of tracts (NCs)	Asthma, respiratory diseases	Concentrated disadvantage factor score (6 variables including race) Residential stability factor score: • Same residence 5 years earlier • % owner-occupied housing units Collective efficacy Disorder	Neighborhood collective efficacy is protective against asthma. Residential stability is positively associated with asthma but significant only when collective efficacy is controlled. Perceived disorder does not predict asthma
Browning, Cagney, & Wen (2003) • Multilevel logistic regression; spatial analysis – NCs	Self-rated health	Level 1: individual Level 2: across time Level 3: poverty, affluence, residential stability scale (above), immigrant concentration	Affluence partially explains variation across neighborhoods. Poverty is not a predictor. Affluence accounts for a substantial portion of African American–White health disparity. Affects hold controlling for spatial autocorrelation.
Browning & Cagney (2003) • Multilevel linear and logistic regression – NCs	Self-rated health	Economic structure: • % poverty • % affluence Residential stability scale: • 5 years same house • % owner occupied Immigrant concentration: • % Latino • % foreign born Stability x affluence interaction	Neighborhood affluence more powerful predictor than poverty. Affluence + residential stability interact: If low affluence, residential stability is negatively associated with health. Neighborhood affluence accounts for large part of racial gap. Collective efficacy predicts health but does not mediate effects of structural factors.

Browning & Cagney (2002) • Multilevel logistic regression – Neighborhood Clusters	Self-rated physical health	Concentrated disadvantage factor score (5 years include poverty, race) Residential stability factor score: • 5 years same house • % owner-occupied housing Immigrant concentration: • % Latino • % foreign born	No neighborhood socioeconomic effect. Residents of higher collective efficacy neighborhoods report better health. Disadvantage and collective efficacy condition positive effects of individual level education on health.
Silver, Mulvey, Swanson (2002) • PCA factor analysis to create indices • HLM	Mental disorder (DIS) Schizophrenia, major depression, substance abuse disorder	Socioeconomic disadvantage: • 7 census factors Residential mobility: • % not 5 yrs LOR • % rented housing Racial/ethnic heterogeneity: • <90% white or <90% black	Structural characteristics affect mental health net of individual characteristics. Disadvantage ↑ depression, substance abuse. Mobility ↑ depression, substance abuse, schizophrenia. Mechanism: Authors suspect social disorganization.
Ross, Reynolds, & Geis (2000) • Mln - Tract	Psychological distress	% poverty + % 5 years same residence (LOR) Interaction	Effects of Residential Stability: Test of cohesiveness vs. social isolation theories supports isolation theory: • Stability does not reduce perceived disorder. • Psychological distress does not stem from lack of social ties. • Stability at high poverty ↑ depression • Stability at low poverty ↓ depression

Table 3.2 Summary of Empirical Studies on Neighborhood Economic Structure and Health

Authors • Method of Analysis – Neighborhood Definition	Health Outcomes	Neighborhood Socioeconomic Structure Measures	Main Findings
Kubzansky *et al.* (2005) • Multilevel linear regression – Tract	Depressive symptoms (CES-D)	% poverty % Black residents % > 5 years living in same home % over age 65 % individuals with income over $75,000 Service environment (services listed in Yellow Pages)	Living in poor neighborhood was associated with higher levels of depressive symptoms in older adults. Higher proportion elderly associated with better mental health. No significant association with affluence, residential stability, racial heterogeneity
Wen, Cagney, Christakis (2005) • Cox proportional hazards models – Zip codes	Mortality	Contextual SES • % household income >$50,000 • % poverty • % college graduates Contextual social index: Collective efficacy, social support, network density, organizations, participation, violence, victimization Separate social factors above.	Affluence, education, composite SES are protective; poverty is deleterious. Collective efficacy is protective, but not with violence and victimization in the model. Social support, civic involvement have no effect. Social network density detrimental. Contextual social index protective. Some social environment factors mediate the effect of community SES on mortality
Hou & Miles (2005) • HLM – Tract	Self-perceived health	Income quintiles based on median income Income inequality quintiles (using 6 different measures: 4 standard measures, Gini index, and median share)	The negative ecological correlations between neighborhood health and income inequality is partly due to contextual effects associated with low and high inequality neighborhoods.
Galea *et al.* (2003) • GEE	Fatal drug overdose	Income maldistribution (separately) • Gini coefficient (income distribution and extent of inequality)	Both neighborhood-level income maldistribution measures were associated with fatal drug overdose.

Authors • Method of Analysis – Neighborhood Definition	Health Outcomes	Neighborhood Socioeconomic Structure Measures	Main Findings
– CDs		• % total income earned by lowest 70% (equitable income distribution)	
Wen, Browning, & Cagney (2003) • Hierarchical logistic regression – NCs	Self-rated health	Affluence (household income >$50,000) Poverty Income inequality (Gini coefficient) Physical disorder Services Crime Aggregated education Aggregated social resources	Affluence significantly associated with health. Poverty and income inequality were not predictive. Social resources (social capital) explains affluence effect and has independent contextual effect Physical disorder mediates effect of affluence on health although less than social resources. Aggregated education highly significant
Browning, Cagney, & Wen (2003) • Hierarchical logistic regression – NCs	Self-rated health	Level 2: across time Level 3: % poverty % affluence (incomes > $50,000) Residential stability scale: • 5 years same house • % owner occupied Immigrant concentration • % Latino • % foreign born	Affluence partially explains variation across neighborhoods. Poverty is not a predictor. Affluence accounts for a substantial portion of African American–White health disparity. Affects hold controlling for spatial autocorrelation.
Browning & Cagney (2003) • Hierarchical logistic regression – NCs	Self-rated health	Economic structure: • % poverty • % affluence Residential stability scale: • 5 years same house • % owner occupied Immigrant concentration:	Neighborhood affluence more powerful predictor than poverty. Affluence + residential stability interact: If low affluence, residential stability is negatively associated with health. Neighborhood affluence accounts for large part of racial gap. Collective efficacy predicts health but does not

Authors • Method of Analysis – Neighborhood Definition	Health Outcomes	Neighborhood Socioeconomic Structure Measures	Main Findings
		• % Latino • % foreign born Stability-affluence interaction	mediate effects of structural factors.
Robert (1998) • OLS regression	Disease (# chronic conditions) Disability (functional limitations) Self-rated health	Separately, simultaneously, and as index: % households receiving public assistance % adult unemployment % families with incomes > $30,000 Economic disadvantage index (sum of the above three measures)	Neighborhood affluence and % unemployed predicted chronic conditions independent of individual SES. % of households receiving public assistance predicted self-rated health.

Table 3.3 Summary of Empirical Studies on Mental Health and Neighborhood Socioeconomic Structure

Authors • Method of analysis – Neighborhood definition	Outcomes, Measures	Neighborhood Structural Measures	Findings
Henderson *et al.* (2005) • Multiple regression (Stratified by race, gender) – Block group	Depressive symptoms (CES-D)	Neighborhood score & separate: • median income • median house value • % w/ interest income • % HS • % college • % exec/management occupancy • % black, white	Neither neighborhood socioeconomic characteristics nor ethnic density were consistently related to depressive symptoms once individual characteristics were taken into account.
Kubzansky *et al.* (2005) • Multilevel linear regression – Tract	Depressive symptoms (CES-D)	% poverty % Black residents % > 5 years living in same home % over age 65 % individual income over $75,000 Service environment (services listed in Yellow Pages)	Poverty associated with higher depressive symptoms in older adults. Higher proportion elderly associated with better mental health. No significant association with affluence, residential stability, racial heterogeneity
Matheson *et al.* (2005) • Multilevel logistic regression – Census block group clusters	Depression (CES-D 4+ symptoms)	4 neighborhood chronic stress factor scores: Residential instability (7 census variables) Material deprivation (6 variables) Dependency (3 age structure variables) Ethnic diversity (immigrants and minorities)	Neighborhood instability and material deprivation predict depression. Neighborhood dependency and ethnic diversity do not predict depression

Authors • Method of analysis – Neighborhood definition	Outcomes, Measures	Neighborhood Structural Measures	Findings
Cutrona *et al.* (2005) • Multilevel logistic regression – Block group cluster	Major depression (UM-CIDI)	Combined index of 2 other indices: Neighborhood disadvantage index: mean income, female headed, public assistance, poverty, unemployed men Perceived social disorder index: community dilapidation and community deviance (aggregated survey responses)	Modest but not significant cross-level interaction: higher neighborhood disadvantage/disorder modified effect of negative life events on depression
Ostir *et al.* (2003) • Multilevel analysis – Tract	Depressive symptoms (CES-D)	% poverty % Mexican American	Neighborhood poverty positively associated with depression. Mexican American concentration associated with decrease in depression.
Leventhal & Brooks-Gunn (2003) • Regression	Depression, anxiety (parental) Child behavior	Census: • % race • median income • % poverty • % rentals Parent reported disorder, satisfaction Interviewer-rated poor environment	Impoverished parents who moved to low poverty neighborhoods experienced less distress than those who stayed in high poverty. Boys had fewer problems.
Ross *et al.* (2000) • Multilevel analysis – Tract	Depression (modified CES-D) Anxiety (3 items)	Interaction: • % poverty + % 5 years same residence	Supports isolation theory not cohesiveness theory of effects of stability: • Stability does not reduce perceived disorder. • Psychological distress does not stem from lack of social ties. (Statewide sample 84% white, includes rural, suburban)

Authors • Method of analysis – Neighborhood definition	Outcomes, Measures	Neighborhood Structural Measures	Findings
Elliott (2000) • SEM – Zip code	Depressive symptoms (CES-D) Self-report physical health	Neighborhood SES index Median income, % black, public assistance, female headed, female headed in poverty	Social support is protective only in higher SES neighborhoods. Financial strain mediates individual SES-health relationship. Sense of community mediates SES-mental health relationship.
Ross (2000) • Multilevel analysis – Tract	Depressive symptoms (CES-D)	Neighborhood Disadvantage Index: • % poverty • % mother-only households	Individual factors (composition) account for half the effect of neighborhood disadvantage on depression but significant contextual effect remains. Neighborhood disorder mediates the association.
Schulz *et al.* (2000) • OLS regression – Tract	Psychological distress Life satisfaction	>20% below poverty Split sample by race and High-Low poverty area	Mental health negatively associated with both unfair treatment and neighborhood poverty. Racial differences disappeared.
Caughy *et al.* (2003) • OLS Regression – Block group	Child behavior (CBCL)	Neighborhood impoverishment factor score (4 items based on Korbin and Coulton 1997), also stratified by racial composition AA or mixed, others	Effects of parental attachment to community differ depending on degree of neighborhood impoverishment: Poor: Low attachment $\rightarrow$ low child behavior problems. Wealthy: Low attachment $\rightarrow$ high child behavior problems. Social isolation protective in high poverty

Silver *et al.* (2002) • Multilevel and ordinary logistic regression – Tract	Mental disorder: • Schizophrenia • Major depression • Substance abuse disorder	Socioeconomic disadvantage (factor score): • 7 census factors Residential mobility • % not same house 5 years earlier • % rented housing Racial heterogeneity • <90% white or <90% black	Neighborhood Disadvantage ↑ depression, substance abuse. Neighborhood Mobility ↑ depression, substance abuse, schizophrenia. Racial heterogeneity Hypothesized mechanism: social disorganization.
Goldsmith *et al.* (1998) • Logistic regression – Tract	Schizophrenia Affective disorders Other disorders	Economics: use median to determine quartiles Hi/Med/Low. Lifestyle: family, married Race: 90% white, 90% minority, mixed	Neighborhood characteristics not associated with mental illness except “social rank” was significant.
Galea et al (2005) • Multilevel logistic regression – Community districts	Depression (National Women’s Study module)	Neighborhood built environment: Internal and external housing conditions	Living in neighborhood with poor quality built environment is associated with greater likelihood of depression.

CHAPTER 4.

THEORETICAL FRAMEWORK AND CONCEPTUAL MODEL

A. Fundamental Causes

Fundamental causes of disease are those social conditions that affect multiple diseases through multiple pathways because they determine access to resources that promote health and enable people to avoid disease (Cassell 1976; Link and Phelan 1995). Fundamental causes are durable and influence a variety of health outcomes. Because fundamental causes "embody" resources, such as knowledge, wealth, power, and prestige, their association with disease remains even if the intervening mechanisms change.

Socioeconomic position has long been accepted as a fundamental cause of disease, shaping one's access to physical, social, political and economic resources for avoiding illness and promoting health. Economic segregation, the spatial concentration of wealth and poverty, extends the fundamental causes concept from the individual to the community level by sorting people into environments of risk or opportunity.

Racial residential segregation is an institutional mechanism of racism that is widely considered a fundamental cause of disease. Racial segregation structures access to education and employment opportunities that then determine racial differences in socioeconomic status (Schulz, Williams, Israel, and Lempert 2002; Williams and Collins 2001). In addition, segregation and other forms of racial discrimination expose African Americans and other minorities to environments that are injurious to health.

Public health, and in particular the field of health education and behavior, has inordinately focused on individual level risk factors for disease without paying sufficient attention to the underlying structural causes. Operating from a fundamental cause framework compels us to address inequitable social and economic relations that are among the most enduring and consequential fundamental causes of disease.

B. Social Ecological Framework

The social ecological framework posits that health is determined through interaction between people and their physical and sociocultural environments (Stokols 1992). In ecological models of health, “environment” refers to space external to the individual, rather than to psychological processes interior to the individual (Sallis and Owen 1997).

In addition, an ecological framework recognizes that determinants of health exist at multiple levels. Individuals are embedded in sequentially larger systems that influence their exposure as well as response to health risks and resources. McLeroy and colleagues identified five levels of influence: intrapersonal, interpersonal, institutional, community, and public policy (McLeroy, Bibeau, Steckler, and Glanz 1988).

Ecological models have been developed and adapted for a range of health issues. However, five principles have been proposed for applying an ecological framework (Sallis and Owen 1997).

1. There are multiple dimensions of influence on health behaviors, including those mentioned above.
2. Influences across dimensions interact.
3. There are multiple levels of influence within each of the larger levels listed above.
4. Environmental factors directly as well as indirectly influence behavior.
5. Specific models must be developed for a particular health outcome and population.

C. Ecosocial Framework and Social Determinants of Health

The ecosocial framework is a model that incorporates ways in which social factors simultaneously influence biological patterns of exposure, susceptibility, and disease (Krieger 1994). Krieger developed the ecosocial framework in response to the ecological model, which has been critiqued as implying that determinants of health are comparable to environments in the natural world. According to ecosocial theory, the fundamental determinants of health are social conditions that result from ideologies of exclusion that are often framed as being biologically based, and that have consequences that may manifest as "natural."

The concept of embodiment is the core principle of ecosocial theory, which suggests that social conditions constructed to purposefully distribute resources to the advantage of particular groups become "embodied" in "class physiognomies," that is, revealing characteristics of social class (Krieger 1994). An example is the way in which the structure of immune systems has changed in populations exposed to HIV in racially segregated communities (Wallace & Wallace, 2005).

Social ideologies determine institutional polices and practices that result in unequal distribution of resources and burdens at multiple levels that then become self-perpetuating. Pertinent to this dissertation, racial and class ideologies determine and maintain disadvantageous and advantageous neighborhood environments through racial and economic residential segregation and their interrelationship (Schulz and Northridge 2004; Schulz, Williams, Israel, and Lempert 2002; Williams and Collins 2001). These patterns of exposure then accumulate and become embodied in populations.

D. Conceptual Model for Understanding the Effects of Neighborhood Residential Environments on Depression

The health outcome of this study is major depression. Major depression is a serious medical illness affecting approximately five to eight percent of the adult population in a given year (Blazer, Kessler, McGonagle, and Swartz 1994; Robins and Regier 1990). One of the most common mental disorders, depression is the leading cause of disability in the U.S. from illness, and is a substantial public health burden in terms of reduced physical and social functioning (Lloyd, Jenkins, and Mann 1996), higher mortality (Huppert and Whittington 1995), and increased risk for heart disease and other chronic illnesses (U.S. Department of Health & Human Services 1999).

Unlike normal emotional experiences of sadness or anxiety, depression causes significant distress and impairment in social, work, and other areas of functioning. Major depression is manifested by a combination of symptoms that include persistent sad or empty mood, loss of interest, feelings of hopelessness and helplessness, social withdrawal, unusual fatigue, loss of concentration, problems with sleep and appetite, physical symptoms that do not respond to treatment, and thoughts of suicide (American Psychiatric Association 1994).

Environmental stressors and resources are widely regarded as influential factors in the onset and course of mental disorders. The conceptual model for this dissertation is based on the literature review and three theoretical frameworks discussed above, and is illustrated in Figure 4.1. I describe the components of the model moving from left to right The specific components to be tested in this study are in bold type and shaded. Diagrams of separate models to be tested are displayed in the next chapter for each hypothesis.

From the left, the model shows two macro-level social and economic forces, institutionalized racism and economic restructuring. As described in Chapter 2, economic restructuring and persistent institutionalized racial discrimination have jointly produced an inequitable geographic redistribution of populations and economic resources in the Detroit metropolitan region, that is manifested in racial residential segregation and concentration of wealth and poverty (Jargowsky 1997a; Jargowsky 1997b; Massey and Denton 1993).

Racial residential segregation and concentration of economic resources combine to profoundly shape the socioeconomic structure of Detroit's residential neighborhoods, in particular the three structural characteristics that are central to this dissertation: residential stability, income composition, and racial composition, shown in the center of Figure 4.1. These three interrelated characteristics of neighborhoods are consequential to mental health in that they influence the availability of material and social resources that are essential to mental well being, as well as conditions that are detrimental to mental health. Structural characteristics of neighborhoods can be an important source of chronic stress because they are relatively persistent and uncontrollable at the individual level. Uncontrollable stressors may undermine mental health more than controllable ones (Pearlin, Lieberman, Menaghan, and Mullan 1981).

Drawing on the ecological framework and structural and environmental stress models of mental health (Pearlin, Lieberman, Menaghan, and Mullan 1981; Selye 1956; Silver, Mulvey, and Swanson 2002; Wandersman and Nation 1998), I conceptualize stability, income, and racial composition as jointly influencing the neighborhood resource environment that mediates between neighborhood socioeconomic structure and individual experience of stress or resources. This resource environment is illustrated in the diagram as "Neighborhood Mediating Features: economic climate, social environment, physical environment, infrastructure and services, and political influence." (In this dissertation I did not test this component of the conceptual model.)

For example, neighborhood stability may influence neighborhood and individual economic standing through property values, access to opportunity structures, infrastructure and services, and the character of physical and social environments to which residents are exposed on a daily basis. Stable neighborhoods may also enable residents to develop lasting social networks that can influence neighborhood conditions through organization, provide social and material support, and provide psychological coping resources that are important to mental well being.

Neighborhood income composition both determines and is a marker of the quality and quantity of salutogenic resources or pathogenic exposures. In the context of substantial population decline and economic disinvestment, a sufficient proportion of middle income residents may be essential for maintaining neighborhood economic standing through political influence, housing stock and property values, markets for local business and services, and a source of social and economic support for individual residents. Higher percentage of middle income residents may provide a buffer against residents' sense of hopelessness and fears of further neighborhood decline, as well as a collective and individual buffer against economic vulnerability.

However, residential stability and neighborhood middle income composition may interact such that the protective value of stability depends on adequate stocks of economic, political, social, and other resources within the neighborhood (shown as neighborhood mediating features in the conceptual model diagram). In neighborhoods with few middle income and affluent residents, residential stability may expose residents to chronic environmental stress over which they have little or no control, leaving them financially vulnerable and at increased risk of mental disorder. In addition, the persistent daily experience of being unable to influence or move from such circumstances may engender a sense of hopelessness and powerlessness. The experience of financial vulnerability is represented at the individual level in the conceptual model diagram as a mediator between neighborhood structure and individual depression. The model suggests that people living in stable (constrained mobility) neighborhoods with few middle income residents will experience higher rates of depression compared to those in neighborhoods with relatively more middle income residents.

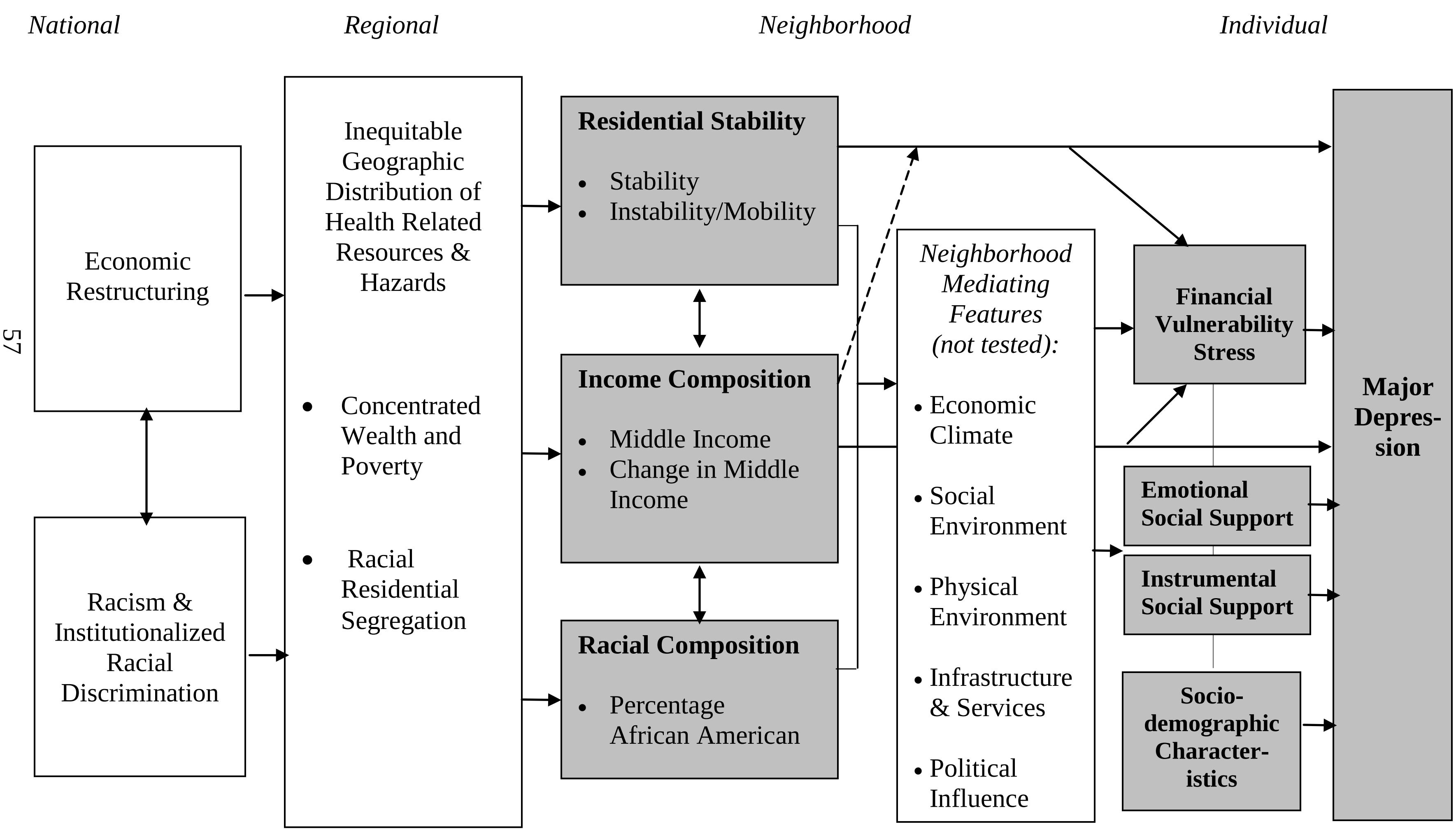
Further, social networks may not have adequate resources to buffer the effects of chronic structural stress or provide connections to opportunities outside the neighborhood, either in stable or unstable neighborhoods. While it is likely that neighborhoods with more economic advantage have higher social support resources, I predict that individual level social support will not be sufficient to mediate the relationship between structural stress and depression.

Detroit neighborhoods continue to lose middle income residents, as described in Chapter 2, contributing to reduced neighborhood resources, increased stress, and feelings of psychological distress among those who remain. In this conceptual model I propose that residential stability will be associated with higher rates of depression among current residents in neighborhoods with relative decline in proportion middle income, compared to neighborhoods with the same or a higher proportion of middle income residents.

The racial concentration of African Americans in less economically advantaged neighborhoods has been pervasive and substantial in Detroit and has resulted in the city now being 81% African American. In this context, I suggest that the impact of neighborhood residential stability on depression will not be influenced by the percent of African Americans in the neighborhoods.

The next chapter presents a set of research questions and hypotheses that I will examine to test this conceptual framework.

Figure 4.1 Conceptual Model of Social Determinants of Neighborhood Residential Environments on Depression in Detroit, Michigan



CHAPTER 5.

RESEARCH QUESTIONS AND HYPOTHESES

As previously described, neighborhood residential stability and neighborhood income composition may interact in ways that are consequential to mental health, above and beyond the characteristics of the individuals who live there. In this dissertation I investigate how these two structural characteristics of neighborhoods jointly affect mental health in economically disinvested older cities with a high degree of economic and racial segregation. In particular, I hypothesize that stability is beneficial to mental health in neighborhoods with a higher percentage of middle income residents, but is deleterious to mental health in neighborhoods with low percentage of middle income residents. I further suggest that the racial composition of neighborhoods does not predict mental health or the relationship between stability and mental health, above and beyond residents' individual socioeconomic characteristics. Finally, I explore potential pathways through which stability and middle income affect mental health. In particular I separately examine whether financial vulnerability, emotional social support, or instrumental social support, as experienced by individual residents, mediate the effects of neighborhood stability and middle income on mental health. I test these hypotheses in three geographic areas of Detroit, Michigan.

I extend the literature by using diagnosable depression (CIDI) as the indicator of mental health for this dissertation. I found only two published studies that examined the prevalence of major depression. Although my literature review found a small body of research examining the link between neighborhood effects and depressive symptoms, the effects are relatively small and there is a more consistent association with neighborhood social disorder than with neighborhood economic status. Major depression, while less prevalent, may be a more sensitive measure than depressive symptoms at capturing the chronic effects of neighborhood structure. Daily exposure to the persistent, cumulative stress of living in an environment of low collective resources and from which residents are powerless to leave, may trigger the onset of major depression.

Based on my review of the literature and conceptual model, I test three sets of hypotheses to investigate these relationships. Figures 5.1 – 5.4 at the end of this chapter display the model for each research question.

A. Research Question 1

First, I examine the relationships between neighborhood residential stability, middle income composition, and mental health, as indicated by major depression:

Does neighborhood residential stability affect mental health above and beyond characteristics of individual residents, and does that effect vary based on the proportion of middle income households in the neighborhood?

This investigation extends the literature by examining the effects of that segment of the neighborhood income composition comprised of middle income households, rather than upper income households. I further extend the literature by conducting this study in a primarily low to moderate income older urban community with a compressed income distribution. In this context, I hypothesize that higher proportion of middle income residents will be beneficial to mental health. I hypothesize that neighborhood residential stability will have a modest protective effect on mental health overall. Based on prior research that neighborhood affluence modifies the effect of stability on health, I hypothesize that percent middle income will similarly modify the effect of stability on mental health as described below. Figure 5.1 is a model of the first set of hypotheses.

Hypothesis 1.1: Neighborhood residential stability will be significantly associated with lower probability of depression, controlling for individual characteristics.

Hypothesis 1.2: Neighborhood percent middle income will be significantly associated with lower probability of depression, controlling for individual characteristics.

Hypothesis 1.3: Neighborhood percent middle income will modify the effect of neighborhood residential stability on depression, with stability predicting lower rates of depression when the proportion of middle income households is high and higher rates of depression when the proportion of middle income households is low, controlling for individual characteristics.

I further contribute to our knowledge in this domain by testing whether a change in the neighborhood proportion of middle income residents modifies the effect of stability on mental health. I found no other studies of the effects of neighborhood structural change on health in the literature.

Hypothesis 1.4:

Change in neighborhood percent middle income between 1990 and 2000 will modify the effect of neighborhood residential stability on depression, with stability associated with higher rates of depression under conditions of declining neighborhood middle income, accounting for individual factors.

B. Research Question 2

In the second research question, I investigate whether the effects of neighborhood stability and middle income on mental health differ based on neighborhood racial composition, measured by percent African American residents, as illustrated in Figure 5.2. This question investigates the role neighborhood effects might play in racial health disparities:

In the context of ongoing regional and local racial residential segregation, does the effect of neighborhood residential stability on depression differ based on neighborhood racial composition, measured by percent African American residents?

Hypothesis 2.1:

Neighborhood racial composition (% African American) will have no main effect on the probability of depression among residents, accounting for individual characteristics.

Hypothesis 2.2:

Neighborhood racial composition will not modify the effect of neighborhood residential stability on depression.

C. Research Question 3

In the third set of analyses I investigate the mechanisms through which residential stability influences mental health. I examine whether financial vulnerability and social support as experienced at the individual level mediate the effects of neighborhood stability and neighborhood middle income on mental health (Figure 5.3):

Are financial vulnerability and the resources available through social networks pathways through which neighborhood residential stability and neighborhood middle income affect mental health?

Departing from the social isolation theory that dominates the literature, I suggest that the structural resource advantages in neighborhoods with higher stability and higher economic standing are somewhat enduring and provide a measure of individual financial security in an otherwise severely economically stressed city, above and beyond that provided through individual social relationships. To test this, I hypothesize that perceived financial vulnerability mediates the relationship between residential stability and depression, and between neighborhood middle income and depression. People living in stable neighborhoods or neighborhoods with higher percent middle income residents will experience lower rates of depression than those living in unstable neighborhoods or neighborhoods with proportionately fewer middle income residents, in part because they experience lower financial vulnerability. Based on findings in the literature, I hypothesize that neither emotional nor instrumental social support will mediate these neighborhood effects on depression.

Hypothesis 3.1:

Financial vulnerability of individual residents will mediate the effects of neighborhood residential stability on mental well being.

Hypothesis 3.2:

Financial vulnerability of individual residents will mediate the effects of neighborhood middle income on depression.

Hypothesis 3.3:

Perceived emotional social support will not mediate the effects of neighborhood residential stability on depression.

Hypothesis 3.4:

Perceived instrumental social support will not mediate the effects of neighborhood residential stability on depression.

Hypothesis 3.5:

Perceived emotional social support will not mediate the effects of neighborhood middle income on depression.

Hypothesis 3.6:

Perceived instrumental social support will not mediate the effects of neighborhood middle income on depression.

In the next chapter, I describe the design and methods I will use in conducting this investigation.

Figure 5.1 Research Question 1

Do neighborhood residential and middle income composition separately predict depression? Does middle income composition modify the effect of residential stability on depression, controlling for individual factors?

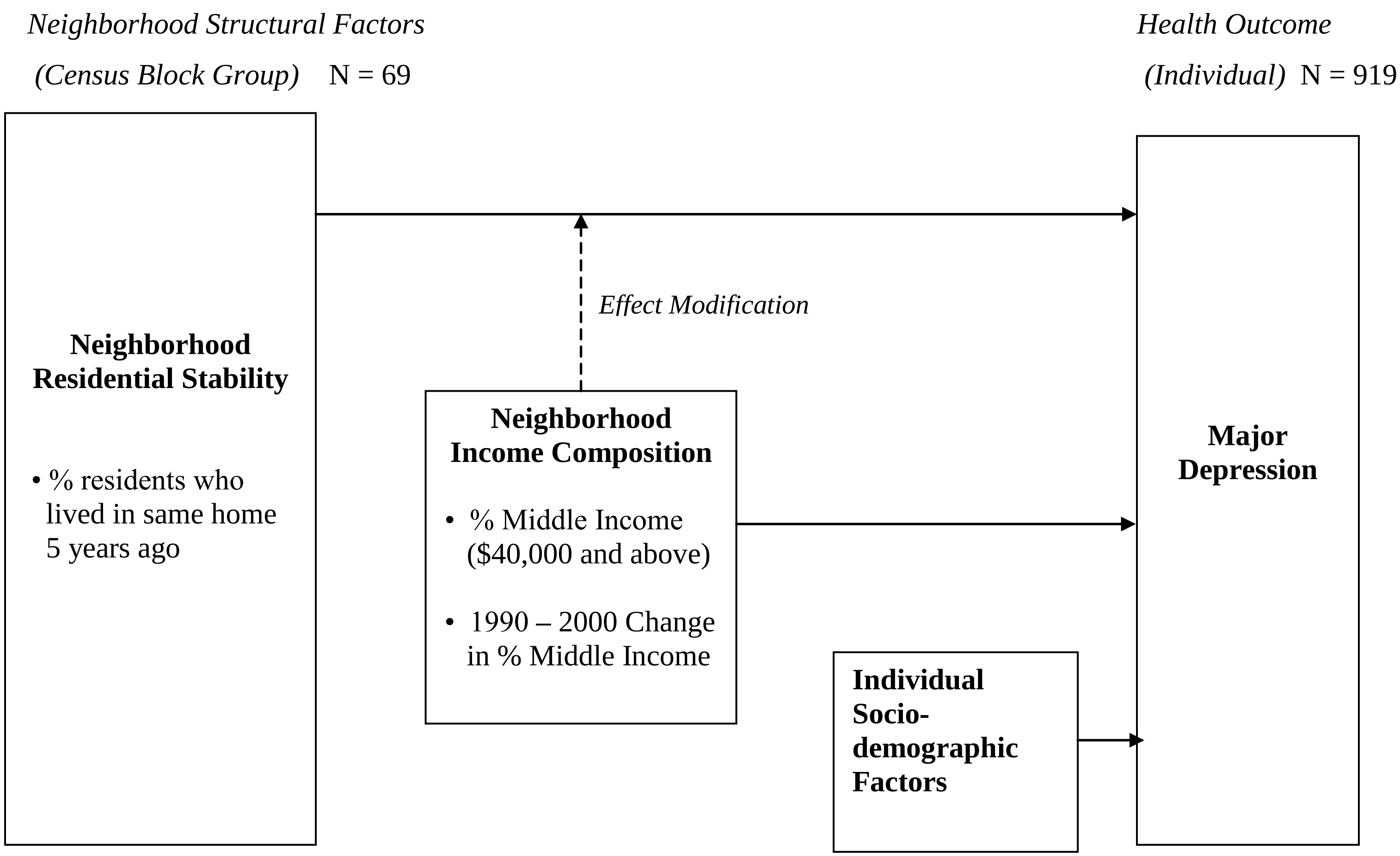


Figure 5.2 Research Question 2

Does neighborhood racial composition predict depression? Does neighborhood racial composition modify the effect of residential stability on depression, controlling for individual factors? (Hypothesized no effects)

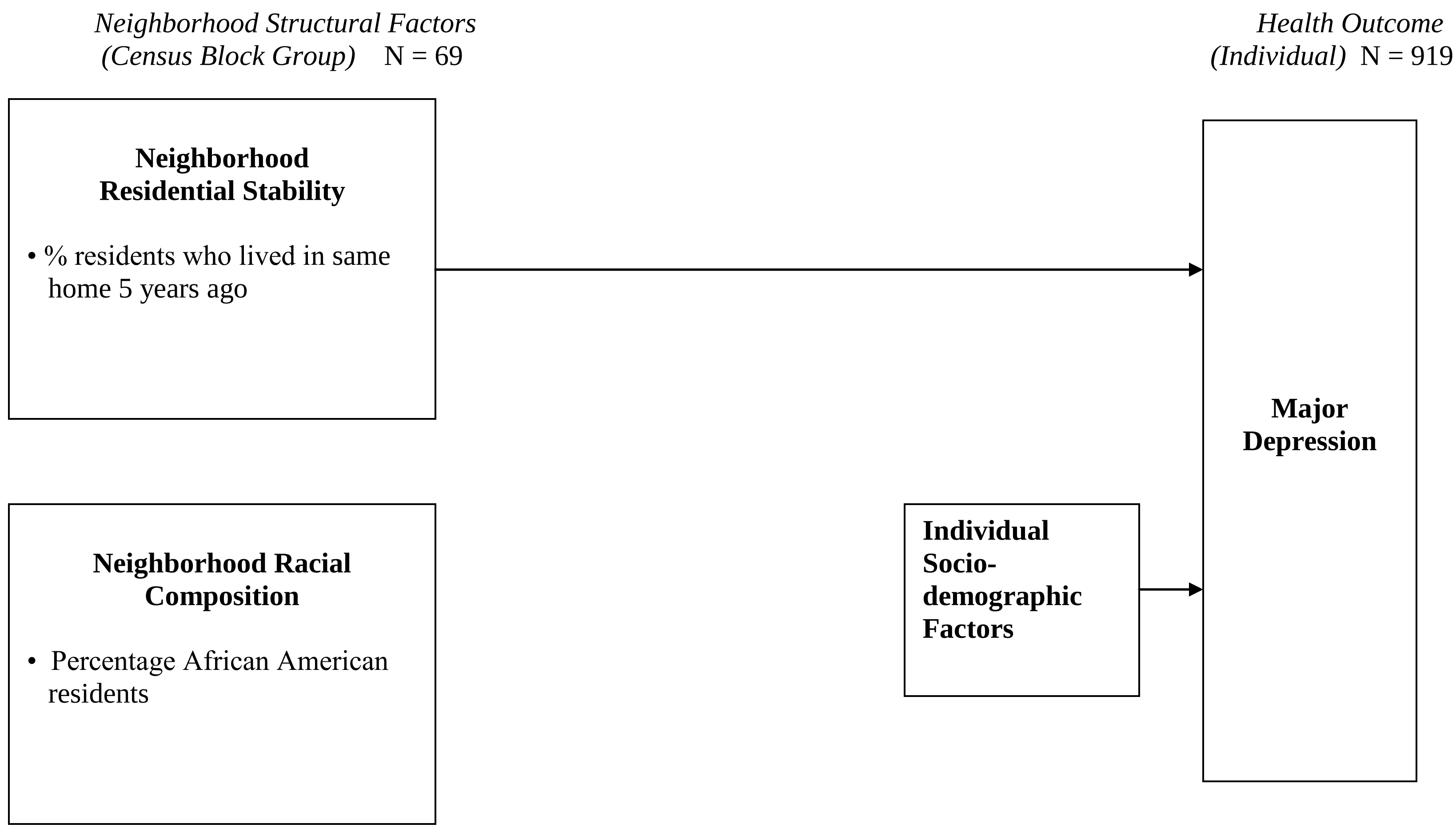
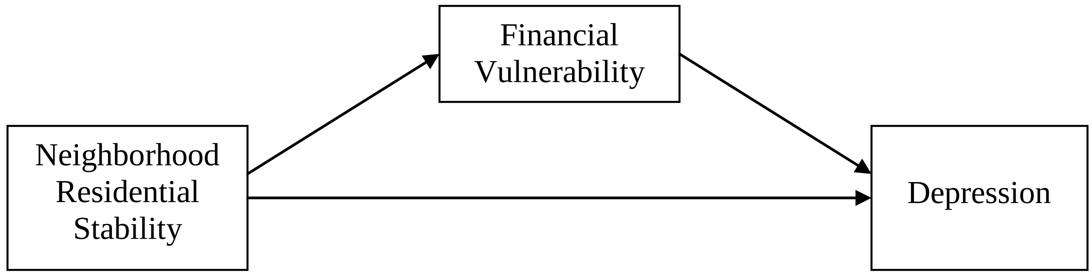


Figure 5.3 Research Question 3, Hypotheses 3.1 – 3.2

Does financial vulnerability mediate the relationship between residential stability and depresson? Between neighborhood middle income and depression?



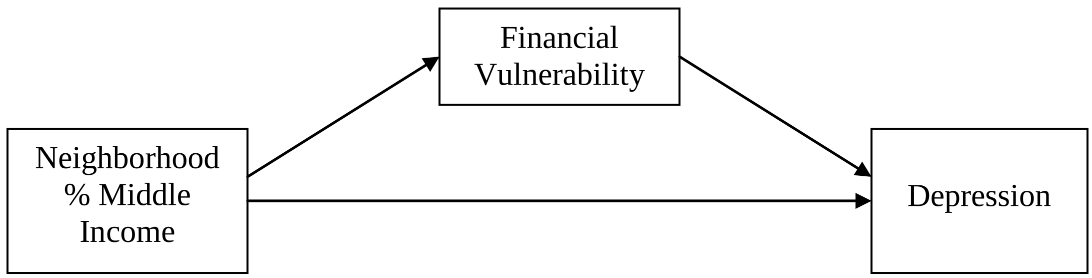
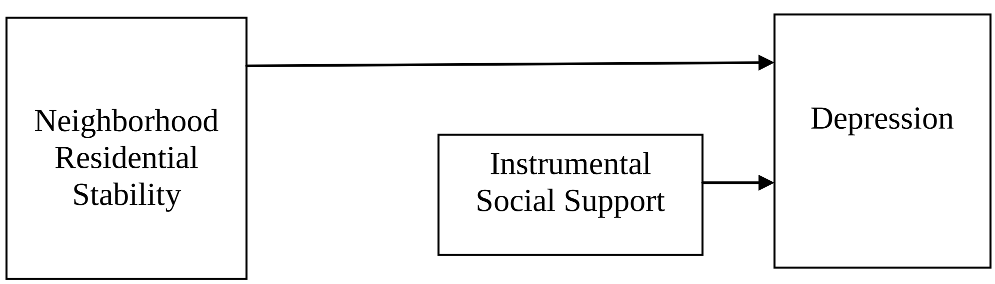


Figure 5.4 Research Question 3: Hypothesis 3.4

Instrumental social support does not mediate the relationship between residential stability and depression.



CHAPTER 6.

RESEARCH DESIGN AND METHODS

A. Overview of research design

I use multilevel analysis to investigate the effects of neighborhood context on the mental health of individual residents for all three research questions. In hierarchical data, individuals within neighborhoods are more similar to each other than they are to individuals in different neighborhoods with respect to exposure to the residential environment, and most likely with respect to individual characteristics. This violates the assumption of independence necessary for simple regression. Multilevel analysis (hierarchical modeling) accounts for this non-independence by statistically partitioning the variability in individual outcomes into two levels: between-group and within-group (Diez Roux 2004). In this way the effects of neighborhood environments on individuals can be estimated while still accounting for their non-independence.

I use two-level hierarchical logistic regression to test the first set of hypotheses, that neighborhood stability and percent middle income separately predict depression among individual residents, and that the neighborhood percent middle income residents modifies the effect of stability on depression. I include individual characteristics associated with depression to assess whether the effects of stability on depression are over and above individual characteristics. Next I examine the second set of hypotheses to determine if the effects of stability on depression are independent of the racial composition of neighborhoods. Finally, in the third set of analyses I explore mediation effects of three pathways to explain the observed relationship between stability, percent middle income, and depression. First, I test the extent to which financial vulnerability mediates the relationship between residential stability and depression, and the extent to which financial vulnerability mediates the relationship between percent middle income and depression. Next I test whether emotional social support mediates the relationship between each of the two neighborhood factors and depression. Finally, I test whether instrumental social support mediates the relationship between residential stability and depression, and the relationship between neighborhood middle income and depression.

B. Data and Measurement

Sample

All individual level data are from the Healthy Environments Partnership Community Survey. The Healthy Environments Partnership (HEP) is a community-based participatory research project established in 2000 to conduct research on relationships between social inequalities, the physical and social environments, and cardiovascular disease, and to develop interventions to address racial and socioeconomic disparities in cardiovascular disease risk in Detroit.

The HEP survey is a stratified, multi-stage probability sample survey of 919 adults age 25 and older in three Detroit neighborhoods. The survey was conducted in 2002 and

2003 and included items on a range of physical and mental health indicators, including depression, behavioral and biological risk factors for cardiovascular disease, social stressors, responses to stress, conditioning factors, such as social support, and aspects of the neighborhood social and physical environment.

The HEP sampling strategy was designed to attain approximately equal representation by race, ethnicity, and socioeconomic status in the final sample, in order to allow comparisons across and within groups by racial, ethnic, and socioeconomic status. Because of disparate composition on all three characteristics, some groups were oversampled, resulting in a set of respondents that is not fully representative of the population. To account for this complex sampling design, weights were computed to allow the findings to be interpreted as representative of the population. The final weighted sample consisted of 515 (56%) non-Hispanic African American, 203 (22%) Hispanic/Latino, 168 (18%) non-Hispanic white, and 25 (3.3%) other race residents (Table 7.1). All regression analyses are weighted using Strata and Sampling Error Computing Units (SECU) to properly account for design features of HEP that would yield biased estimations of variance. These weights were developed for HEP by the University of Michigan Survey Research Center (Lepkowski and Xie 2004).[2]

The geographic area I use for neighborhood data is comprised of those census block groups for which there are HEP survey respondents. All neighborhood level data are from

[2] For a detailed description of the HEP survey see Schulz, Amy J., Srimathi Kannan, J. Timothy Dvonch, Barbara A. Israel, Alex III Allen, and Sherman A. James. 2005. "Social and physical environments and disparities in risk for cardiovascular disease: the Healthy Environments Partnership conceptual model." *Environmental Health Perspectives* 113:1817-1824.

Summary File 3 of the 2000 US Census (US Bureau of the Census) and are at the block group level. The rationale for selecting block groups as the unit of analysis is discussed in the measures section, below. 1990 data for the change in affluence variable (Hypothesis 1.4) is from the Neighborhood Change Data Base in which 1990 SF-3 data has been spatially adjusted to conform to 2000 census boundaries for geographic areas that changed over that time period (Geolytics Inc. 2004).

The HEP block groups range in population from 321 to 2020 with a mean population of 944 residents 5 years and older per block group. The number of survey respondents ranges from 1 to 39 per block group, with an average of 13.3 respondents per block group. Because the survey data is weighted to account for the complex sampling design, all HEP block groups are used in the analyses.

Measures

Dependent Variable: Depression

Depression was measured by the University of Michigan Composite International Diagnostic Interview (UM-CIDI). The UM-CIDI is a modification of the CIDI, a structured psychiatric diagnostic interview that can be used by lay interviewers to assess mental disorders according to the definitions and criteria of ICD-10 (World Health Organization 1991) and DSM-IV (American Psychiatric Association 1994). A UM-CIDI statistical algorithm was used to map symptoms reported on 28 survey items onto depression diagnostic criteria yielding a classification of whether the individual met diagnostic criteria for major depression sometime within the previous 12 months.

The CIDI was developed as a collaborative project between the World Health Organization and the US National Institutes of Health and has been extensively used in a variety of settings and populations worldwide (World Health Organization 1997). The UM-CIDI was initially developed for use in the National Comorbidity Study, and has been shown to have excellent inter-rater reliability, good test-retest reliability, and good validity in diverse populations (Kessler, Wittchen, Abelson, McGonagle, Schwarz, Kendler, Knauper, and Zhao 1998; Kessler, Wittchen, Abelson, and Zhao 2000; Williams, Gonzales, Neighbors, Nesse, Abelson, Sweetman, and Jackson 2007; Wittchen 1994; Wittchen and Kessler 1994).

Independent Variables: Neighborhood Level Measures

Defining Neighborhood

How to define and measure neighborhood is a topic of considerable discussion in the neighborhood effects literature (Diez Roux 2001; Krieger, Chen, Waterman, Rehkopf, and Subramanian 2003; Krieger, Waterman, Chen, Soobader, Subramanian, and Carson 2002; O'Campo 2003). “Neighborhood” is an ambiguous term that refers to a meaningful locality that may be characterized by some degree of homogeneity, social interaction, and place identity (White, 1987). Neighborhood boundaries are often not clearly defined, and public health researchers must rely on available standardized statistical definitions of place such as zip codes, census geographies, and administrative areas. In order to select the appropriate neighborhood unit of analysis, we must conceptualize pathways through which particular neighborhood contexts may affect a specific health outcome (Galea, Ahern, and Karpati 2005).

I used U.S. Census Bureau block group geography as a proxy for neighborhoods in order to examine an area small enough to capture aspects of the everyday residential environment that may be consequential to depression, yet large enough to contain sufficient variability to detect effects on mental health. Census block groups have an average population size of 1000 people and are the smallest geographic areas for which all of the data for these analyses are publicly available. Census block groups are more homogeneous than tracts, which have an average population size of 4000 people. Because block groups are smaller than tracts, they are more likely to approximate locally defined neighborhoods where residents spend time, interact, and establish relationships over time with institutions, services, and people.

Using block groups extends the literature because in my literature review I located only two studies that used block group data (Caughy, O'Campo, and Muntaner 2003; Henderson et al. 2005). One study was at the block level, but the measures were aggregates of the individuals in the sample. Although census data is also aggregate sample data, it is based on a larger population than a survey sample and therefore may more accurately capture the population of the area.

All neighborhood measures for this dissertation were continuous percentages expressed as whole numbers. Although interactions between continuous variables can be difficult to interpret, creation of categorical variables would reduce the power to detect significant effects even if they do exist (Aiken and West 1991; Cohen 1988). I conducted diagnostic tests and examined plots to assess normality and look for extreme outliers, as will be discussed in Chapter 6. However, regression with binary outcomes does not require normally distributed variables. Additionally, I created median split and three level categorical variables for all neighborhood factors for descriptive purposes and for plotting and interpreting interactions.

Residential stability

Residential stability and mobility are two ends of a continuum that characterize the flux of people into and out of a residential neighborhood. Stable neighborhoods are those that have a high proportion of persons who have lived in the same residence for at least the past five years. In my review of the literature I found that six of the seven studies of residential stability and health used a composite measure comprised of two highly correlated items—percent of persons living in the same residence five years earlier and percent of housing units occupied by owners. Although homeowners are typically more stable than renters, in some areas, such as in public housing, renters have high rates of stability. While there is substantial evidence that homeownership is associated with better health compared to renting (Hiscock, Macintyre, Kearns, and Ellaway 2003), homeownership is conceptually different than stability and may more accurately be a measure of wealth than a proxy for stability. Therefore, I measured residential stability as a single item continuous variable, the percentage of individuals who reported in 2000 having lived in the same residence in 1995, derived from the US Census variable for residential stability, P024.

Neighborhood Income Composition: Middle Income, Poverty, and Change

As described in the literature review, published research to date has examined the health effects of neighborhood poverty and affluence, but not middle income. In selecting a measure, I needed to define middle income, maximize the available data, retain sufficient statistical power to detect interaction effects, and be able to interpret results.

To measure the extent of middle income residents in the neighborhood, I used the percent of residents reporting annual household income of $40,000 or more. This cutpoint corresponds to the census income category closest to the national median household income, which was $41,994 in 2000. I used the national median instead of a more local median, such as Detroit city or Detroit metropolitan area, because of the extreme concentrations of low and high income in the region. Additionally, the national median may capture a more comparable and absolute standard of middle income than local medians.

Because definitions of middle income are less standardized and more contextually relative than definitions of poverty or socioeconomic disadvantage, I considered several other measures of middle income. The US Census does not have an official definition, although the middle quintile is commonly used. The Department of Housing and Urban Development uses a relative standard, defining middle income as between 80 and 120% of the median income for the region under study (U.S. Department of Housing and Urban Development 2004). Absolute measures based on the federal poverty standard include: 200% of poverty ($38,300 for family of four), 250% of the poverty threshold, and a definition of economic middle class as the range of two to five times the federal poverty standard (Farley, Danziger, and Holzer 2000).

Although labeled as “middle income” throughout this dissertation, the measure I selected included all household incomes at or above the cutpoint of $40,000. Thus, any high income households (affluent) were also included. The decision to use a continuous measure with no upper limit was based on several factors.

First, the neighborhood distribution of incomes in Detroit is skewed such that the proportion of affluent residents is very low in most neighborhoods. When affluence is defined as $75,000 or more, which is 180% of the US median household income and is consistent with affluence measures in other studies reviewed), the mean affluence for the HEP neighborhoods is 11%. This compares with a mean of 18% affluence in the Chicago studies (2003, 2005) and 24% in the nationally representative sample used by Robert (Robert 1998). Ninety percent of the HEP Detroit neighborhoods were below 18% affluence.

Second, in order to restrict my variable to middle income, a capped definition of household income would be needed, for example $40,000 - $75,000. This would not adequately capture the broader economic standing of the neighborhood because the effects of low and high ends of the income distribution would be confounded. For example, a block group with 30% middle income and 70% poverty could not be distinguished from a block group with 30% middle income and 70% affluence. This would make it difficult to interpret results, particularly when interactions are present.

To avoid this problem, I used a continuous measure that included middle income and above. However, throughout this dissertation I will refer to this variable as "middle income" and will further discuss the implications in the limitations section.

In addition to middle income, I wanted to examine other dimensions of neighborhood income composition to determine whether the effects of middle income were due to its correspondence with percent poverty, low income, ore moderate income. In other words, as percent middle income increases, percent low income decreases. Because area based socioeconomic measures are highly correlated, it is not appropriate to include several in the same model, and composite indicators mask the relative contributions of their component measures (Wen, Browning, and Cagney 2003).

Therefore I additionally conducted separate analyses of all models replacing the middle income variable with neighborhood poverty to predict depression. I use percentage of household poverty from US Census variable P092, which is the proportion of households in the population who are poor according to the federal poverty standard. Persons are considered poor if they live in households whose total household income is less than a standard threshold meant to represent the cost of basic necessities. The Census Bureau uses a set of monetary income thresholds that vary by household size and composition (U.S. Census Bureau 2006; U.S. Department of Health & Human Services 2006).

To measure change in neighborhood percent middle income from 1990 to 2000 for Hypothesis 1.3, I created a change score by subtracting year 1990 percent middle income from that in 2000. First, I adjusted 1990 income to 2000 dollars using the Inflation Calculator on the Bureau of Labor Statistics website (Bureau of Labor Statistics 2006). The Inflation Calculator estimates adjusted dollars using the average Consumer Price Index for a given calendar year, and represents changes in prices of all goods and services purchased for consumption by urban households. Calculating $30,360 in 1990 as equivalent to $40,000 in 2000, I created a 1990 middle income variable comprised of the corresponding census household income categories. I created a change score by subtracting the resulting percent middle income in 1990 from that for 2000. As described earlier, the middle income variable is comprised of percent residents with middle income or above.

Racial Composition

I define racial composition as the percentage of residents who are non-Hispanic African American based on data from the 2000 U.S. Census. I use this as a continuous measure in regression analyses.

Independent Variables: Individual Level Sociodemographic Variables

Individual sociodemographic and residential characteristics that have been found in prior research to be associated with mental health are included to adjust for their potential impact on depression (Blazer, Kessler, McGonagle, and Swartz 1994; Ross and

Mirowsky 1999; Turner and Lloyd 1999). This enables me to examine whether neighborhood context has effects on individual mental health over and above characteristics of individual residents. These characteristics include age, gender, marital status, race and ethnicity, socioeconomic position, homeownership, and length of residence in the neighborhood. Age in years is continuous and centered on the grand mean. Gender and marital status are dummy variables, with male and married as the respective reference categories in regression analyses reported here. Race and ethnicity is coded as four dummy variables: African American non-Hispanic (NH), Other Race NH, Latino, and White NH. White NH is the omitted category in regression analyses.

Socioeconomic status is operationalized by education and income. Highest year of education completed was coded as dummy variables: less than high school graduate, high school graduate, and more than high school as the omitted category. Household income was categorized as under $10,000, $10,000-19,999, $20,000-39,999, and $40,000 and above, and dummy coded with the highest income category omitted in analyses. A continuous measure of number of persons in the household is included for its relationship with both economic status and depression, and was mean centered in all analyses.

Length of residence in the neighborhood and homeownership are included to distinguish the effects of neighborhood stability from individual stability, usually referred to as length of residence. Homeownership is also considered to be a measure of economic resources that has been associated with mental health independent of income and is conceptually related to my research questions. Homeownership is dummy coded as own

= 0, not own = 1, and length of residence is classified in four categories and dummy coded as less than 5 years, five to under 10 years, 10 to less than 30 years, and 30 years or more.

For dummy coded categorical predictors in regression analyses, I omit the category generally associated with protective effects on mental health in order to assess how degrees of disadvantage affect depression. These reference categories are white, male, married, highest education and income, homeowner, and over 30 years length of residence. For calculating predicted probabilities to display the interaction in graphical form, all dummy variables are recoded with the referents being those categories predicted to have a positive association with depression. This positions the plots on the probability scale for the group with the highest risk of depression—an average aged African American female, unmarried, with low income and education, average size household, renting, and having moved in the past 5 years.

Individual Level Mediators of the Effects of Neighborhood Stability and Middle Income on Depression

To test the first mediation hypothesis, that financial vulnerability will mediate the effects of residential stability and neighborhood middle income on depression, I use a measure of financial vulnerability comprised of responses to two questions on the HEP survey. The first question assesses non-income financial resources while the second captures current income sufficiency. Respondents were asked:

- If you lost all your current sources of household income—your wages, public assistance, or other sources of income—how long could you continue to live at your current address and standard of living? Less than 1 month = 5, 1 to 2 months = 4, 3-6 months = 3, 7-12 months = 2, or more than 1 year = 1

- How hard is it for you to pay for very basics like food housing, medical care, and heating? Would you say:

  very difficult =4, somewhat difficult = 3, not very difficult = 2, or not difficult at all =1

A scale score was created that is the weighted average of responses to the two individual items to account for the difference in scales (standardized Cronbach's alpha = 0.61).

Social Support

Two separate measures of social support adapted from previous research were used to capture distinct types of social network resources (Heaney and Israel 1997; Israel, House, Schurman, Heaney, and Mero 1989; Strogatz and James 1986). Instrumental social support involves the availability of tangible aid and services that directly assist a person (Israel and Heany 1997) and was measured as a mean scale of responses to the following items:

- If you needed help around the house, for example with cleaning or making small repairs, how often could you get somebody to help without paying them?
- If you were sick, how often would there be somebody who would help care for you?
- If you couldn't use your car or your usual way of getting around for a week, how often could you find somebody who would take you wherever you needed to go?

- If you needed to borrow a fairly large sum of money, how often would you have somebody or somewhere you could borrow it from?

Respondents were included if they answered at least three of the four questions above. Cronbach's alpha for the scale is 0.45.

Emotional social support, the availability of empathy, trust and caring, was measured by a mean scale of two items:

- If you were worried about an important personal matter, how often would there be somebody you could confide in?
- When you have problems, how often would there be somebody you could trust to help you solve them?

All social support items were assessed on a five-point Likert scale from never (1) to always (5). Cronbach's alpha is 0.79.

C. Data Analysis

I use SAS 9.1 (SAS Institute Inc.) to calculate descriptive statistics, manipulate data, and perform single-level analyses, using procedures that incorporate weights to account for the complex sample survey design: proc surveymeans, proc surveyfreq, proc surveyreg and proc surveylogistic (SAS Institute Inc. 2004). Multilevel logistic regression models for the binomial outcome of depression are estimated with HLM 6.04 (Scientific Software International 2006), assuming a Bernoulli distribution and using restricted predicted quasi-likelihood (PQL) estimation. I use over-dispersion to produce an actual estimate of level-1 variance rather than setting it equal to one, in order to account for any unspecified level-1 variance (Raudenbush and Bryk 2002). Over-dispersion can occur if there are extreme outliers or if there are very small group sizes, meaning three or fewer cases (Hox 2002). In the HEP survey data there are 5 block groups with three or fewer cases. I use SPSS 14 (SPSS Inc. 2006) and Microsoft Excel 2003 (Microsoft Corporation 2003) for graphically exploring the data and plotting interactions in the final models.

I created three datasets for these analyses: a level-1 dataset with individual data only (N=919), a level-2 dataset with neighborhood data only (J=69), and a combined dataset that links individual records with neighborhood level census data using a census area FIPS code. To determine the need for multiple imputed data at level 1, I examined missing cases for all variables for the dissertation analyses. There are relatively few missing cases, with household income having the highest number of missing cases at 10 missing out of 919 (1.1%). This small proportion of missing data is unlikely to negatively affect my results, therefore I use non-imputed data and handle missing data through listwise deletion of cases when running analyses.

Sample size and Power Calculations

To estimate whether sample size is sufficient to detect significant effects in the final models, I use Optimal Design Software developed by Raudenbush and colleagues for multilevel models (Raudenbush, Spybrook, Liu, and Congdon 2006b). With hierarchical data, the power to detect significant differences is influenced by the number of individuals in each group (n), the number of groups (j), the variability between groups (rho), and the estimated effect size. Setting alpha at .05, I calculated power for 69 groups (the number of block groups in the sample) with an average of 13 individuals per group. I estimated a very small effect size of .10 based on the neighborhood effects and mental health literature, and an ICC of .10 based on prior research that suggests that ICC for neighborhoods and mental health will generally be smaller than 0.05 to 0.10 (Leventhal and Brooks-Gunn 2000; Raudenbush, Spybrook, Liu, and Congdon 2006a). This yields a power of .98.

Although I found significant effects in the final interaction model, indicating sufficient power to detect effects, I still performed post-hoc power analysis using the actual values in the final model. For the most advantaged reference group, I set the probability of depression in low compared to high stability neighborhoods at 0.045 and 0.143 respectively for low affluence, and at 0.135 and 0.044 for high affluence neighborhoods. The resulting power approached 1.0.

I compute the intraclass correlation coefficient (ICC or rho) and design effect for each final model. The ICC is a measure of the extent to which individuals within the same group are more similar to each other than they are to individuals in different groups. The ICC ranges from 0 to 1, with higher values representing stronger clustering effects, and is calculated as follows:

ICC = level 2 variance / (level 1 variance + level 2 variance)

While the ICC provides useful information, it is not as informative in the case of non-linear model with logit link function (binary outcome) because the level-1 variance is heteroscedastic (Bingenheimer and Raudenbush 2004; Raudenbush and Bryk 2002; Snijders and Bosker 1999). I also compute the design effect per Muthen and Muthen to get a more accurate measure, particularly when the ICC is small:

Design Effect = 1 + ((average cluster size – 1)*ICC)

Data Analysis Procedures and Models

First I examine descriptive statistics for all variables in the analyses. I compute appropriate measures of association to examine correlations among predictors and test for multicollinearity. I examine Pearson correlation coefficients between continuous variables both by constructing the correlation matrix and by regressing each independent variable on all others and examining the resulting R-square. I conduct regression analyses with continuous variables as outcome to estimate point-biserial correlations between pairs of categorical and continuous variables, and to calculate the tolerance statistics and variance inflation factor (VIF). I cross tabulate binary and categorical variables to obtain chi square statistics, phi coefficients, and examine the data for empty cells.

Missing data are handled through listwise deletion of cases when running analyses. Continuous variables are grand mean centered in SAS prior to analysis to decrease multicollinearity and facilitate interpretation of interaction analyses (Aiken and West 1991; Kreft, de Leeuw, and Aiken 1995; Paccagnella 2006; Raudenbush and Bryk 2002). Interaction terms are formed by multiplying grand mean centered variables.

For all three research questions, I use a series of two-level hierarchical logistic regression models to examine the effects of neighborhood characteristics and their interaction on the binary outcome of depression. I report results in separate tables as odds ratios and as beta coefficients in log form (log odds), and as predicted probabilities.

In the first step, I run the random intercept model without any explanatory variables to estimate the probability of depression across all individuals and neighborhoods, and to decompose the total variance into group level (tau) and individual level (sigma squared) variances.

$$\mathrm{Y} = \gamma_{00} + u_{0j} + e_{ij}$$

The interclass correlation coefficient (ICC or rho) is then calculated to estimate the proportion of total variability in depression that occurs between, rather than within, neighborhoods.

$$\rho = \frac{\tau}{\tau + \delta^2}$$

This statistic provides an estimate of how similar individuals from the same neighborhood are to each other compared with individuals in different neighborhoods, and is used to assess how much of the variance is at the group level, hence whether to use multilevel modeling.

Next, I add the individual sociodemographic covariates to the model. Intercepts are allowed to vary across groups, but slopes are assumed to be fixed across groups. The fixed effects model estimates variation of the individual level covariates across groups and is shown as Model 1 in the tables in the results section. The equation for the fixed model is the same for all hypotheses in Research Questions 1 and 2:

$$Depression_{ij} = \gamma_{00} + \gamma_{10} age_{ij} + \gamma_{20} female_{ij} + \gamma_{30} africanamerican_{ij} + \gamma_{40} otherrace_{ij} +$$
$$\gamma_{50} latino_{ij} + \gamma_{60} notmarried_{ij} + \gamma_{70} educationLT\_HSgrad_{ij} + \gamma_{80} educationHSgrad_{ij} +$$
$$\gamma_{90} incomeLT10k_{ij} + \gamma_{100} income10-19k_{ij} + \gamma_{110} income20-39k_{ij} + \gamma_{120} numberpersons_{ij} +$$
$$\gamma_{130} nothomeowner_{ij} + \gamma_{140} LengthResidenceLT5_{ij} + \gamma_{150} LengthResidence5-9_{ij} +$$
$$\gamma_{160} LengthRes10-29_{ij} + u_{0j} + e_{ij}$$

I also model the intercept by each neighborhood predictor without individual covariates, to determine how much of the intercept variance is explained by neighborhood factors only.

$$Y = \gamma_{00} + \gamma_{01} Stability_j + u_{0j} + e_{ij}$$

$$Y = \gamma_{00} + \gamma_{01} MiddleIncome_j + u_{0j} + e_{ij}$$

$$Y = \gamma_{00} + \gamma_{01} ChangeInMiddleIncome_j + u_{0j} + e_{ij}$$

$$Y = \gamma_{00} + \gamma_{01} Poverty_j + u_{0j} + e_{ij}$$

$$Y = \gamma_{00} + \gamma_{01} PercentAfricanAmerican_j + u_{0j} + e_{ij}$$

Finally, I add neighborhood variables singly, together, and with their interaction term to test for effect modification. In this step, neighborhood level variables predict variation of the individual level intercept and slopes. For example, for hypothesis 1.3, the full set of models estimates the extent to which the effect of neighborhood residential stability on depression depends on neighborhood middle income, controlling for individual factors. The equation for the full model for hypothesis 1.3 is:

$$
\begin{aligned}
Depression_{ij} &= \gamma_{00} + \gamma_{01} Stability_{j} + \gamma_{02} MiddleIncome_{j} + \gamma_{03} Stability_{j} MiddleIncome_{j} + \\
&\gamma_{10} age_{ij} + \gamma_{20} female_{ij} + \gamma_{30} africanamerican_{ij} + \gamma_{40} otherrace_{ij} + \gamma_{50} latino_{ij} + \gamma_{60} notmarried_{ij} \\
&+ \gamma_{70} educationLT\_HSgrad_{ij} + \gamma_{80} educationHSgrad_{ij} + \gamma_{90} incomeLT10k_{ij} \\
&+ \gamma_{100} income10-19k_{ij} + \gamma_{110} income20-39k_{ij} + \gamma_{120} numberpersons_{ij} + \gamma_{130} not\,\mathrm{hom}\,eowner_{ij} \\
&+ \gamma_{140} Length\,\mathrm{Re}\,sidenceLT5_{ij} + \gamma_{150} Length\,\mathrm{Re}\,sidence5-9_{ij} + \gamma_{160} Length\,\mathrm{Re}\,s10-29_{ij} \\
&+ u_{0j} + e_{ij}
\end{aligned}
$$

The results of multiple regression with interactions between continuous predictors can be challenging to interpret (Aiken and West 1991). In addition, the logit of the probability for a binomial outcome is not easily interpretable. Therefore, to understand my results, I do a series of calculations and plots to graphically display the effects of stability on depression at different levels of percent middle income. First I calculate the logit of the probability of depression for specific low and high values of stability and low, medium, and high values of middle income, using coefficients from the final interaction model in the following formula:

$$\mathrm{logit}(depression) = \beta_0 + \beta_1(Stability) + \beta 2(MiddleInc) + \beta 3(Stability)(MiddleInc)$$

In choosing specific values for neighborhood middle income, I initially set low at one standard deviation below the mean (19%), medium at the mean (32%) and high at one standard deviation above the mean (45%), following the guidelines of Cohen and Cohen (Cohen and Cohen 1983). However, I subsequently selected cutpoints at 20%, 35%, and 50% as more theoretically meaningful values and mean centered them. To plot simple regression lines from the equation I computed probabilities at four values of stability, 20, 40, 60, and 80% centered on the mean.

To put the results on a more understandable scale than logit, I calculate predicted probabilities of depression and plot them from low to high values of stability for three levels of middle income. Because the original models were computed with the most advantaged reference categories in respect to depression, the resulting probability scale is for the group characterized by the lowest risk of depression (male, white, married, highest income and education, homeowner, residing in the neighborhood for at least 30 years). To display the interaction on the probability scale for the group at most risk of depression, I reran final models using the reference categories most associated with higher depression, computed new probabilities and plotted estimated regression lines. While the slopes remain the same, the intercept changes so that the probability scale now reflects the higher probability of depression for women who are African American, unmarried, very low socioeconomic status, renting, and residing in the neighborhood less than five years. These latter graphs give an estimation of the substantial effects a small difference in neighborhood characteristics has on those groups with lowest socioeconomic advantage. In both sets of equations I control for the continuous variables of age and number of persons in the household by centering at the grand mean.

Testing Mediation

The third research question asks whether the separate effects of neighborhood residential stability and middle income on depression are mediated by individual level financial vulnerability, emotional social support, or instrumental social support. However, in testing hypotheses 1.1 and 1.2, I found no direct effects of neighborhood factors to mediate. Therefore, I additionally examine whether the interaction effect between residential stability and middle income is mediated by these factors. Mediated moderation is when there is initially a moderation effect, and the direct effect of the moderator variable on the outcome is mediated at either the A-B path or the B-C path illustrated in Figure 6.3 (Muller, Judd, and Yzerbyt 2005). I follow Baron and Kenny causal steps method for testing mediation (Baron and Kenny 1986; Judd and Kenny 1981), conducting all analyses in HLM.

In describing the steps here, I refer to depression as the outcome, financial vulnerability as the mediator, and "stability-income interaction" as the effect modification between neighborhood stability and middle income. The four steps are:

Step 1: Show that stability-income interaction is correlated with depression.

Step 2: Show that stability-income interaction is correlated with financial vulnerability.

Step 3: Show that financial vulnerability affects depression.

Step 4: Establish whether financial vulnerability completely or partially mediated the relationship between stability-income interaction and depression.

If steps 2 and 3 are not met, then it can be assumed there is no mediation.

In the next chapter, I describe my results.

CHAPTER 7.

RESULTS

A. Descriptive Statistics

Table 7.1 shows weighted descriptive statistics for individual survey participants (unweighted N = 919). The mean age of participants was 46 years (SE = .84), and age ranged from 25 to 96. Slightly over half of the sample were female. The sample is 56% non-Hispanic African American, with the remainder primarily white (18%) and Latino (22%). 26% of respondents were currently married, and the number of persons in the household ranged from 1 to 11, with an average of 3. The majority of respondents were low or very low income, with 55% reporting annual household incomes of less than $20,000 (N = 476); of those over half had incomes below $10,000. 17% (N = 77) of survey respondents reported incomes over $40,000.

The sample was divided roughly in thirds by educational attainment of less than high school graduate, high school graduate, or some college/college graduate. About half of individuals in the sample owned their own home, and the average length of time residing in the neighborhood was 17 years, with 32% of individuals residing there less than five years and 25% residing there longer than 30 years. The average length of residence in Detroit for survey respondents was 33 years.

Table 7.1 Descriptive Statistics for Individual Level Variables Weighted for Complex Survey Design (HEP Community Survey, N=919).

Variables	Percent	Freq.	Weighted Freq.	Mean (Standard Error)	Min.-Max.
Outcome					
Depression (CIDI)	18.1	180	166		
Independent Variables					
Age				46.28 (0.84)	25 – 96
Gender:					
Female	52.3	632	479		
Male	47.7	287	438		
Race/Ethnicity:					
African American (non-Hisp.)	56.2	517	515		
White (non-Hispanic)	18.3	195	168		
Other (non-Hispanic)	3.3	25	30		
Latino (Hispanic)	22.2	182	203		
Marital status:					
Married	26.5	230	242		
Living w/ partner	9.2	76	84		
Separated	6.3	66	57		
Divorced, annulled	16.2	158	148		
Widowed	9.5	87	86		
Never married	32.3	297	295		
Household Income (all sources)					
Less than $5,000	10.3	97	90		
$5,000-9,999	17.7	146	154		
$10,000-19,999	26.9	233	234		
$20,000-29,999	18.4	172	160		
$30,000-39,999	10.4	90	90		
$40,000-49,999	6.5	54	57		
Over $50,000	9.8	77	82		
# persons in household				2.79 (0.09)	1 – 11
1	33.8	298	310		
2	19.7	185	181		
3	15.1	143	138		
4	13.4	119	123		
5 to 11	17.9	174	176		
Education					
Less than HS	13.6	114	123		
Some high school	23.7	213	214		
High school graduate	29.5	258	266		
Some college	26.0	253	234		

College graduate	7.2	67	65		
Home ownership					
Owned or being bought	48.51	423	444		
Rented or other	51.49	495	472		
Years residing in neighborhood				16.70 (0.69)	0 – 82
Less than 5 years	32.39	294	296		
5 to less than 10 years	16.04	146	147		
10 to less than 30 years	26.55	248	243		
30 or more years	25.01	228	229		
Years residing in Detroit				33.0 (0.81)	.08 – 88
Financial Vulnerability				3.06 (0.05)	1 – 5
Emotional Social Support				4.03 (0.04)	1 – 5
Instrumental Social Support				3.40 (0.04)	1 – 5

The average score on the financial vulnerability scale of 1-5 was 3.06 (SE = .05). On average, participants reported relatively high levels of emotional social support, with a mean score of 4.03 on a scale of 1-5 (SE = .04). The mean of instrumental support was somewhat lower: 3.40 on a 5 point scale (SE = .03).

Characteristics of neighborhoods in the sample are reported in Table 7.2. There was wide variation in neighborhood characteristics among block groups within the parameters of the study. Residential stability, the percent of individuals residing in the same home as five years earlier, ranged from 21 to 88 percent, with a mean of 57 percent across all block groups (SD = 13.57). This compares to citywide data from the 2000 US Census at the individual level (not aggregated by block group) that 60% of Detroit residents lived in the same home five years earlier.

Table 7.2 Descriptive Statistics for Neighborhood Characteristics (2000 U.S. Census Block Groups, J=69).

Variables	Mean/Proportion	Median	Standard Deviation	Minimum	Maximum
Total Population in Block Group	944	885	362	321	2020
Residential Stability (percent living in same residence as 1995)	0.57	0.55	0.14	0.21	0.88
Middle Income (≥$40,000)	0.32	0.29	0.13	0.07	0.77
Change in Middle Income (1990 – 2000)	0.05	0.05	0.97	-0.24	0.27
Poverty	0.30	0.31	0.11	0.06	0.58
Concentrated poverty (≥40% households in poverty)	0.19		0.39		
Race/Ethnicity:					
African American (non-hispanic)	0.68	0.83	0.36	0	1.00
White (non-hispanic)	0.14	0.15	0.14	0	0.72
Latino/Hispanic	0.15	0.01	0.27	0	0.84
Foreign born	0.08	0.02	0.13	0	0.44
Median Household Income (average of medians across all block groups)	$ 27,419	24,904	11,137	10,583	83,115*

* Extreme outlier

The mean across neighborhoods of households with middle income or above was 32% (SD = 13), and the range was 7% to 77%. The mean of household poverty was 30 percent, with a low of 6% and a high of 58% of households in the block group having incomes less than the poverty threshold. Nearly a fifth of neighborhoods were characterized by concentrated poverty, that is, having more than 40% of households with incomes below the poverty line.

The change in percent middle income from 1990-2000 ranged widely from a 24% decline to a 27% increase in neighborhood percent middle income. There was an extreme outlier at the low end (-24%) with the next closest value being -12%. The mean among neighborhoods was a 4.8% increase in percent middle income from 1990-2000 (SD = 9.7).

The data were normally distributed for all neighborhood characteristics except percent African American, which was bimodal and skewed (Shapiro-Wilk = .79; p = <.000). As described earlier, racial segregation is a prominent and enduring feature of Detroit city and the metropolitan area. In the sample, percent African American residents ranged from 0 – 100, with a mean of 68% (SD = 35.6). Of the 69 block groups in the sample, only 4 (6%) had a racial composition between 30 and 70% African American, indicating a high degree of racial concentration within and racial segregation among block groups, in spite of a sampling design which attempted to include a range of neighborhood types by race and income.

Correlations Between Independent Variables

As would be expected, a number of socio-demographic characteristics were correlated, however no bivariate correlations exceeded the threshold for exclusion from the regression models due to multicollinearity. Pearson correlation coefficients for continuous individual and neighborhood variables were all under 0.60 with the exception of emotional and instrumental social support (0.68; p<.0001), which will not be included in the same model to avoid problems of multicollinearity. Tabulations of binary and categorical independent variables revealed no empty cells and phi coefficients were all under <0.5. To test for multicollinearity between neighborhood and categorical or binary individual factors, I regressed each of the continuous neighborhood variables on all individual variables in the analyses and examined the variance inflation factor (VIF). The VIF for all bivariate relationships between neighborhood and individual variables were well under the acceptable level of 2.5.

Table 7.3 reports zero-order correlations between neighborhood variables as measured by Pearson Correlation Coefficients. The two neighborhood income variables, percent poverty and percent middle income, are highly correlated (-0.76; p<0.001) and will not be included in the same model to avoid the problem of multicollinearity. Residential stability is correlated only with percent African American (0.36; p<0.01). This is well below the conventional limit of <.60 for preventing excessive multicollinearity.

Table 7.3 Zero-Order Correlation Matrix of Neighborhood Characteristics: Pearson Correlation Coefficients

	Correlation				
Neighborhood Characteristics	1.	2.	3.	4.	5.
1. Residential stability	1.00				
2. Middle income	-0.08	1.00			
3. Household poverty	0.12	-0.76***	1.00		
4. Change middle income	0.06	0.26*	-0.10	1.00	
5. African American	0.36**	-0.12	0.14	-0.17	1.00

*p<0.05, **p<0.01, ***p<0.001

N_j = 69 block groups

Depression

Table 7.4 reports point estimates for depression for categories of individuals and neighborhoods without adjusting for any covariates. Estimates were obtained through cross tabulation and are not multilevel. Across all individuals and neighborhoods, approximately 18% (N = 180, weighted N = 166) of the HEP survey participants met criteria for major depression within the past 12 months. There was substantial variation among subgroups, as can be seen in the table below.

Table 7.4 Point Estimates of Depression by Individual and Neighborhood Characteristics without Controls (weighted for complex survey sample design)

Sample Characteristics	Percent Depression	Standard error of percent
Individual Characteristics		
Gender		
Female	22.3	1.7
Male	13.5	2.1
Race and Ethnicity		
African American (non-Latino)	18.1	1.8
White (non-Latino)	21.8	3.3
Latino	14.4	2.8
Marital Status		
Married	15.1	2.5
Not married	19.2	1.6
Household income		
Less than $10,000	24.9	3.0
$10,000-19,999	19.5	2.8
$20,000-39,999	14.4	2.2
Over $40,000	12.6	2.9
Education		
Less than HS	16.7	2.2
High school graduate	21.5	2.8
More than High school	16.5	2.2
Homeownership		
Owned or being bought	13.6	1.7
Rent or other	22.4	2.1
Length of residence in the neighborhood (years)		
Less than 5 years	22.2	2.6

5 to less than 10 years	23.1	3.9
10 to less than 30 years	15.9	2.4
30 or more years	12.0	2.2
Neighborhood Level Characteristics		
Residential stability		
Low Residential stability (<20%)	27.6	6.9
Medium Residential stability (20-<40%)	15.8	1.8
High Residential stability (>40%)	20.1	2.2
Middle income households		
Low % Middle income (<20%)	20.2	2.6
Medium % Middle income (20-<40%)	18.5	2.1
High % Middle income (>=40%)	15.7	2.4
Household poverty		
Low % Poverty (<20%)	15.6	3.8
Medium % Poverty (20-<40%)	17.9	1.6
High % Poverty (>=40%)	21.6	3.8
Percent African American		
Low % African American (<30%)	17.2	2.1
Medium % African American (30-70%)	24.0	8.1
High % African American (70% and above)	18.3	1.8

Additionally I performed regressions of neighborhood characteristics without individual covariates in the models, as reported in the following table.

Table 7.5 Depression Regressed on Neighborhood Factors Only

Neighborhood Characteristic	Estimate	SE	Odds ratio (CI)	Neighborhood variance
Residential stability	-0.0009	0.0082	0.999 (0.983,1.016)	0.186
Middle Income	-0.0111	0.0085	0.989 (0.972,1.006)	0.173
Poverty	0.0117	0.0100	1.012 (0.992,1.032)	0.177
African American	-0.0000	0.0028	1.0 (0.994,1.006)	0.189

$N_i = 919$, $N_j = 69$ block groups

B. Multilevel Analyses

The first step in the multilevel regression analyses entailed estimating the intercept-only or null model, which revealed statistically significant variation in depression across neighborhoods ($\tau = .207$; $p = .013$). The intraclass correlation, which is the ratio between the level 2 variation and the total variation, is .18. This suggests that, on average, 18% of the variance in depression in this sample can be attributed to the neighborhood level.

$\tau = 0.21$ level 2 variation

$\sigma^2 = 0.93$ level 1 variance

$$\rho = \frac{\tau}{\tau + \sigma^2}$$

While most of the variability in depression is at the individual level, an ICC of 0.18 is substantial, since the typical range of ICCs for neighborhood context and mental health research are well under 0.20 (Leventhal and Brooks-Gunn 2000; Raudenbush, Spybrook, Liu, and Congdon 2006a). In addition, while the proportion of variance may be small, the actual effect of neighborhood can be substantial, as will be described in the discussion chapter.

While the ICC provides useful information, it is not as informative for a binary outcome because the individual level variance is heteroscedastic (Bingenheimer and Raudenbush 2004; Raudenbush and Bryk 2002; Snijders and Bosker 1999). Therefore I computed an additional indicator of the need to account for neighborhood clustering, the design effect. Muthen suggests that incorporating the group size yields a better estimate of the effect of grouping than does the ICC (Muthen 1999). Using the formula, Design Effect = 1 + ((average cluster size – 1)*ICC), I calculated a design effect of 3.2, which is substantially above the 2.0 level considered sufficient for using multilevel analysis. Because the ICC varies across models, I computed ICC and design effect for each model and report them on tables of regression results.

To test each of the hypotheses regarding if and how neighborhood stability and income composition affect depression above and beyond individual factors, I estimated a series of nested hierarchical logistic regression models predicting major depression. Results are reported in Tables 7.8 – 7.15 as odds ratios with 95% confidence intervals in the first table and as coefficients and standard errors in the second table for each analysis.[3] Odds ratios were computed by exponentiating the coefficients from the logistic regression to make results more understandable. I reported only coefficients and not odds ratios for the third research question, Tables 7.17 – 7.20. For all models I report final estimation of fixed effects for the unit-specific model with robust standard errors. Tables are located at the end of this chapter.

Fixed Effects: Individual Characteristics

In the first model, which is the same for all hypotheses, I ask, what are the effects of only individual characteristics on depression? Model 1 estimates the fixed effects of all individual socio-demographic covariates, assuming that the effect of each individual factor on depression is the same across groups (the slopes are fixed), but allowing the intercepts to vary across groups. For example, I assume that the effect of age on

[3] Odds ratios are not given for variables where interactions are present (the final model), as these odds ratios are uninterpretable.

depression is the same in any neighborhood, yet allow depression to vary by neighborhood due to differences in age composition.

As reported in Model 1 of Tables 7.8-15, five of the 16 individual factors are significantly associated with depression. Consistent with previous research (Blazer, Kessler, McGonagle, and Swartz 1994), the odds of depression were higher on average among women compared to men and among residents with very low income compared to those with incomes of $40,000 or more. Holding all other factors constant at their reference category[4], women had a 75% higher odds of depression than men ($p<.01$). Persons with household incomes less than $10,000 had nearly two and a half times the odds of being depressed compared to someone whose household income is $40,000 or above ($p<.05$). Age, African American, and Latino ethnicity decreased the probability of depression relative to their comparison group. The odds of being depressed are 2% lower for each additional year of age ($p<.01$).

African Americans have 41% lower odds of depression than non-Hispanic whites in this sample, controlling for other socio-demographic characteristics. While these findings are consistent with the literature, it appears inconsistent with African Americans' disproportionate exposure to a wide range of socioeconomic and structural conditions associated with poorer mental health (Schulz et al. 2006; Williams and Collins 2001;

[4] Reference categories are as follows: mean age (46 years), male, white non-Hispanic, married, with at least some college, household income $40,000 or above, mean number of persons in the household (2.8), homeowner, length of residence in the neighborhood 30 years or more.

Williams and Harris-Reid 1999). Finally, the odds of depression are 55% lower among Latinos than whites.

Fixed Effects: Neighborhood Characteristics

Parallel to the previous step, I examine whether there is any overall association between depression and each of the neighborhood level characteristics, without individual covariates. Table 7.5 reports the results of multilevel regression of depression on each continuous neighborhood variable without controlling for individual factors. None of the neighborhood factors are significant predictors of depression, although the coefficients are in the expected direction. Neighborhood stability, middle income, and percent African American are each negatively associated with depression, while poverty is positively associated. The intercept variance which is explained by each neighborhood factor ranges from 17 to 19%.

C. Research Question 1: Neighborhood Residential Stability, Middle Income Composition, and Depression

> <u>Hypothesis 1.1:</u> Neighborhood residential stability will have a positive direct effect on individual mental well being, independent of individual characteristics.

In Model 2 of each series, I add residential stability to individual covariates to test whether residents in more stable neighborhoods are likely to have better mental health than those in less stable neighborhoods, independent of their own characteristics.

Contrary to my hypothesis, neighborhood stability is not significant and the sign is positive (log odds = 0.007, $p = 0.458$).

The effects of the individual covariates do not change appreciably when neighborhood stability is included, and significance levels remain the same. The effects of all three categories of length of residence increase, suggesting that some effects of neighborhood stability may be due to compositional effects resulting from racial segregation and longtime residence. The Pearson correlation coefficient between stability and a continuous measure of individual length of residence is .18 ($p < .000$).

> <u>Hypothesis 1.2:</u> Neighborhood percent middle income will have a positive direct effect on individual mental well being independent of individual characteristics.

In Model 3, I replace stability with neighborhood middle income, to test whether residents of neighborhoods with a high percentage of middle income households will have a lower probability of depression, net of individual characteristics. Again, the hypothesis is not supported, however the nonsignificant effect is larger than the effect of stability and in the expected direction (log odds = -0 .015, $p = 0.11$ as reported in Model 3, Table 7.8).

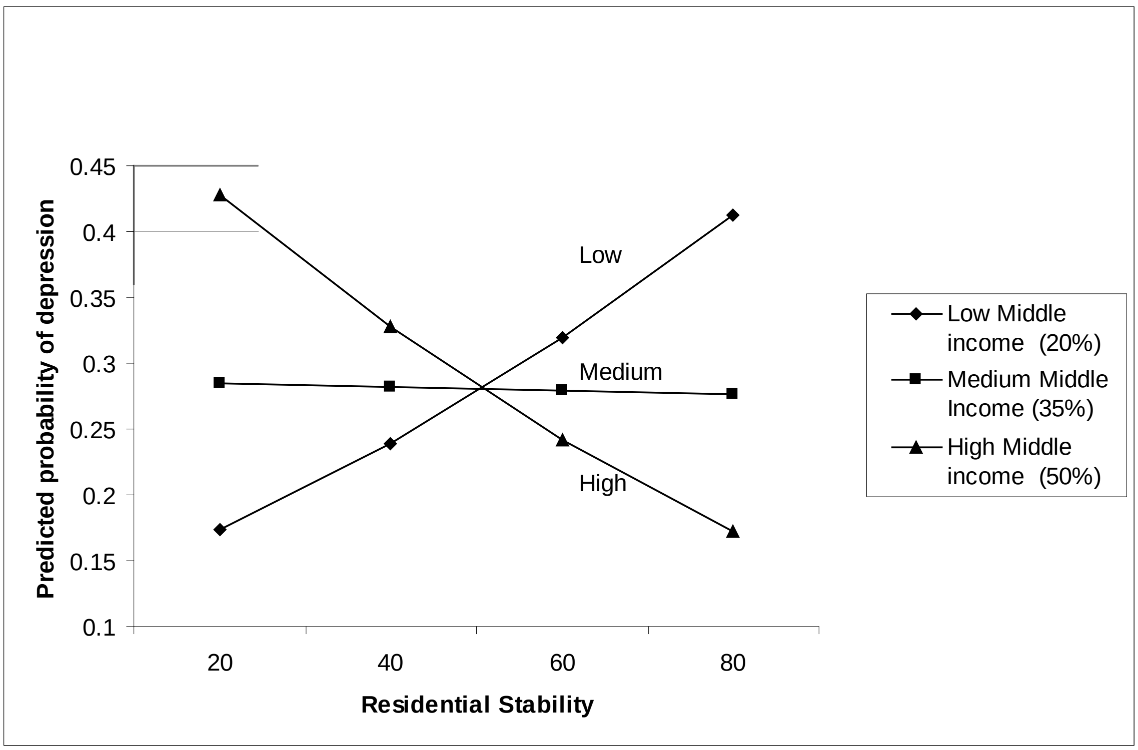
The effects of the individual covariates do not change appreciably when neighborhood middle income is added, and significance levels remain the same. However, the amount of change in individual covariates is greater than for stability and trends in the same direction for all individual variables.

In Model 4, I include both stability and middle income but without an interaction term. While neither neighborhood factor predicts depression, the coefficient for stability decreases somewhat while the coefficient for middle income increases slightly (0.007 to 0.005 and -0.015 to -0.014 respectively). My central interest, however, is not whether there is a linear and additive effect of the two neighborhood characteristics on depression, as tested in Model 4. Based on previous research and my conceptual model, my central research question is whether neighborhood middle income modifies the effect of stability on depression, such that stability is protective of mental health when there is a higher proportion of middle income households, and is detrimental to health when there are relatively few middle income residents. To test for effect modification as stated in Hypothesis 1.3, I add an interaction term in Model 5.

> Hypothesis 1.3: Neighborhood percent middle income will modify the effect of neighborhood stability on mental well being, with stability being beneficial to mental health when percent middle income is high and detrimental when percent middle income is low, net of individual factors.

The results reported in Model 5, Tables 7.8 – 7.9 confirm a highly significant interaction between neighborhood stability and middle income, indicating that the effect of stability on depression depends on the percentage of middle income households in the neighborhood, even when individual characteristics are taken into account (-0.001; p = .008). The negative sign of the interaction coefficient indicates that at higher levels of middle income, residential stability decreases the odds of depression. To interpret the interactions, I plotted the predicted probabilities of depression on nearly the full range of the stability scale for three levels of neighborhood middle income: low (20%), medium (35%), and high (50%).

Figure 7.1 Predicted Probability of Depression by Neighborhood Stability for High, Medium, and Low Percent Middle Income Neighborhoods



*Predicted probabilities of depression are for the following group:
Average age (46), female, African American, not married, income less than $10,000, 3 persons in household, less than high school education, not homeowner, length of residence in neighborhood less than 5 years
Crossing point: Residential stability = 51%, Middle income composition = 34%

Figure 7.1 presents the probabilities estimated for a person in the categories at highest risk of depression and of average age and household size: female, African American, unmarried, very low income, less than high school education, renting, and residing in the neighborhood less than five years. Consistent with my hypothesis, at low levels of middle income residents, stability is associated with higher rates of depression, while at high levels of middle income, stability is associated with lower rates of depression.

The following table illustrates these effects by reporting the predicted probability of depression for two types of individuals—those at highest risk of depression and those at lowest risk of depression. These two groups are then further divided based on different levels of residential stability and neighborhood middle income composition.

Table 7.6 Predicted Probability of Depression by Residential Stability and Neighborhood Middle Income for Two Groups

	Group with Highest Risk of Depression			Group with Lowest Risk of Depression		
	Neighborhood Middle Income Composition					
Residential Stability	Low (20%)	Medium (35%)	High (50%)	Low (20%)	Medium (35%)	High (50%)
21% Minimum	.18	.28	.42	.05	.08	.14
30%	.20	.28	.38	.05	.08	.12
40%	.24	.28	.33	.07	.08	.10
50%	.28	.28	.28	.08	.08	.08
60%	.32	.28	.24	.09	.08	.07
70%	.36	.28	.20	.11	.08	.05
88% Maximum	.45	.27	.15	.15	.08	.04

*Predicted probabilities of depression are estimated for people of average age (46 years) and average number of persons in the household (three), and with the following sets of characteristics associated with risk of depression or socioeconomic disadvantage:

Highest risk of depression:
Female, African American, not married, income less than $10,000, less than high school education, not homeowner, length of residence in neighborhood less than 5 years

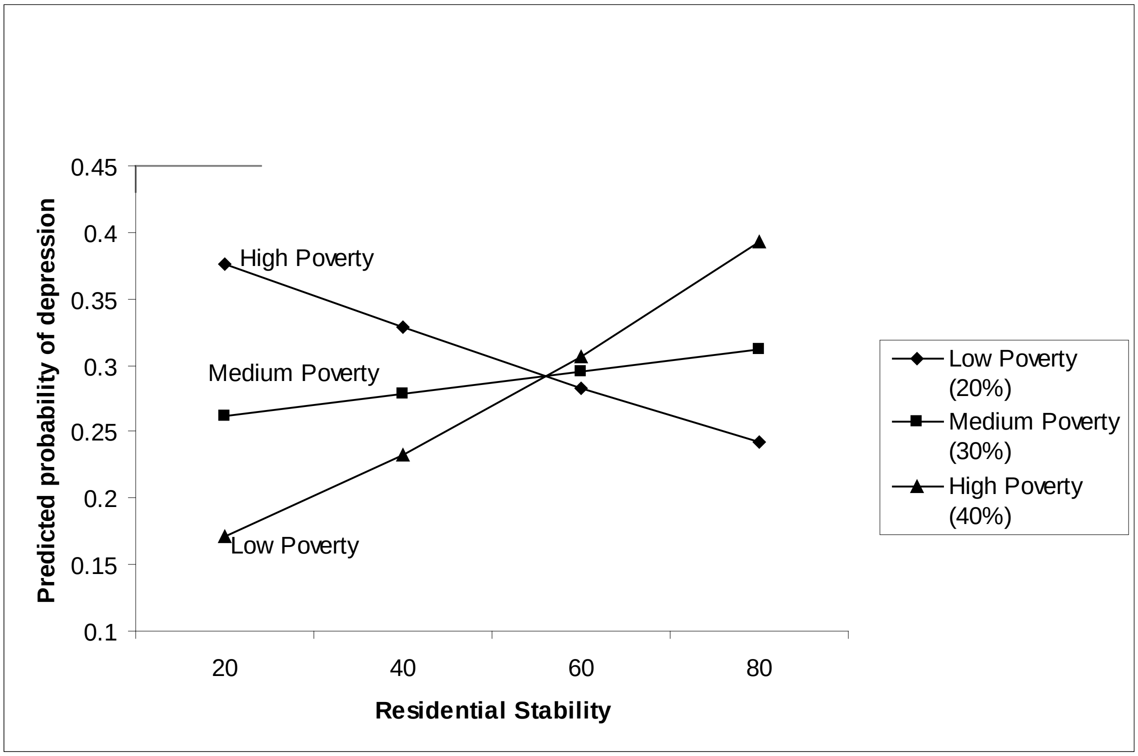
Lowest risk of depression:
Male, white, married, income over $40,000, college education, homeowner, length of residence in neighborhood over 30 years

For example, looking at the left side of the table, for an individual in the highest risk group, in neighborhoods with high percent middle income (50%) the probability of depression decreases as stability increases: from .42 in unstable neighborhoods to .15 in very stable neighborhoods. In neighborhoods with low percent middle income, the slope is reversed and the probability of depression increases as stability increases: from .18 to .45. In neighborhoods with a modest proportion of middle income residents (35%), the probability of depression does not change based on level of stability, and is .28.

The simple regression lines crossing over within the range of the values in the sample, indicating a disordinal interaction (Lubin 1961). The crossing point is at 51% residential stability and 34% middle income, as calculated algebraically from the three coefficients in interaction model 5 (Aiken and West 1991).

In the next set of models, middle income is replaced with percent poverty to explore whether the observed effects of middle income differ from the effects of poverty, which are highly correlated (Pearson correlation coefficient = 0.71). Analyzing these measures in the same model would introduce multicollinearity, therefore I estimated a set of models with neighborhood poverty to compare results.

Figure 7.2 Predicted Probability of Depression by Neighborhood Stability for High, Medium, and Low Poverty Neighborhoods



Predicted probabilities of depression are for the following group:
Average age (46), Female, African American, not married, income less than $10,000, 3 persons in household, less than high school education, not homeowner, length of residence in neighborhood less than 5 years
Crossing point: Residential stability = 56%, Poverty = 27%

Results are very similar to those found for middle income and are reported in Table 7.10 as odds ratios and 95% confidence intervals, and in Table 7.11 as coefficients and standard errors. I find no main effect of neighborhood poverty on depression (0.010, p = .39). In the final interaction model, as expected, neighborhood poverty modifies the effects of residential stability on depression comparable to the relationship found with middle income, (0.001, p = .01). In higher poverty neighborhoods, stability is associated with increased risk of depression among residents, while in lower poverty neighborhoods, stability predicts lower depression, as illustrated in Figure 7.2. Among those individuals with the highest individual risk for depression, the predicted probability of depression in high poverty neighborhoods ranges from 17% under conditions of instability to 39% in very stable conditions. In low poverty neighborhoods the range is nearly reversed, with 38% probability of depression in unstable and 24% depression in stable conditions. The interaction is disordinal, with the crossing point at 56% stability, which is somewhat higher than for the middle income interaction, and at 27% poverty.

The following table compares the coefficients for the two measures of neighborhood income composition.

Table 7.7 Comparison of Neighborhood Middle Income and Neighborhood Poverty in Interaction Models with Residential Stability

	Main Effects (Model 3)		Full Interaction (Model 5)			
	Middle Income	Poverty	Middle Income		Poverty	
Log odds (s.e.)	-0.015	0.010	0.003	(0.010)	0.004	(0.008)
	(0.009)	(0.011)	-0.009	(0.009)	0.001	(0.010)
			-0.001**	(0.001)	0.001*	(0.001)
Chi Square	78.77	80.92		72.60		73.74
(p-value)	(0.15)	(0.12)		(0.24)		(0.21)
Level 1 variance	0.96	0.95		0.97		0.96
Level 2 variance	0.14	0.16		0.11		0.12
ICC				0.10		0.11

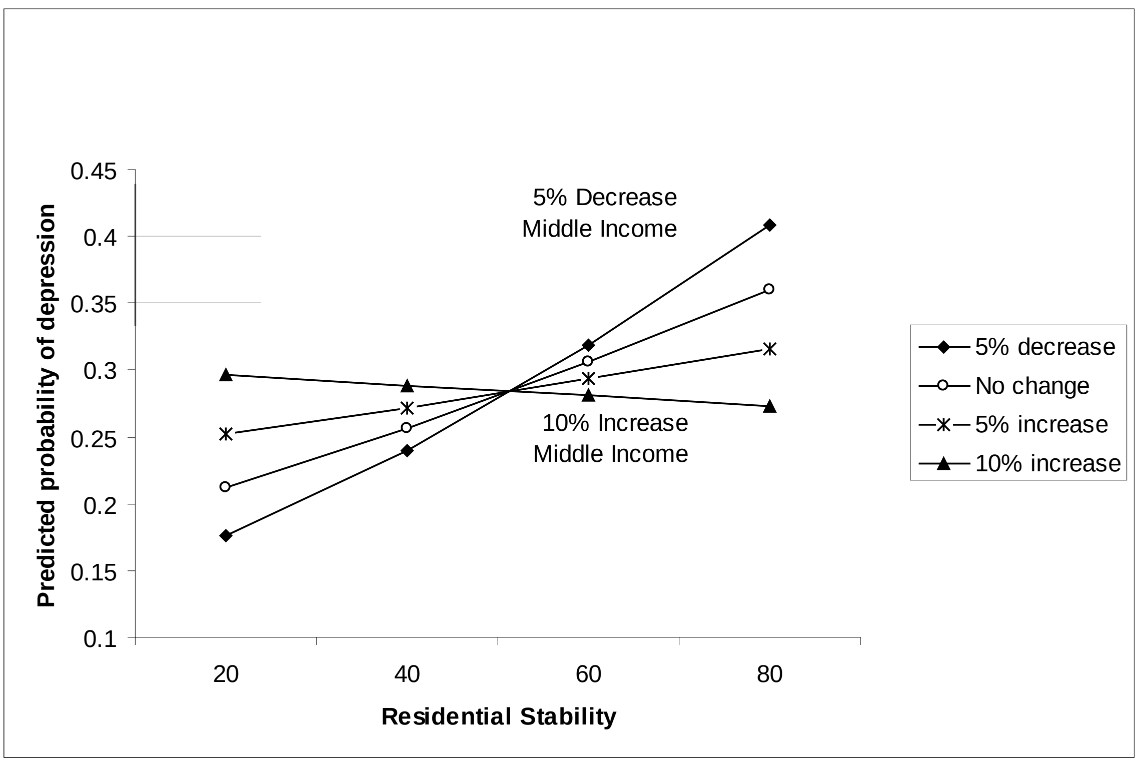
<u>Hypothesis 1.4</u>: Change in neighborhood percent middle income between 1990 and 2000 will modify the effect of neighborhood residential stability on depression, with stability associated with higher rates of depression under conditions of declining neighborhood middle income, net of individual factors.

In the next set of models, I further explore the relationship between stability and neighborhood income composition by testing whether a decline in neighborhood middle income over time may be detrimental to residents' mental health by modifying the effect of stability on depression.

As described in the Measurement and Data section of Chapter 4, change in neighborhood middle income composition is measured by a continuous change score computed by subtracting the percentage of middle income households in 1990 from the percentage of middle income households in 2000. 1990 income is adjusted to 2000 dollars (Bureau of Labor Statistics 2006). The amount and direction of change varies greatly between neighborhoods (mean = 4.8%, S.E. = 9.7), ranging from a 24 percent decline to a 27 percent increase in neighborhood middle income.

Results of the nested models are in Table 7.12 (odds ratios) and Table 7.13 (coefficients). Models 1 – 2 are the same as in previous analyses. In Model 3 I introduce neighborhood change in middle income without residential stability but controlling for individual factors. There is no significant main effect of neighborhood change on depression, although the sign is in the predicted direction: as neighborhood middle income increases the odds of depression declines (coefficient = -0.01, p = .34). Adding stability to the model without an interaction term does not substantially change any of the coefficients (Model 4). When an interaction term is added in Model 5, the results are consistent with the two previous neighborhood income analyses: change in middle income composition over the past 10 years significantly modifies the effects of stability on depression (-0.001, p=.004). Figure 7.3 indicates support for hypothesis 1.4, that neighborhood stability has a negative effect on mental health under conditions of declining middle income composition. However, stability is also associated with poorer mental health when there is no change or slight increase in middle income. Because the change data do not include an indication of the absolute level of middle income, the effect is averaged across all neighborhood income types and does not reflect the conditional relationships of income and depression described in the previous results.

Figure 7.3 Predicted Probability of Depression by Neighborhood Stability for Neighborhoods With Decrease, No Change, and Increase in Percent Middle Income Households 1990 to 2000



Predicted probabilities of depression are for the following group:

Average age (46), Female, African American, not married, income less than $10,000, 3 persons in household, less than high school education, not homeowner, length of residence in neighborhood less than 5 years
Crossing point: Residential stability = 52%, Change in middle income composition = 8.7%

Looking at Figure 7.3, we first examine the effects of stability in neighborhoods with a 5% decline in percent middle income. In a highly stable neighborhood in which 80% of the residents have lived there at least five years, the probability of depression for those at highest risk of depression is estimated at 41%. This compares with a probability of 18% in a very unstable neighborhood. In neighborhoods with no change in middle income composition, the probability of depression is 21% if the neighborhood has low stability compared with 36% if the neighborhood has high stability. In a neighborhood with a 5% increase in middle income the probability of depression is estimated at 25% if unstable and 32% if the neighborhood is highly stable. The interaction is disordinal, with the crossing point at 52% stability, and when the percent of middle income residents has increased by 8.7%. These results are consistent with my other findings described above.

D. Research Question 2: Neighborhood Stability, Racial Composition, and Depression

I next consider whether the effect of neighborhood residential stability on depression differs based on neighborhood racial composition, in particular by the percent of residents who are African American.

> Hypothesis 2.1: The effect of neighborhood residential stability on mental health will not differ based on current neighborhood racial composition (% African American).

Table 7.14 – 7.15 report results for nested models, following the same steps as used in the previous analyses. Model 1 examines the fixed effects of individual characteristics on depression across all neighborhoods, and Model 2 adds the effect of residential stability at the neighborhood level. These models are identical to those described for Models 1 and 2 in the previous research question. In Model 3, however, I replace neighborhood stability with percent African American. There are no main effects for percent African American (.000075; $p = 0.986$) and there is negligible change in the effects of the individual covariates on depression. In Model 4 stability is added and in Model 5 an interaction term is included. Neither the conditional nor the interaction effects are significant (0.0000, $p = 0.633$), consistent with the second set of hypotheses that neighborhood racial composition, as measured by percent African American, does not have an effect either on depression or on the relationship between neighborhood residential stability and depression, net of individual factors.

E. Research Question 3: Financial Vulnerability and Social Support as Mediators of the Effects of Neighborhood Stability and Middle Income on Depression

I next ask whether financial vulnerability and social support are possible pathways through which neighborhood residential and economic structure influence mental health.

> Hypothesis 3.1: Financial vulnerability of individual residents will mediate the effects of neighborhood residential stability on depression.

> Hypothesis 3.2: Financial vulnerability of individual residents will mediate the effects of neighborhood middle income on depression.

> Hypothesis 3.3: Emotional social support will not mediate the effects of neighborhood residential stability on depression.

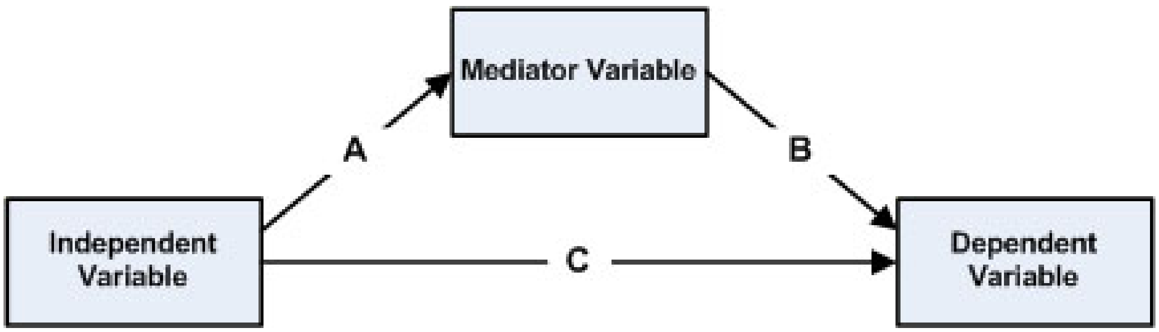
> Hypothesis 3.4: Instrumental social support will not mediate the effects of neighborhood residential stability on depression.

> Hypothesis 3.5: Emotional social support will not mediate the effects of neighborhood middle income on depression.

> Hypothesis 3.6: Instrumental social support will not mediate the effects of neighborhood middle income on depression.

The first step in testing for mediation is to determine that there is a main effect between the independent variable and depression, denoted as path C in Figure 7.4. This was tested in the previous analyses and reported in Table 7.8 in Model 2 for stability and Model 3 for middle income composition. No main effects were detected, therefore there is nothing to mediate and hypotheses 3.1 – 3.6 can not be tested further.

Figure 7.4 Effect Modification



However, to better understand the mechanisms through which residential neighborhoods influence depression, I decided to test for mediated moderation, that is, whether financial vulnerability and social support separately mediate the moderation that I found in Research Question 1 (Muller, Judd, and Yzerbyt 2005).

Following Baron and Kenny's procedures for testing mediation (Baron and Kenny 1986), I first establish that the interaction between stability and middle income is correlated with depression (path C in Figure 7.4). This is significant at p=.008, as discussed above and reported in Model 5 of Table 7.9.

Hypothesis 3.5: Financial vulnerability of individual residents will mediate the moderated effects of neighborhood residential stability and middle income on mental well being.

The next step is to establish whether path A exists, that the stability-middle income interaction predicts individual financial vulnerability. Table 7.16 displays the series of nested models in which financial vulnerability is regressed on the individual covariates, stability, middle income, and the interaction between stability and middle income.

Model 1 of Table 7.16 reports coefficients for the fixed effects model of individual characteristics only. As would be expected, socioeconomic factors of low education, lack of homeownership and low income are highly predictive of financial vulnerability ($p<.001$). Living in the neighborhood fewer than ten years also predicted financial vulnerability. These effects remained virtually unchanged when neighborhood factors were introduced in Models 2 to 4, and the ICC indicates that only 1.3% of the variance in the model is attributable to neighborhood effects. In the final model, the interaction between stability and middle income does not predict financial vulnerability (-0.000, $p=.11$); therefore there is not sufficient evidence to conclude that financial vulnerability mediates the moderated effect of stability of depression.

Hypothesis 3.6: Emotional social support of individual residents will not mediate the moderated effects of neighborhood residential stability and middle income on mental well being.

To test hypothesis 3.6, I test for path A, whether the stability-middle income interaction is associated with emotional social support (Table 7.17). In the fixed effects Model 1 with only individual characteristics in the model, being unmarried, having very low income, and having more persons in the household are each associated with lower emotional social support. In Models 2 – 4, neither of the neighborhood characteristics, individually or together, predicts emotional support. In the final model, Model 5, there is no significant effect of the stability-middle income interaction on emotional social support (-0.000, p=.24), confirming the hypothesis that emotional social support does not mediate the effect of neighborhood stability and middle income on depression. In all models, consistent with other research, being unmarried and having very low income predict lower social support at the level of p<.001. Additionally, as the number of persons in the household increases, emotional social support decreases (-0.08. p=.02). Only 3.8% of the variance in the final model is due to neighborhood effects.

> <u>Hypothesis 3.7:</u> Perceived social support (instrumental) will not mediate the effects of neighborhood middle income on mental well being.

Finally, in hypothesis 3.7, I replace emotional with instrumental social support as the mediator (Table 7.18). Again, there is no evidence of a path between the stability-middle income interaction and social support (-0.000, p=.97), confirming the hypothesis that instrumental social support is not a mediator of neighborhood stability-middle income effect on depression. As with emotional support, being unmarried and low income predict lower instrumental support, however the effect of income is stronger than for emotional support, as would be expected. While household size also predicts lower instrumental support, when neighborhood factors are in the model the effect drops slightly to exceed the .05 significance level. In addition, residing in the neighborhood for five to ten years compared to over thirty years is significantly associated with instrumental support, having nearly twice the negative effect of either fewer than five or more than ten years in the neighborhood. The proportion of total variance that is at the neighborhood level, 5.7%, is insubstantial.

Although beyond the hypotheses in this dissertation, I further explored whether financial vulnerability and social support, separately and together, are associated with depression in models with individual but not neighborhood level factors (path B in Figure 7.4). All three variables are significantly associated with depression at the $p<.001$ level, as displayed in Table 19. Financial vulnerability predicts higher depression, both emotional and instrumental support predicted lower depression.

I then conduct three series of neighborhood models, one that includes financial vulnerability as an individual covariate, one that includes emotional social support, and one that includes instrumental support. In each of the three series the effect of the added covariate remains highly significant in all models, however the effect of the stability-middle income interaction on depression does not change substantially. Financial vulnerability absorbs some of the individual socioeconomic effects, and the proportion of the variance explained at the neighborhood compared to the individual level increases, yielding a higher ICC of .13 compared to .10 without financial vulnerability in the model. In both sets of analyses with social support, the ICC decreases from .10 to .07 and the design effect drops below 2.0, indicating that only 7% of the variance in depression occurs at the neighborhood rather than at the individual level when social support is in the model.

F. Summary of Results

Figure 7.5 presents the findings of this dissertation illustrated as the revised conceptual model. Examining the first research question, I find that the percent of middle income residents in a neighborhood modifies the effect of stability on depression, such that when neighborhood middle income is high (above 35%), stability decreases the odds of depression. When the percent of middle income households is low, stability increases the odds of depression, independent of individual socioeconomic characteristics. A similar effect is found when percent poverty is substituted for middle income, but in the opposite direction. In high poverty neighborhoods, stability increases the odds of depression, while in low poverty neighborhoods, stability decreases the odds of depression.

Consistent with these findings, in neighborhoods that experienced a decline or no change in percent middle income between 1990 and 2000, stability increased the probability of depression, whereas in neighborhoods that experienced an increase in middle income households, stability reduced the probability of depression. Although there were no main effects of any neighborhood characteristics on depression, the findings presented here support the central hypothesis of this dissertation that the effect of neighborhood stability on residents' mental well being depends on neighborhood income composition.

Examining the second research question, I find that the percent of African American residents in a neighborhood does not affect the probability of depression, nor does it influence the relationship between neighborhood residential stability and depression above and beyond individual characteristics. Finally, for research question 3, I find that at the individual level, neither financial stability nor social support mediates the effects of neighborhood residential and income environments on depression.

In the next chapter I discuss these findings.

Figure 7.5 The Effects of Neighborhood Residential Environments on Depression in Detroit

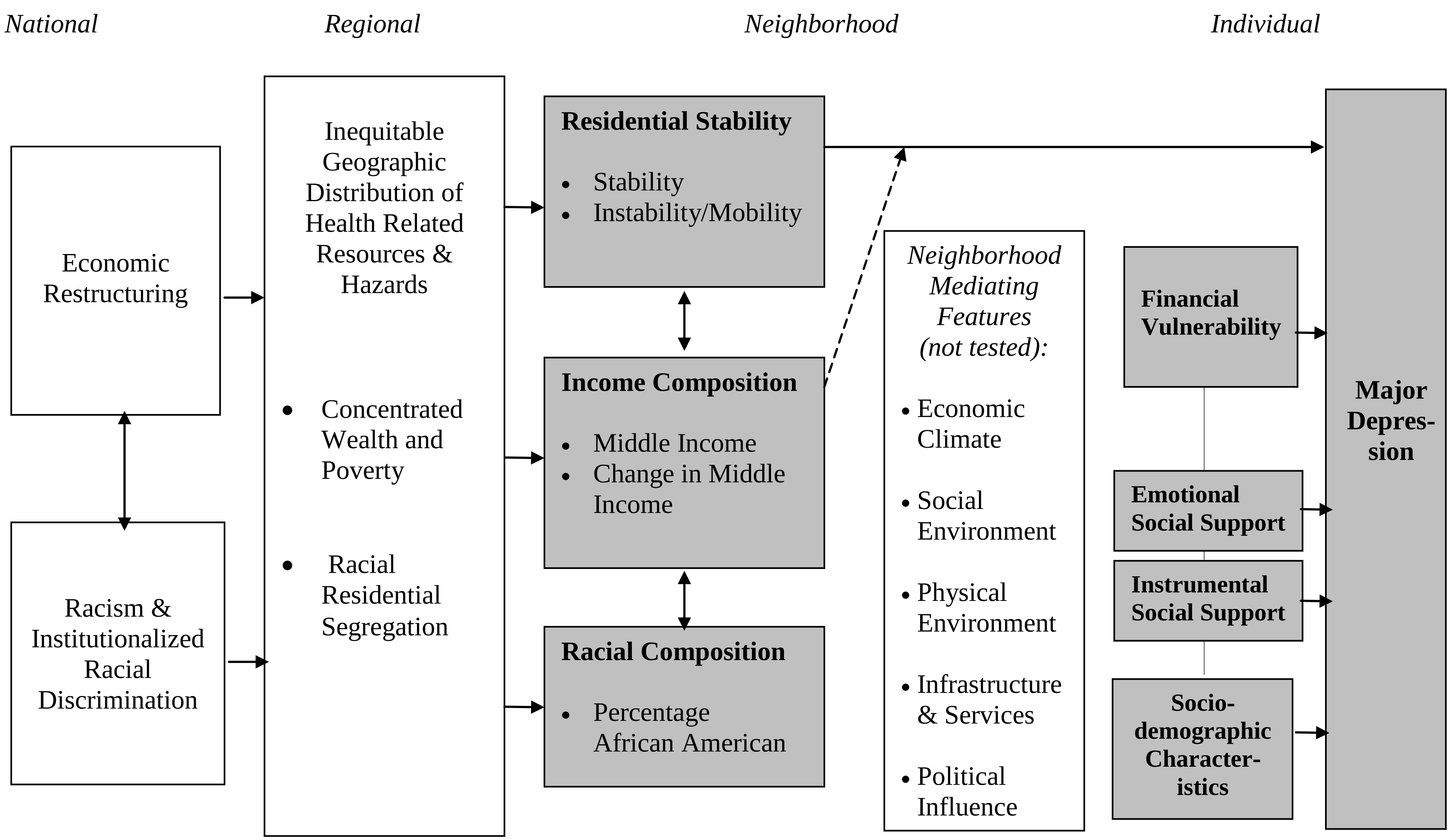


Table 7.8 Multilevel Logistic Regression of Depression on Neighborhood Stability and Neighborhood Middle Income (Odds Ratios)

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Individual:										
Intercept	0.09	(0.04,0.21)	0.09	(0.04,0.22)	0.10	(0.04,0.24)	0.10	(0.04,0.24)	0.09	(0.04,0.21)
Age	0.98	(0.97,0.99)	0.98	(0.96,0.99)	0.98	(0.96,0.99)	0.98	(0.96,0.99)	0.98	(0.97,0.99)
Female	1.75	(1.17,2.61)	1.75	(1.17,2.61)	1.76	(1.18,2.63)	1.76	(1.18,2.63)	1.82	(1.22,2.73)
African American NH	0.59	(0.36,0.98)	0.56	(0.33,0.96)	0.56	(0.34,0.92)	0.54	(0.32,0.92)	0.54	(0.33,0.91)
Other race NH	0.85	(0.27,2.71)	0.85	(0.27,2.69)	0.83	(0.26,2.69)	0.83	(0.27,2.61)	0.81	(0.26,2.56)
Latino	0.45	(0.21,0.99)	0.45	(0.21,0.98)	0.43	(0.20,0.95)	0.43	(0.20,0.95)	0.44	(0.20,0.97)
Not married	1.14	(0.62,2.10)	1.13	(0.61,2.09)	1.10	(0.59,2.05)	1.09	(0.58,2.04)	1.11	(0.59,2.07)
Education <High School	0.90	(0.58,1.41)	0.91	(0.58,1.42)	0.88	(0.56,1.38)	0.88	(0.56,1.39)	0.88	(0.56,1.38)
Education high school	1.30	(0.81,2.08)	1.30	(0.82,2.09)	1.26	(0.77,2.05)	1.26	(0.77,2.05)	1.24	(0.77,2.02)
Income <$10,000	2.45	(1.12,5.37)	2.44	(1.12,5.33)	2.34	(1.08,5.09)	2.34	(1.08,5.08)	2.35	(1.07,5.18)
Income $10-19,000	1.68	(0.87,3.25)	1.66	(0.86,3.22)	1.62	(0.84,3.14)	1.61	(0.84,3.12)	1.66	(0.86,3.23)
Income $20-39,000	1.13	(0.61,2.09)	1.11	(0.60,2.06)	1.08	(0.58,2.00)	1.07	(0.58,1.99)	1.11	(0.59,2.07)
Number in household	1.02	(0.92,1.14)	1.02	(0.92,1.14)	1.02	(0.91,1.13)	1.01	(0.91,1.13)	1.01	(0.90,1.13)
Not homeowner	1.25	(0.83,1.89)	1.24	(0.82,1.89)	1.23	(0.81,1.86)	1.22	(0.81,1.86)	1.22	(0.80,1.87)
Length of residence <5yrs	1.46	(0.74,2.88)	1.51	(0.76,3.03)	1.53	(0.79,2.97)	1.57	(0.80,3.09)	1.63	(0.82,3.24)
Length of residence 5-10	1.74	(0.83,3.68)	1.81	(0.84,3.91)	1.85	(0.88,3.89)	1.90	(0.88,4.10)	1.99	(0.92,4.31)
Length of residence 10-29	1.13	(0.64,2.00)	1.16	(0.66,2.02)	1.17	(0.67,2.05)	1.18	(0.68,2.06)	1.21	(0.69,2.12)
Neighborhood:									*Beta*	*p-value*
Residential Stability			1.01	(0.99,1.03)			1.00	(0.99,1.02)	0.003	
% Middle Income					0.98	(0.966,1.004)	0.99	(0.968,1.004)	-0.009	
Stability * Middle Income									-0.001	0.008

Odds ratios for variables where interactions are present are uninterpretable, and therefore not shown. Model parameters must be used to determine relative odds of the relation between specific variables and the outcome.

Table 7.9 Multilevel Logistic Regression of Depression on Neighborhood Stability and Neighborhood Middle Income (Betas)

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.	
Individual:															
Intercept	-2.40	0.43	***	-2.38	0.44	***	-2.32	0.44	***	-2.31	0.44	***	-2.43	0.44	***
Age	-0.02	0.01	**	-0.02	0.01	**	-0.02	0.01	**	-0.02	0.01	**	-0.02	0.01	**
Female	0.56	0.20	**	0.56	0.20	**	0.56	0.21	**	0.57	0.20	**	0.60	0.21	**
African American NH	-0.53	0.26	*	-0.57	0.27	*	-0.58	0.25	*	-0.61	0.27	*	-0.61	0.26	*
Other race NH	-0.16	0.59		-0.16	0.58		-0.18	0.58		-0.18	0.58		-0.21	0.59	
Latino	-0.79	0.40	*	-0.80	0.40	*	-0.84	0.40	*	-0.84	0.40	*	-0.81	0.40	*
Not married	0.13	0.31		0.12	0.32		0.09	0.32		0.09	0.32		0.10	0.32	
Education <High School	-0.10	0.23		-0.10	0.23		-0.13	0.23		-0.13	0.23		-0.13	0.23	
Education high school	0.26	0.24		0.27	0.24		0.23	0.25		0.23	0.25		0.22	0.25	
Income <$10,000	0.90	0.40	*	0.89	0.40	*	0.85	0.40	*	0.85	0.40	*	0.86	0.40	*
Income $10-19,000	0.52	0.34		0.51	0.34		0.48	0.34		0.48	0.34		0.51	0.34	
Income $20-39,000	0.12	0.31		0.10	0.32		0.08	0.31		0.07	0.31		0.10	0.32	
Number in household	0.02	0.06		0.02	0.06		0.01	0.06		0.01	0.06		0.01	0.06	
Not homeowner	0.22	0.21		0.22	0.21		0.20	0.21		0.20	0.21		0.20	0.22	
Length of residence <5yrs	0.38	0.35		0.41	0.35		0.43	0.34		0.45	0.35		0.49	0.35	
Length of residence 5-10	0.56	0.38		0.60	0.39		0.62	0.38		0.64	0.39		0.69	0.39	
Length of residence 10-29	0.13	0.29		0.15	0.28		0.16	0.29		0.17	0.28		0.19	0.29	
Neighborhood:															
Residential Stability				0.01	0.01					0.00	0.01		0.003	0.010	
% Middle Income							-0.02	0.01		-0.01	0.01		-0.009	0.009	
Stability * Middle Income													-0.001	0.001	**

*p<0.05, **p<0.01, ***p<0.001

ICC 0.10 — Level 1 variance 0.97

Design effect 2.22 — Level 2 variance 0.11

Table 7.10 Multilevel Logistic Regression of Depression on Neighborhood Stability and Poverty (Odds Ratios)

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Individual:										
Intercept	0.09	(0.04, 0.21)	0.09	(0.04, 0.22)	0.10	(0.04, 0.23)	0.10	(0.04, 0.24)	0.08	(0.03, 0.21)
Age	0.98	(0.97, 0.99)	0.98	(0.96, 0.99)	0.98	(0.96, 0.99)	0.98	(0.96, 0.99)	0.98	(0.96, 0.99)
Female	1.75	(1.17, 2.61)	1.75	(1.17, 2.61)	1.75	(1.17, 2.61)	1.75	(1.17, 2.61)	1.83	(1.22, 2.75)
African American NH	0.59	(0.36, 0.98)	0.56	(0.33, 0.96)	0.58	(0.35, 0.95)	0.56	(0.33, 0.95)	0.57	(0.34, 0.96)
Other race NH	0.85	(0.27, 2.71)	0.85	(0.27, 2.69)	0.84	(0.27, 2.68)	0.85	(0.27, 2.67)	0.84	(0.26, 2.69)
Latino	0.45	(0.21, 0.99)	0.45	(0.21, 0.98)	0.45	(0.20, 0.99)	0.44	(0.20, 0.98)	0.46	(0.21, 1.02)
Not married	1.14	(0.62, 2.10)	1.13	(0.61, 2.09)	1.12	(0.60, 2.09)	1.11	(0.59, 2.09)	1.14	(0.60, 2.15)
Education <high school	0.90	(0.58, 1.41)	0.91	(0.58, 1.42)	0.89	(0.57, 1.40)	0.90	(0.57, 1.41)	0.90	(0.57, 1.41)
Education high school	1.30	(0.81, 2.08)	1.30	(0.82, 2.09)	1.28	(0.80, 2.07)	1.29	(0.80, 2.08)	1.26	(0.78, 2.03)
Income <$10,000	2.45	(1.12, 5.37)	2.44	(1.12, 5.33)	2.38	(1.10, 5.17)	2.38	(1.10, 5.17)	2.45	(1.12, 5.35)
Income $10-19,999	1.68	(0.87, 3.25)	1.66	(0.86, 3.22)	1.64	(0.86, 3.15)	1.63	(0.85, 3.14)	1.72	(0.89, 3.32)
Income $20-39,999	1.13	(0.61, 2.09)	1.11	(0.60, 2.06)	1.10	(0.59, 2.03)	1.09	(0.59, 2.02)	1.14	(0.61, 2.14)
Number in household	1.02	(0.92, 1.14)	1.02	(0.92, 1.14)	1.02	(0.91, 1.14)	1.02	(0.91, 1.14)	1.01	(0.91, 1.14)
Not homeowner	1.25	(0.83, 1.89)	1.24	(0.82, 1.89)	1.24	(0.81, 1.88)	1.23	(0.81, 1.88)	1.20	(0.78, 1.83)
Length residence <5yrs	1.46	(0.74, 2.88)	1.51	(0.76, 3.03)	1.49	(0.76, 2.93)	1.53	(0.77, 3.04)	1.60	(0.81, 3.17)
Length residence 5-10	1.74	(0.83, 3.68)	1.81	(0.84, 3.91)	1.79	(0.85, 3.76)	1.84	(0.85, 3.96)	1.91	(0.88, 4.11)
Length residence 10-29	1.13	(0.64, 2.00)	1.16	(0.66, 2.02)	1.15	(0.66, 2.01)	1.16	(0.67, 2.02)	1.19	(0.68, 2.09)
Neighborhood:									*Beta*	*p-value*
Residential Stability			1.01	(0.99, 1.03)			1.01	(0.99, 1.02)	0.004	
Poverty					1.01	(0.99, 1.03)	1.01	(0.99, 1.03)	0.001	
Stability * Poverty									0.001	0.01

Odds ratios for variables where interactions are present are uninterpretable, and therefore not shown. Model parameters must be used to determine relative odds of the relation between specific variables and the outcome.

Table 7.11 Multilevel Logistic Regression of Depression on Neighborhood Stability and Poverty (Betas)

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.	
Individual:															
Intercept	-2.40	(0.43)	***	-2.38	(0.44)	***	-2.35	(0.44)	***	-2.34	(0.45)	***	-2.49	(0.46)	***
Age	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**
Female	0.56	(0.20)	**	0.56	(0.20)	**	0.56	(0.21)	**	0.56	(0.20)	**	0.61	(0.21)	**
African American NH	-0.53	(0.26)	*	-0.57	(0.27)	*	-0.55	(0.25)	*	-0.58	(0.27)	*	-0.56	(0.27)	*
Other race NH	-0.16	(0.59)		-0.16	(0.59)		-0.17	(0.59)		-0.17	(0.59)		-0.18	(0.60)	
Latino	-0.79	(0.40)	*	-0.80	(0.40)	*	-0.81	(0.40)	*	-0.81	(0.40)	*	-0.78	(0.41)	
Not married	0.13	(0.31)		0.12	(0.32)		0.11	(0.32)		0.10	(0.32)		0.13	(0.33)	
Education <high school	-0.10	(0.23)		-0.10	(0.23)		-0.11	(0.23)		-0.11	(0.23)		-0.11	(0.23)	
Education high school	0.26	(0.24)		0.27	(0.24)		0.25	(0.24)		0.25	(0.24)		0.23	(0.25)	
Income <$10,000	0.90	(0.40)	*	0.89	(0.40)	*	0.87	(0.40)	*	0.87	(0.40)	*	0.90	(0.40)	*
Income $10-19,000	0.52	(0.34)		0.51	(0.34)		0.50	(0.33)		0.49	(0.33)		0.54	(0.34)	
Income $20-39,000	0.12	(0.32)		0.1	(0.32)		0.09	(0.32)		0.09	(0.32)		0.13	(0.32)	
Number in household	0.02	(0.06)		0.02	(0.06)		0.02	(0.06)		0.02	(0.06)		0.01	(0.06)	
Not homeowner	0.22	(0.21)		0.22	(0.21)		0.21	(0.21)		0.21	(0.22)		0.18	(0.22)	
Length of residence <5yrs	0.38	(0.35)		0.41	(0.35)		0.40	(0.35)		0.42	(0.35)		0.47	(0.35)	
Length of residence 5-10	0.56	(0.38)		0.60	(0.39)		0.58	(0.38)		0.61	(0.39)		0.65	(0.39)	
Length of residence 10-29	0.13	(0.29)		0.15	(0.28)		0.14	(0.28)		0.15	(0.28)		0.18	(0.29)	
Neighborhood:															
Residential Stability				0.01	(0.01)					0.005	(0.009)		0.004	(0.01)	
% Poverty							0.01	(0.01)		0.008	(0.010)		0.001	(0.01)	
Stability * Poverty													0.001	(0.00)	*

*p<0.05, **p<0.01, ***p<0.001

ICC	0.11	Level 1 variance	0.96
Design effect	2.36	Level 2 variance	0.11

Table 7.12 Multilevel Logistic Regression of Depression on Neighborhood Stability and Change in Middle Income Between 1990 and 2000 (Odds Ratios)

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Individual:										
Intercept	0.09	(0.04,0.21)	0.09	(0.04,0.22)	0.09	(0.04,0.21)	0.09	(0.04,0.22)	0.08	(0.04,0.20)
Age	0.98	(0.97,0.99)	0.98	(0.96,0.99)	0.98	(0.96,0.99)	0.98	(0.96,0.99)	0.98	(0.96,0.99)
Female	1.75	(1.17,2.61)	1.75	(1.17,2.61)	1.75	(1.17,2.61)	1.75	(1.18,2.61)	1.82	(1.22,2.73)
African American NH	0.59	(0.36,0.98)	0.56	(0.33,0.96)	0.59	(0.36,0.97)	0.56	(0.33,0.95)	0.55	(0.33,0.93)
Other race NH	0.85	(0.27,2.71)	0.85	(0.27,2.69)	0.82	(0.26,2.60)	0.82	(0.26,2.58)	0.80	(0.26,2.53)
Latino	0.45	(0.21,0.99)	0.45	(0.21,0.98)	0.46	(0.21,1.0)	0.45	(0.21,0.99)	0.46	(0.21,1.00)
Not married	1.14	(0.62,2.10)	1.13	(0.61,2.09)	1.12	(0.61,2.07)	1.10	(0.59,2.06)	1.12	(0.60,2.09)
Education <12yrs	0.90	(0.58,1.41)	0.91	(0.58,1.42)	0.90	(0.57,1.40)	0.90	(0.58,1.41)	0.89	(0.57,1.39)
Education 12yrs	1.30	(0.81,2.08)	1.30	(0.82,2.09)	1.29	(0.81,2.06)	1.29	(0.81,2.07)	1.26	(0.78,2.02)
Income <$10k	2.45	(1.12,5.37)	2.44	(1.11,5.33)	2.51	(1.14,5.53)	2.50	(1.14,5.49)	2.45	(1.10,5.44)
Income $10-19k	1.68	(0.87,3.25)	1.66	(0.86,3.22)	1.73	(0.89,3.34)	1.71	(0.89,3.31)	1.72	(0.89,3.34)
Income $20-39	1.13	(0.61,2.09)	1.11	(0.60,2.06)	1.14	(0.61,2.12)	1.12	(0.60,2.09)	1.14	(0.61,2.15)
Number in household	1.02	(0.92,1.14)	1.02	(0.92,1.14)	1.02	(0.92,1.14)	1.02	(0.91,1.14)	1.01	(0.90,1.13)
Not homeowner	1.25	(0.83,1.89)	1.24	(0.82,1.89)	1.28	(0.85,1.93)	1.27	(0.84,1.93)	1.25	(0.82,1.92)
Length residence <5yrs	1.46	(0.74,2.88)	1.51	(0.76,3.03)	1.43	(0.72,2.82)	1.48	(0.74,2.96)	1.58	(0.78,3.17)
Length residence 5-10	1.74	(0.83,3.68)	1.81	(0.84,3.91)	1.72	(0.81,3.62)	1.79	(0.83,3.85)	1.92	(0.88,4.19)
Length residence 10-29	1.13	(0.64,2.00)	1.16	(0.66,2.02)	1.13	(0.64,1.99)	1.15	(0.66,2.00)	1.19	(0.68,2.09)
Neighborhood:									*Beta*	*p-value*
Residential Stability			1.01	(0.99,1.03)			1.01	(0.99,1.03)	0.006	
Change Middle Income					0.99	(0.97,1.01)	0.99	(0.97,1.01)	-0.008	
Stability * Change Middle Income									-0.001	0.004

Odds ratios for variables where interactions are present are uninterpretable, and therefore not shown. Model parameters must be used to determine relative odds of the relation between specific variables and the outcome.

Table 7.13 Multilevel Logistic Regression of Depression on Neighborhood Stability and Change in Middle Income (Betas)

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.	
Individual:															
Intercept	-2.40	(0.43)	***	-2.38	(0.44)	***	-2.41	(0.43)	***	-2.38	(0.44)	***	-2.47	(0.44)	***
Age	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**
Female	0.56	(0.20)	**	0.56	(0.20)	**	0.56	(0.20)	**	0.56	(0.20)	**	0.60	(0.21)	**
African American NH	-0.56	(0.26)	*	-0.57	(0.27)	*	-0.53	(0.25)	*	-0.58	(0.27)	*	-0.59	(0.26)	*
Other race NH	-0.16	(0.59)		-0.16	(0.59)		-0.20	(0.59)		-0.19	(0.58)		-0.22	(0.59)	
Latino	-0.79	(0.40)	*	-0.80	(0.40)	*	-0.78	(0.40)		-0.79	(0.40)	*	-0.78	(0.40)	*
Not married	0.13	(0.31)		0.12	(0.32)		0.11	(0.31)		0.10	(0.32)		0.11	(0.32)	
Education <high school	-0.10	(0.23)		-0.10	(0.23)		-0.11	(0.23)		-0.10	(0.23)		-0.12	(0.23)	
Education high school	0.26	(0.24)		0.27	(0.24)		0.25	(0.24)		0.26	(0.24)		0.23	(0.24)	
Income <$10,000	0.90	(0.40)	*	0.89	(0.40)	*	0.92	(0.40)	*	0.92	(0.40)	*	0.90	(0.41)	*
Income $10-19,000	0.52	(0.34)		0.51	(0.34)		0.55	(0.34)		0.54	(0.34)		0.54	(0.34)	
Income $20-39,000	0.12	(0.32)		0.10	(0.32)		0.13	(0.32)		0.12	(0.32)		0.13	(0.32)	
Number in household	0.02	(0.06)		0.02	(0.06)		0.02	(0.06)		0.02	(0.06)		0.01	(0.06)	
Not homeowner	0.22	(0.21)		0.22	(0.21)		0.25	(0.21)		0.24	(0.21)		0.23	(0.22)	
Length residence <5yrs	0.38	(0.35)		0.41	(0.35)		0.36	(0.35)		0.40	(0.35)		0.46	(0.36)	
Length residence 5-10	0.56	(0.38)		0.60	(0.39)		0.54	(0.38)		0.58	(0.39)		0.65	(0.40)	
Length residence 10-29	0.13	(0.29)		0.15	(0.28)		0.12	(0.29)		0.14	(0.28)		0.18	(0.29)	
Neighborhood:															
Residential Stability				0.007	(0.009)					0.007	(0.01)		0.006	(0.009)	
Change % Middle Income							-0.011	(0.01)		-0.011	(0.01)		-0.008	(0.011)	
Stability * Change Middle Income													-0.001	(0.000)	**

*p<0.05, **p<0.01, ***p<0.001

ICC	0.11	Level 1 variance	0.96
Design effect	2.36	Level 2 variance	0.11

Table 7.14 Multilevel Logistic Regression of Depression on Neighborhood Stability and Percent African American (Odds Ratios)

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Individual:										
Intercept	0.09	(0.04,0.21)	0.09	(0.04,0.22)	0.09	(0.04,0.23)	0.09	(0.04,0.22)	0.09	(0.03,0.23)
Age	0.98	(0.97,0.99)	0.98	(0.96,0.99)	0.98	(0.97,0.99)	0.98	(0.97,0.99)	0.98	(0.96,0.99)
Female	1.75	(1.17,2.61)	1.75	(1.17,2.61)	1.75	(1.17,2.61)	1.75	(1.17,2.61)	1.75	(1.17,2.61)
African American NH	0.59	(0.36,0.98)	0.56	(0.33,0.96)	0.59	(0.30,1.17)	0.58	(0.29,1.17)	0.58	(0.29,1.16)
Other race NH	0.85	(0.27,2.71)	0.85	(0.27,2.69)	0.85	(0.27,2.73)	0.87	(0.28,2.76)	0.87	(0.27,2.79)
Latino	0.45	(0.21,0.99)	0.45	(0.21,0.98)	0.45	(0.21,0.98)	0.44	(0.21,0.96)	0.44	(0.20,0.95)
Not married	1.14	(0.62,2.10)	1.13	(0.61,2.09)	1.14	(0.62,2.12)	1.13	(0.61,2.11)	1.14	(0.61,2.14)
Education <high school	0.90	(0.58,1.41)	0.91	(0.58,1.42)	0.90	(0.57,1.42)	0.90	(0.57,1.42)	0.90	(0.57,1.41)
Education high school	1.30	(0.81,2.08)	1.30	(0.82,2.09)	1.30	(0.81,2.08)	1.30	(0.82,2.08)	1.30	(0.81,2.08)
Income <$10,000	2.45	(1.12,5.37)	2.44	(1.12,5.33)	2.45	(1.12,5.35)	2.45	(1.12,5.33)	2.43	(1.11,5.31)
Income $10-19,000	1.68	(0.87,3.25)	1.66	(0.86,3.22)	1.68	(0.87,3.25)	1.66	(0.86,3.21)	1.65	(0.86,3.17)
Income $20-39,000	1.13	(0.61,2.09)	1.11	(0.60,2.06)	1.13	(0.61,2.10)	1.11	(0.60,2.07)	1.11	(0.60,2.06)
Number in household	1.02	(0.92,1.14)	1.02	(0.92,1.14)	1.02	(0.92,1.14)	1.02	(0.92,1.14)	1.02	(0.92,1.14)
Not homeowner	1.25	(0.83,1.89)	1.24	(0.82,1.89)	1.25	(0.83,1.87)	1.24	(0.82,1.86)	1.24	(0.82,1.86)
Length of residence <5yrs	1.46	(0.74,2.88)	1.51	(0.76,3.03)	1.46	(0.74,2.90)	1.52	(0.77,3.01)	1.53	(0.78,3.04)
Length of residence 5-10	1.74	(0.83,3.68)	1.81	(0.84,3.91)	1.75	(0.81,3.76)	1.81	(0.83,3.93)	1.82	(0.84,3.94)
Length of residence 10-29	1.13	(0.64,2.00)	1.16	(0.66,2.02)	1.14	(0.64,2.00)	1.16	(0.67,2.02)	1.16	(0.67,2.03)
Neighborhood:									*Beta*	*P-value*
Residential Stability			1.01	(0.99,1.03)			1.01	(0.99,1.03)	0.007	
% African American					1.00	(0.99,1.01)	1.00	(0.99,1.01)	-0.001	
Stability * % African Am.									0.000	0.63

Odds ratios for variables where interactions are present are uninterpretable, and therefore not shown. Model parameters must be used to determine relative odds of the relation between specific variables and the outcome.

Table 7.15 Multilevel Logistic Regression of Depression on Neighborhood Stability and Percent African American (Betas)

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta.	S.E.		Beta	S.E.	
Individual:															
Intercept	-2.40	(0.43)	***	-2.38	(0.44)	***	-2.40	(0.46)	***	-2.41	(0.46)	***	-2.44	(0.48)	***
Age	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**	-0.02	(0.01)	**
Female	0.56	(0.20)	**	0.56	(0.20)	**	0.56	(0.21)	**	0.56	(0.20)	**	0.56	(0.20)	**
African American NH	-0.53	(0.26)	*	-0.57	(0.27)	*	-0.53	(0.35)		-0.54	(0.35)		-0.54	(0.35)	
Other race NH	-0.16	(0.59)		-0.16	(0.59)		-0.16	(0.59)		-0.14	(0.59)		-0.14	(0.59)	
Latino	-0.79	(0.40)	*	-0.80	(0.40)	*	-0.79	(0.39)	*	-0.81	(0.39)	*	-0.82	(0.39)	*
Not married	0.13	(0.31)		0.12	(0.32)		0.13	(0.32)		0.12	(0.32)		0.13	(0.32)	
Education <high school	-0.10	(0.23)		-0.10	(0.23)		-0.11	(0.23)		-0.10	(0.23)		-0.11	(0.23)	
Education high school	0.26	(0.24)		0.27	(0.24)		0.26	(0.24)		0.27	(0.24)		0.26	(0.24)	
Income <$10,000	0.87	(0.40)	*	0.89	(0.40)	*	0.90	(0.40)	*	0.89	(0.40)	*	0.89	(0.40)	*
Income $10-19,000	0.52	(0.34)		0.51	(0.34)		0.52	(0.34)		0.51	(0.34)		0.50	(0.33)	
Income $20-39,000	0.12	(0.32)		0.10	(0.32)		0.12	(0.32)		0.11	(0.32)		0.10	(0.32)	
Number in household	0.02	(0.06)		0.02	(0.06)		0.02	(0.06)		0.02	(0.06)		0.02	(0.06)	
Not homeowner	0.22	(0.21)		0.22	(0.21)		0.22	(0.21)		0.21	(0.21)		0.21	(0.21)	
Length residence <5yrs	0.38	(0.35)		0.41	(0.35)		0.38	(0.35)		0.42	(0.35)		0.43	(0.35)	
Length residence 5-10	0.56	(0.38)		0.60	(0.39)		0.56	(0.39)		0.59	(0.40)		0.60	(0.39)	*
Length residence 10-29	0.13	(0.29)		0.15	(0.28)		0.13	(0.29)		0.15	(0.28)		0.15	(0.28)	
Neighborhood:															
Residential Stability				0.007	(0.009)					0.008	(0.009)		0.008	(0.009)	
% African American							0.000	(0.004)		-0.001	(0.004)		-0.0007	(0.004)	
Stability * % African Am.													0.0001	(0.000)	

*p<0.05, **p<0.01, ***p<0.001

ICC 0.16
Design effect 2.91

Level 1 variance 0.95
Level 2 variance 0.18

Table 7.16 Mediation Step 2: Financial Vulnerability Regressed on Neighborhood Stability and Middle Income

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.	
Individual:															
Intercept	1.92	(0.18)	***	1.92	(0.18)	***	1.90	(0.18)	***	1.89	(0.18)	***	1.86	(0.19)	***
Age	-0.01	(0.00)	*	-0.01	(0.00)	*	-0.01	(0.00)		-0.01	(0.00)		-0.01	(0.00)	
Female	0.03	(0.07)		0.04	(0.07)		0.03	(0.07)		0.04	(0.07)		0.04	(0.07)	
African American NH	-0.06	(0.10)		-0.05	(0.11)		-0.04	(0.11)		-0.04	(0.11)		-0.03	(0.11)	
Other race NH	0.14	(0.33)		0.13	(0.33)		0.14	(0.33)		0.14	(0.33)		0.13	(0.33)	
Latino	0.23	(0.12)		0.23	(0.12)		0.25	(0.12)	*	0.25	(0.12)	*	0.26	(0.12)	*
Not married	-0.03	(0.10)		-0.03	(0.10)		-0.02	(0.10)		-0.02	(0.10)		-0.01	(0.11)	
Education <high school	0.30	(0.12)	*	0.30	(0.12)	*	0.31	(0.12)	**	0.31	(0.12)	**	0.31	(0.12)	**
Education high school	-0.10	(0.10)		-0.10	(0.10)		-0.08	(0.10)		-0.09	(0.10)		-0.09	(0.10)	
Income <$10,000	1.02	(0.16)	***	1.02	(0.16)	***	1.04	(0.16)	***	1.04	(0.16)	***	1.03	(0.16)	***
Income $10-19,000	0.70	(0.14)	***	0.70	(0.14)	***	0.71	(0.14)	***	0.71	(0.14)	***	0.72	(0.14)	***
Income $20-39,000	0.46	(0.12)	***	0.47	(0.12)	***	0.48	(0.12)	***	0.48	(0.12)	***	0.48	(0.13)	***
Number in household	0.05	(0.03)		0.05	(0.03)		0.06	(0.03)	*	0.06	(0.03)	*	0.05	(0.03)	
Not homeowner	0.46	(0.11)	***	0.46	(0.11)	***	0.47	(0.11)	***	0.47	(0.11)	***	0.47	(0.11)	***
Length residence <5yrs	0.33	(0.12)	**	0.32	(0.11)	**	0.31	(0.12)	*	0.31	(0.12)	**	0.32	(0.12)	**
Length residence 5-10	0.27	(0.12)	*	0.26	(0.12)	*	0.25	(0.13)	*	0.24	(0.12)	*	0.25	(0.13)	*
Length residence 10-29	0.12	(0.10)		0.12	(0.10)		0.10	(0.10)		0.10	(0.10)		0.11	(0.10)	
Neighborhood:															
Residential Stability				-0.001	(0.004)					-0.001	(0.004)		-0.0005	(0.004)	
% Middle Income							0.004	(0.004)		0.004	(0.004)		0.0066	(0.004)	
Stability * Middle Income													-0.0004	(0.000)	

*$p<0.05$, **$p<0.01$, ***$p<0.001$

ICC	0.01	Level 1 variance	1.06
Design effect	1.16	Level 2 variance	0.01

Table 7.17 Mediation Step 2: Emotional Social Support Regressed on Neighborhood Stability and Middle Income

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.	
Individual:															
Intercept	4.48	(0.13)	***	4.47	(0.13)	***	4.48	(0.14)	***	4.48	(0.14)	***	4.46	(0.14)	***
Age	-0.00	(0.00)		-0.00	(0.00)		-0.00	(0.00)		-0.00	(0.00)		-0.00	(0.00)	
Female	0.14	(0.07)		0.14	(0.07)		0.14	(0.07)		0.14	(0.07)		0.14	(0.07)	*
African American NH	-0.03	(0.09)		-0.02	(0.09)		-0.03	(0.09)		-0.02	(0.10)		-0.02	(0.10)	
Other race NH	0.04	(0.24)		0.03	(0.24)		0.03	(0.24)		0.03	(0.24)		0.03	(0.24)	
Latino	-0.07	(0.11)		-0.07	(0.11)		-0.07	(0.11)		-0.07	(0.11)		-0.07	(0.11)	
Not married	-0.26	(0.08)	**	-0.26	(0.08)	**	-0.27	(0.08)	**	-0.27	(0.08)	**	-0.26	(0.08)	**
Education <high school	-0.13	(0.07)		-0.13	(0.07)		-0.13	(0.07)		-0.13	(0.07)		-0.13	(0.07)	
Education high school	-0.02	(0.07)		-0.02	(0.07)		-0.02	(0.07)		-0.02	(0.07)		-0.03	(0.07)	
Income <$10,000	-0.33	(0.11)	**	-0.33	(0.11)	**	-0.33	(0.11)	**	-0.33	(0.11)	**	-0.33	(0.11)	**
Income $10-19,000	-0.04	(0.10)		-0.04	(0.10)		-0.05	(0.10)		-0.05	(0.10)		-0.05	(0.10)	
Income $20-39,000	0.06	(0.10)		0.07	(0.10)		0.06	(0.10)		0.06	(0.10)		0.07	(0.10)	
Number in household	-0.04	(0.02)	*	-0.04	(0.02)	*	-0.04	(0.02)	*	-0.04	(0.02)	*	-0.04	(0.02)	*
Not homeowner	-0.12	(0.07)		-0.12	(0.07)		-0.12	(0.07)		-0.13	(0.07)		-0.12	(0.07)	
Length of residence <5yrs	-0.11	(0.12)		-0.12	(0.12)		-0.11	(0.12)		-0.11	(0.12)		-0.10	(0.12)	
Length of residence 5-10	-0.13	(0.12)		-0.13	(0.12)		-0.12	(0.12)		-0.13	(0.12)		-0.12	(0.12)	
Length of residence 10-29	-0.15	(0.12)		-0.15	(0.12)		-0.14	(0.12)		-0.14	(0.12)		-0.14	(0.12)	
Neighborhood:															
Residential Stability				-0.001	(0.00)					-0.001	(0.00)		-0.001	(0.003)	
% Middle Income							-0.001	(0.00)		-0.001	(0.00)		0.000	(0.004)	
Stability * Middle Income													-0.000	(0.000)	

*p<0.05, **p<0.01, ***p<0.001 ICC 0.04 Design effect 1.45 Level 1 variance 0.71 Level 2 var 0.03

Table 7.18 Mediation Step 2: Instrumental Social Support Regressed on Neighborhood Stability and Middle Income

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.	
Individual:															
Intercept	3.93	(0.14)	***	3.92	(0.14)	***	3.92	(0.14)	***	3.91	(0.15)	***	3.91	(0.15)	***
Age	-0.00	(0.00)		-0.00	(0.00)		-0.00	(0.00)		-0.00	(0.00)		-0.00	(0.00)	
Female	0.11	(0.08)		0.11	(0.08)		0.11	(0.08)		0.11	(0.08)		0.11	(0.08)	
African American NH	-0.09	(0.09)		-0.07	(0.10)		-0.09	(0.10)		-0.06	(0.10)		-0.06	(0.10)	
Other race NH	-0.17	(0.26)		-0.17	(0.25)		-0.16	(0.26)		-0.17	(0.25)		-0.17	(0.25)	
Latino	0.05	(0.13)		0.05	(0.13)		0.05	(0.14)		0.06	(0.13)		0.06	(0.14)	
Not married	-0.17	(0.08)	*	-0.16	(0.08)	*	-0.16	(0.08)	*	-0.16	(0.08)	*	-0.16	(0.08)	*
Education <high school	-0.05	(0.08)		-0.05	(0.08)		-0.04	(0.08)		-0.05	(0.08)		-0.05	(0.08)	
Education high school	0.04	(0.07)		0.04	(0.07)		0.04	(0.08)		0.04	(0.07)		0.04	(0.08)	
Income <$10,000	-0.50	(0.12)	***	-0.50	(0.12)	***	-0.49	(0.12)	***	-0.49	(0.12)	***	-0.49	(0.12)	***
Income $10-19,000	-0.23	(0.11)	*	-0.23	(0.11)	*	-0.23	(0.11)	*	-0.23	(0.11)	*	-0.23	(0.11)	*
Income $20-39,000	-0.06	(0.09)		-0.06	(0.09)		-0.06	(0.09)		-0.06	(0.09)		-0.06	(0.09)	
Number in household	-0.04	(0.02)	*	-0.04	(0.02)		-0.04	(0.02)		-0.04	(0.02)		-0.04	(0.02)	
Not homeowner	-0.17	(0.07)		-0.12	(0.07)		-0.11	(0.07)		-0.12	(0.07)		-0.16	(0.07)	
Length residence <5yrs	-0.15	(0.11)		-0.16	(0.11)		-0.15	(0.11)		-0.17	(0.11)		-0.17	(0.11)	
Length residence 5-10	-0.23	(0.11)	*	-0.25	(0.12)	*	-0.24	(0.11)	*	-0.26	(0.16)	*	-0.26	(0.12)	*
Length residence 10-29	-0.16	(0.18)		-0.17	(0.11)		-0.16	(0.11)		-0.17	(0.11)		-0.17	(0.11)	
Neighborhood:															
Residential Stability				-0.004	(0.004)					-0.004	(0.004)		-0.004	(0.004)	
% Middle Income							0.002	(0.004)		0.001	(0.004)		0.001	(0.004)	
Stability * Middle Income													-0.000	(0.000)	

*p<0.05, **p<0.01, ***p<0.001

ICC 0.06 Level 1 variance 0.85

Design effect 1.68 Level 2 variance 0.04

Table 7.19 Multilevel Logistic Regression of Depression on Financial Vulnerability, Emotional Social Support, and Instrumental Social Support with Individual Level Factors Only

	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
Variable	Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.		Beta	S.E.	
Individual:																		
Intercept	-2.40	-0.43	***	-2.06	0.45	***	-2.27	0.42	***	-2.03	0.43	***	-2.21	0.43	***	-1.99	0.44	***
Age	-0.02	-0.01	**	-0.02	0.01	**	-0.03	0.01	**	-0.03	0.01	**	-0.02	0.01	**	-0.02	0.01	**
Female	0.56	-0.20	**	0.56	0.21	**	0.68	0.21	**	0.68	0.22	**	0.65	0.20	**	0.64	0.21	**
African American NH	-0.53	-0.26	*	-0.52	0.26	*	-0.57	0.26	*	-0.57	0.25	*	-0.58	0.26	*	-0.58	0.26	*
Other race NH	-0.16	-0.59		-0.25	0.67		-0.11	0.57		-0.19	0.63		-0.24	0.59		-0.32	0.66	
Latino	-0.79	-0.40	*	-0.91	0.40	*	-0.87	0.43	*	-0.95	0.43	*	-0.79	0.44		-0.88	0.43	*
Not married	0.13	-0.31		0.15	0.30		-0.01	0.32		0.03	0.31		0.06	0.32		0.10	0.31	
< high school	-0.10	-0.23		-0.21	0.25		-0.18	0.24		-0.27	0.25		-0.12	0.24		-0.21	0.26	
High school	0.26	-0.24		0.31	0.26		0.30	0.26		0.31	0.27		0.32	0.26		0.35	0.27	
Income <$10,000	0.90	-0.40	*	0.56	0.40		0.72	0.39		0.50	0.41		0.63	0.40		0.43	0.41	
Income $10-19,000	0.52	-0.34		0.28	0.33		0.51	0.33		0.34	0.33		0.40	0.33		0.26	0.33	
Income $20-39,000	0.12	-0.32		-0.04	0.32		0.20	0.31		0.06	0.31		0.07	0.31		-0.04	0.31	
Number in household	0.02	-0.06		0.01	0.05		0.00	0.06		0.00	0.05		0.00	0.06		0.00	0.05	
Not homeowner	0.22	-0.21		0.05	0.21		0.13	0.21		0.00	0.20		0.16	0.22		0.02	0.21	
Length residence <5yrs	0.38	-0.35		0.28	0.36		0.31	0.36		0.26	0.36		0.28	0.35		0.23	0.36	
Length residence 5-10	0.56	-0.38		0.50	0.40		0.47	0.39		0.46	0.41		0.45	0.39		0.43	0.41	
Length residence 10-29	0.13	-0.29		0.07	0.29		0.03	0.28		-0.01	0.28		0.04	0.28		0.01	0.29	
Financial Vulnerability				0.37	0.10	***				0.27	0.10	*				0.27	0.10	**
Emotional Social Support							-0.62	0.12	***	-0.55	0.12	***						
Instrumental Social Support													-0.50	0.12	***	-0.44	0.12	**

*$p<0.05$, **$p<0.01$, ***$p<0.001$

CHAPTER 8.

DISCUSSION

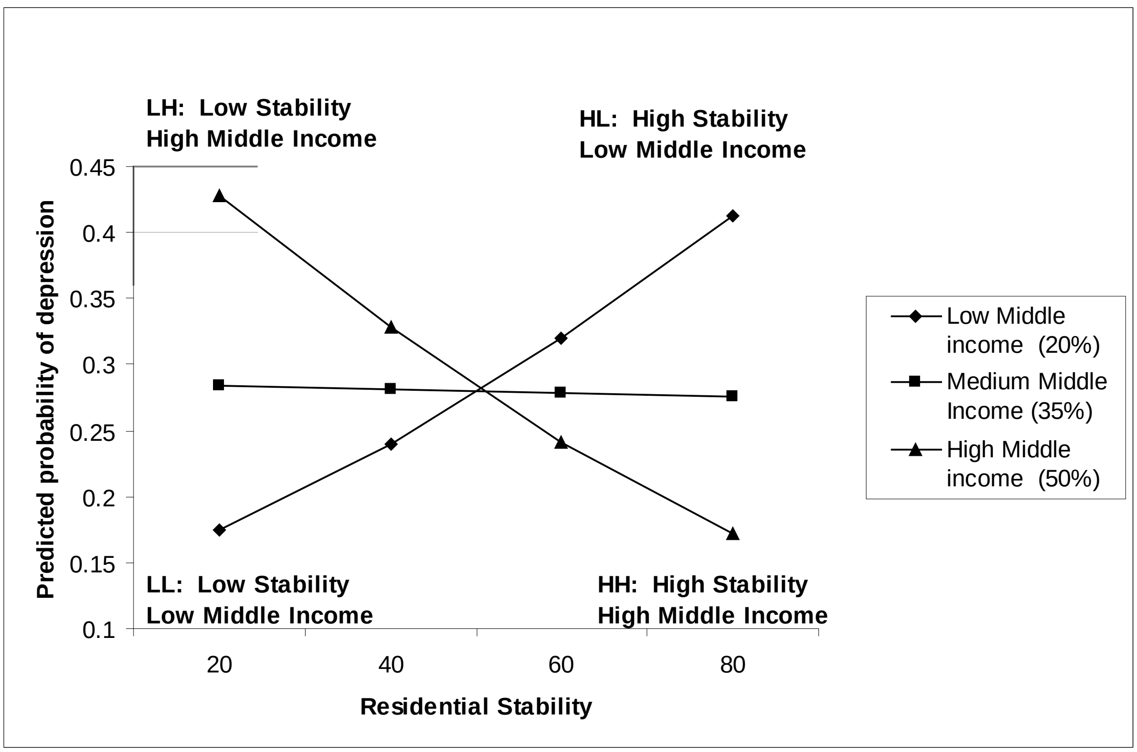
In this chapter I discuss the major findings for each of the three research questions, including how these results compare with published research to date, and the contribution of this research to our understanding of neighborhood effects on health. I detail strengths and limitations of the study, and suggest implications for future research, policy, and intervention.

A. Research Question 1: The Effects of Neighborhood Residential Stability and Middle Income Composition on Depression

My conceptual model proposes that the effects of neighborhood stability on depression depend on the extent to which there are middle income residents in the neighborhood. The results of my investigation support this model. Neighborhood residential stability is beneficial to mental health when there is a high proportion of middle income residents in the neighborhood, and is detrimental to mental health when there are few middle income residents.

To further understand these results, I present Figure 8.1, a modification of Figure 7.1, that shows the effects of stability on major depression at three levels of percent neighborhood middle income. The slopes of the three lines indicate that the impact of stability on depression varies depending on the proportion of middle income households in the neighborhood. To aid in interpretation, I label probability of depression at four points: Low Stability & High Middle Income (LH), Low Stability & Low Middle Income (LL), High Stability & Low Middle Income (HL), and High Stability & High Middle Income (HH). Table 8.1 presents values for the probability of depression for persons living in each of these four "types" of neighborhoods.

Figure 8.1 Predicted Probability of Depression by Neighborhood Stability for High, Medium, and Low Percent Middle Income Neighborhoods



*Predicted probabilities of depression are for the following group:
Average age (46), female, African American, not married, income less than $10,000, 3 persons in household, less than high school education, not homeowner, length of residence in neighborhood less than 5 years
Crossing point: Residential stability = 51%, Middle income composition = 34%

Stable Neighborhoods and Neighborhood Middle Income

The right side of the plot displays the probability of depression for persons living in stable neighborhoods. These results support my central hypothesis that at low levels of middle income, stability is associated with higher odds of depression, while at high levels of middle income, stability is associated with lower odds of depression. The effects on depression are substantial, as reported in Table 8.1 as predicted probabilities for those at highest individual risk for depression). Residents of stable neighborhoods with a low proportion of middle income have a three times higher probability of major depression (.45) compared to those in neighborhoods with high proportion middle income (.15).

Table 8.1 Predicted Probability of Depression by Neighborhood Type for Group with Highest Risk of Depression*

		Percent Middle Income		
		Low (20%)	High (50%)	Ratio of highest to lowest probability of depression
Residential Stability	Low (21%)	.18	.42	2.3
	High (88%)	.45	.15	3.0
	Ratio of highest to lowest probability of depression	2.5	2.8	

*Persons of average age (46 years) and average number of persons in the household (three), and with the following characteristics associated with high risk of depression or socioeconomic disadvantage: Female, African American, not married, income less than $10,000, less than high school education, not homeowner, length of residence in neighborhood less than 5 years

The difference is even more pronounced among persons with low individual risk for depression (Table 8.2): those persons living in stable low income neighborhoods have nearly four times the probability of being depressed (.15) compared to those living in stable high proportion middle income neighborhoods (.04).

Table 8.2 Predicted Probability of Depression by Neighborhood Type for Group with Lowest Risk of Depression*

		Percent Middle Income		
		Low (20%)	High (50%)	Ratio of highest to lowest probability of depression
Residential Stability	Low (21%)	.05	.14	2.8
	High (88%)	.15	.04	3.75
	Ratio of highest to lowest probability of depression	3.0	3.5	

*Persons of average age (46 years) and average number of persons in the household (three), and with the following characteristics associated with lowest risk of depression or socioeconomic disadvantage: Male, white, married, income over $40,000, college education, homeowner, length of residence in neighborhood over 30 years

These findings are consistent with the published research on the joint effects of stability and poverty on mental health (Ross, Reynolds, and Geis 2000), and the effects of stability, poverty, and affluence on physical health (Browning and Cagney 2003;

Browning, Cagney, and Wen 2003). This dissertation is the first study to my knowledge to examine the effects of stability and middle income composition on any health indicator.

Unstable Neighborhoods and Neighborhood Income

Examining the left side of the plot, we see that the neighborhood income lines cross at about 50% stability. This indicates that when about half the population has turned over, depression in higher income neighborhoods begins to exceed depression in low income neighborhoods. Although the slope is the same, this crossover suggests that stability/instability takes on a different meaning in terms of health advantage. At the highest level of turnover (only 20% lived in the same house five years earlier), people residing in the most income advantaged neighborhoods are 2.3 times more likely to have major depression than those in very low income neighborhoods.

What is unexpected is that under conditions of very high turnover (unstable), persons living in poor neighborhoods have a substantial mental health advantage over those living in more middle income neighborhoods. Likewise, people living in unstable neighborhoods with more middle income residents have considerably worse mental health than those living in unstable neighborhoods with few middle income residents.

The size of the effect is striking: the probability of major depressive disorder in unstable neighborhoods is .42 in middle income compared to .18 in low income neighborhoods. Further, residents of unstable poor neighborhoods have nearly the same relatively low probability of depression as those living in stable advantaged neighborhoods (.18 compared to .15). Likewise, people in advantaged unstable neighborhoods have nearly the same relative high probability of depression that as those living in the poorest stable neighborhoods (.42 and .45 respectively).

These findings are contrary to the notion that instability is particularly detrimental to mental health in disadvantaged neighborhoods because of the need for strong social ties to buffer material adversity, but is supported on the "stability" side of my findings (Faris and Dunham 1939; Silver, Mulvey, and Swanson 2002). Faris and Dunham maintained that highly mobile (unstable) disadvantaged neighborhoods make it difficult for individuals to sustain supportive social contacts, increasing their vulnerability to stress and mental disorders. They proposed that this may be particularly detrimental because residents are exposed to a greater number of stressors and have less access to health promoting resources.

The explanation for the findings in this investigation that is prevalent in the literature is referred to as social isolation theory. This view suggests that residential stability is a proxy for social attachments, which may be detrimental to health in very poor neighborhoods by connecting residents to negative social norms, behaviors, and social stressors, such as hopelessness (Portes and Landolt 1996; Shaw and McKay 1942; Wilson 1987; Wilson 1996). This view suggests that having few social ties in the neighborhood protects health by limiting exposure to "social disorder" (Ross, Reynolds, and Geis 2000). However, the few empirical studies in this area have found limited or no evidence that social ties or social disorder mediate the effects of neighborhood structural factors on health (Cutrona et al. 2005; Elliott 2000; Ross, Reynolds, and Geis 2000; Wen, Browning, and Cagney 2003). Based on this literature, I hypothesized and found, in the results presented here, that social support is influential at the individual level but does not mediate neighborhood effects on depression.

I suggest several alternative explanations for these findings that are not rooted in the notion of social isolation. Low stability in predominantly low income neighborhoods may be an indicator of residential mobility rather than instability. Low stability low income neighborhoods may be working class transition or “newcomer” neighborhoods of low income people who are economically mobile, such as younger workers and immigrants (Morenoff and Tienda 1997). Such neighborhoods may have a high supply of affordable rental housing and jobs that, while low wage, may provide a moderate income with some protection against poverty, as well as a means for economic mobility from low to more moderate income neighborhoods.

Mobile, low income neighborhoods may also have a higher proportion of immigrants compared to other neighborhoods or be historically “transition” neighborhoods with social networks that extend across neighborhood boundaries. It is plausible that persons living in such neighborhoods are able to maintain hopefulness and a sense of control, despite exposure to structural stress. According to this interpretation, these mobile neighborhoods would have lower rates of depression than do low income stable neighborhoods because residents are not exposed to the chronic stress and hopelessness of being "stuck" in a place with few economic resources.

This may in part explain the finding that individual financial vulnerability does not mediate neighborhood structural effects. However, according to this view, we would expect to find mediation effects in high stability neighborhoods. Testing for cross-level interactions may reveal a more complex relationship between stability and both financial vulnerability and social support.

Similarly, there may be historical and structural characteristics of unstable neighborhoods with a high proportion of middle income residents that contribute to mental disorder. In contrast to poor "mobile" neighborhoods, high turnover in middle income neighborhoods may be the result of job loss, home foreclosures, white flight, middle class flight, or conversion of properties from owner-occupied to rental. Unstable middle income neighborhoods may be experiencing disinvestment that creates both structural stress and the experience of powerlessness and hopelessness in the face of what appears to be an inevitable tide of change.

Investigating how neighborhoods differ by structural characteristics may provide more insight into what attributes of stability and middle income composition have beneficial effects on mental and physical health. Ecological measures of stressors and resources in the residential environment, such as declining property values, population loss, proportion of owners, housing stock, gentrification, and recency and cause of neighborhood transition (if unstable), may help explain how structural factors interact.

The prevalence of diagnosable depression in this study, 18%, was substantially higher than that found in the two studies cited in the literature review and in national samples. Cutrona found 12-month prevalence using CIDI in a national sample of African Americans to be 6.8 percent (Cutrona et al. 2005). This is comparable to what Williams and colleagues found for the 12-month prevalence for a national sample of African Americans as measured by the CIDI, which was 7.1 percent (Williams et al. 2007).

The substantially higher prevalence of major depression in this study is likely due to differences in composition between this sample and the others cited, which were nationally representative. In contrast, Detroit is urban, relatively low income, and has a high rate of poverty, crime, racial discrimination, and other environmental stresses associated with higher rates of depression. In spite of the higher burden of illness experienced by cities such as Detroit, there has been little research on neighborhood effects on mental disorders. This investigation makes an important contribution to the literature in that it expands our knowledge of the ways in which social inequality structures patterns of risk and disease

Discussion of the prevalence of depression in this study raises the issue of the magnitude of the effects observed in this study. Although the estimated effects of neighborhood stability and middle income is relatively small (beta = -0.00138) compared to the effects of individual factors on depression, neighborhood effects can be important because even modest shifts in the residential environment may affect many individuals. A number of researchers have cautioned about making causal inferences and estimating effects of change in complex, macro-level conditions. However, cautious estimation of effects based on these findings may help us more clearly specify policies and interventions aimed at reducing mental disorder (Bingenheimer and Raudenbush 2004; Diez Roux 2004; Kaufman forthcoming).

For example, the overall prevalence of depression in the sample was 18%, suggesting an average of 180 cases of diagnosable depression per block group based on mean block group size of 1000. A 5% change in middle income residents in an average size block group would be comprised of 17 households. In those neighborhoods with the highest risk of depression, high stability and low middle income, a small number of middle income families remaining or moving into the neighborhood may prevent a neighborhood from tipping into poverty. Although it is unlikely that changing any one aspect of neighborhood context can have an independent causal effect on health, this study provides evidence that a small difference in neighborhood context is associated with a significantly higher probability of mental disorder in neighborhoods.

To my knowledge, this is the first study to examine how a change in the proportion of middle income residents in a neighborhood affects health, either directly or in interaction with other structural characteristics of neighborhoods. Although there has been substantial discussion of the impact of the loss of middle income residents and the increasing concentration of poverty in central cities (Massey and Denton 1993; Quercia and Galster 1997; Wilson 1987), there is little empirical work on the effects of change in neighborhood residential environments on mental health in predominantly low income communities. Metropolitan areas are undergoing tremendous economic, social, and physical change that will have both short and long term consequences for health, and understanding the impact of those changes may contribute to policies that promote the health of city residents and reduce racial and economic inequities in health.

The analysis of change in this investigation was very preliminary and should be expanded upon in future studies. Because this measure was a simple change score, it measures only the magnitude and direction of change in percent middle income, but gives no indication of the overall income composition or the relative effect of that change on existing income composition. For example, a change score of -5 could indicate a change in a predominantly middle income neighborhood from 70% to 65% middle income, or it could indicate a proportionately greater loss of middle income households from a predominantly moderate or low income neighborhood, for example, from 30% to 25%. In the latter case of a highly stable low income neighborhood, the effect on depression may be substantial, for example, hitting a “tipping point” which either triggers or prevents movement of remaining middle income families out of the neighborhood (Ottensmann 1995; Quercia and Galster 1997). The resulting increase in chronic stress may contribute to higher risk of depression among residents.

In spite of the limitations of this change measure, the finding of a significant interaction suggests the need to further examine the relationship between changing neighborhood income composition, stability, and depression. In addition, this arena may be amenable to change or protection through zoning and lending policies that consider the existing residential composition of neighborhoods in community development planning, as will be detailed in the section on implications for policy.

B. Research Question 2: Racial Composition, Stability, and Depression

In the next research question I investigated whether the effects of residential stability on depression are influenced by the racial composition of neighborhoods in Detroit. Social class and race are tightly intertwined in the U.S. Most studies in the literature review found that most effects of neighborhood racial composition on health disappear when controlling for individual characteristics. I hypothesized that in Detroit, the effect of stability on depression is not contingent on racial composition. My findings found no effect of percent African American on depression or the stability-depression relationship.

Evidence from several studies have suggested that living in racially mixed neighborhoods may be detrimental to the mental health of African Americans because of exposure to racism, while living in an ethnic enclave may be protective (Ostir, Eschbach, Markides, and Goodwin 2003; Williams et al. 2007). While I did not test the above in this dissertation, I found that in the HEP neighborhoods (as shown in Table 7.4), the unadjusted prevalence of depression is substantially higher in neighborhoods with 30 – 70% African Americans (24%, SD = 8.1), as compared to neighborhoods with low or high percent African Americans (respectively 17.2, SD = 2.1 and 18.3, SD = 1.8). As described previously, Detroit is 81% African American and highly racially segregated.

C. Research Question 3: Individual Financial Vulnerability and Social Support as Mediators of the Relationship between Neighborhood Residential Structure and Depression

The third research question explores the right side of the conceptual model (Figure 4.1), which tests whether individual level stress (financial vulnerability) and resources (social support) are pathways through which neighborhood residential structure affects depression. Based on the literature that stable neighborhoods with a high proportion of middle income residents engenders structural resources or structural stress at low levels of middle income residents at a collective level that is beneficial to mental health, I proposed that this neighborhood structural resource or stress manifests at the individual level as financial vulnerability. I selected the financial vulnerability measure as a conceptually more proximate measure of the economic insecurity engendered by the neighborhood structural factors examined than an ecological measure. I found no mediating effects.

The first portion of the financial vulnerability scale is a measure of income insufficiency, which may be more sensitive for mental health than income because it takes into account the relationship of needs to income. The second portion of the scale is in part a measure of “wealth” or housing stability. Housing accounts for a substantial portion of the cost of living for both renters and homeowners. A recent study of housing affordability in Detroit found that 32% of Detroit’s households faced cost burdens in 2000, that is, they paid 30% or more of their income on housing costs (Thomson 2004). About half of those households faced severe cost burdens, spending 50% or more of their income on housing costs. This greatly exceeds comparison areas in the region, state and nation.

More ecological measures may capture economic stress in the residential environment engendered by the interaction of stability and middle income, such as property values, denial rates for home repair loans, housing costs, and vacancy rate. However, neighborhood effects are relatively small and related in complex ways. Any individual effects on depression may be difficult to detect.

Although I found no mediation effects, the highly significant effects of financial vulnerability suggest that this measure may be a more sensitive measure of socioeconomic position than income alone and may capture additional factors, such as wealth and housing

The finding that neither emotional nor instrumental social support mediated the relationship between stability and depression was consistent with the literature, in spite of prevalent theories regarding the benefits of stability. As can be seen by the low ICC, most of the effects in these models are at the individual level. Future research on the relationship between social support, financial vulnerability, and depression would contribute to the knowledge base in this area..

D. Strengths and Limitations

This study contributes to our understanding of how aspects of the neighborhood residential environment affect the mental health of residents. It is one of the few studies to look at the joint effects of residential stability, neighborhood income, and mental health, and may be the first to study the effects of middle income composition rather than affluence within an economically disinvested city. In addition, it is one of only a few studies to investigate neighborhood effects on diagnosable depression.

Testing whether a change in neighborhood middle income composition affects the relationship between residential stability and depression provides a temporal dimension to this research as well. Although the measure was crude, it indicates that changes in the structural composition at the neighborhood level are consequential for health.

Understanding how neighborhood socioeconomic conditions affect health may provide further evidence that the racial sorting of African Americans and ethnic minorities into economically distressed communities and Whites into more economically advantaged communities accounts for a substantial share of racial health disparities. Detroit is an ideal site for exploring these effects and the HEP sample was designed to allow comparisons across income and racial groups. A challenge in Detroit, as in many US cities, is that because of entrenched racial segregation, there are few neighborhoods with a racially mixed population. Therefore neighborhood percent African American is bimodal. However, normal distribution of predictors is not an assumption for logistic regression, making it advantageous to examine binary depression as an outcome.

A particular contribution is that this study conceptualized and tested financial vulnerability as a pathway by which neighborhoods affect depression. The emphasis in the literature on a social disorder explanatory framework has largely used measures of the social environment, with less attention to the ways in which material and economic conditions operate to affect health other than through individual income. However, as described in the discussion section, financial vulnerability may not have captured the more ecological construct I was intending. The strength of the association with depression warrants further exploration.

There are several limitations related to measures. The commonly used census measure of residential stability does not account for the substantial loss of population that many otherwise "stable" urban neighborhoods have experienced. For example, a neighborhood may have lost fifty percent of its population and still have 100% residential stability. This loss of population may contribute to systematic differences in who remains. For example, people with mental disorders may be less able to move, therefore contributing to higher prevalence of depression in some neighborhoods. In addition, neighborhood stability may confer different effects at different levels due to racial segregation, or have different effects if the instability is due to gentrification. These limitations of the residential stability measure have not been addressed in the literature to my knowledge. Future studies might employ statistical controls or neighborhood typologies to examine the joint and separate effects of these interrelated structural factors.

Using the national median as a cutpoint for middle income afforded some comparability across cities, and because of the restricted range of income in Detroit, I was able to use a continuous measure defined as $40,000 and above. However, because this measure includes all incomes up to the maximum, it also includes a small proportion of affluent households and is more accurately labeled middle income and above, as described in Chapter 6. Methods. Expanding measures of neighborhood income structure to include middle income as well as affluence extends the scant literature on the effects of neighborhood economic advantage on health, and in particular mental health.

Based on examination of the data, I do not believe this limitation substantially affected the results; however, the sample size was not large enough to compare results using a capped measure. Additionally, a data set with both more respondents and a larger number of neighborhoods with affluent residents would allow comparison of the results from the $40,000 and above measure with a concurrent analysis of neighborhood affluence only ($75,000 and above), or allow stratification for comparing neighborhood types.

The substantial crossover effect illustrated in Figures 7.1, 7.2, and 7.3 is an additional contribution to our knowledge of the complex interaction of different structural characteristics of neighborhoods.

Another strength of this study is the use of a relatively small area definition of neighborhood, the census block group. Most of the published studies reviewed earlier used clusters of tracts and only three examined neighborhood effects at lower than the tract level (Caughy, O'Campo, and Muntaner 2003; Cutrona et al. 2005; Henderson et al. 2005). While there has been much discussion over the limitations of using census boundaries as proxies for “neighborhood,” block groups may be small enough to be relatively homogeneous but still large enough to capture differences in the spatial distribution of structural resources that influence mental health.

When estimating the influence of neighborhood characteristics on major depression it is important to know whether the individual was residing in the same neighborhood during the time of onset. The CIDI measure used in this study assessed symptoms within the previous 12 months only; however, I was unable to limit cases to those who were living in the neighborhood at least 12 months because of inadequate sample size. This may result in mis-estimation of neighborhood effects, for example, as described with population loss.

A limitation of using hierarchical linear modeling is that linear regression is designed to eliminate co-varying predictors. However, structural characteristics of place are interrelated in complex ways. These models may underestimate variations in particular configurations of place and complex relationships to individual outcomes (Bingenheimer and Raudenbush 2004; Diez Roux 2004; Gorman-Smith, Tolan, and Henry 2000).

Finally, a strength of this research was that it was conducted through my participation in the Healthy Environments Partnership, a community-based participatory research project. My engagement with community and academic partners informed all aspects of the dissertation and will help to insure that findings will be relevant to improving the health of communities for Detroit residents.

E. Implications for Future Research

The findings of this dissertation suggest a number of areas for future research, some of which have been described in more detail in the strengths and limitations section.

There is a substantial literature indicating that mental health is associated with neighborhood factors (Galea et al. 2005; Truong and Ma 2006; Wandersman and Nation 1998); however, little is understood about the mechanisms through which residential neighborhoods influence mental health, and in particular, major depression. Future research on the pathways through which particular structural factors contribute to specific mental health outcomes, may enable us to identify aspects of the environment that may be modified to prevent depression.

Specifically, investigation into the ways in which middle income composition moderates the effect of stability on depression would provide a sounder basis for developing policies and interventions. My conceptual model suggested a set of neighborhood features that may mediate the effects of the three structural characteristics on depression. Further testing of specific features and measures would expand our understanding of how structural stress becomes embodied in urban populations.

The findings of this dissertation also suggest a need to identify specific characteristics of neighborhood types that may be consequential to mental health. Developing a typology of neighborhoods may help clarify what aspects of stability and income composition jointly contribute to depression (Marans and Gocman 2005; Morenoff and Tienda 1997). For example, while there are many explanations in the literature for the effects of stability on residents of poor and affluent neighborhoods, as detailed in the literature review, the findings of the current study regarding unstable neighborhoods is new and warrants further investigation. What are the conditions in very unstable high advantage neighborhoods that contribute to the high probability of depression, particularly compared to unstable low advantage neighborhoods? Including a measure of onset of depression, for example, may indicate whether the high rate of depression in unstable middle income neighborhoods is based on selection. In other words, those remaining in an otherwise unstable environment may be unable to leave because of their depression.

Understanding how patterns of structural change in neighborhoods over time influence health would contribute to our understanding of racial and economic health inequities, as well as structural effects. Qualitative research may be particularly useful in understanding historical context. For example, in one neighborhood instability may be an indicator of white flight, while in another it may be an indicator of opportunities for economic mobility. The consequences for mental health may be quite different. Public health research in this arena would be strengthened by better incorporating the substantial literature on neighborhood change, economic segregation, and racial segregation that is being generated in disciplines such as economics, demography, and sociology (Collins and Margo 2005; Jargowsky 1997b; Logan 2002; Sethi and Somanathan 2004; Waitzman and Smith 1998).

A key question for future research that has implications for policy and intervention is whether there is a critical mass of long-term residence and homeownership that reduces adverse health effects and the risk of displacement of longtime residents. Collaborative interdisciplinary research involving community members, public health, urban planning, and demography, among others, may contribute to theory, measures, sources of data, and avenues for intervention that can promote mental health of urban residents.

Several other findings in this study warrant further research. This investigation extended the conceptualization of neighborhood income advantage to include middle income. However, as described in the previous section, being able to distinguish between middle income and affluent, and further, to examine the overall income mix of neighborhoods, would be an important extension of this research.

Another significant area for future research is the high rate of depression in this population. Given low treatment rates and the high rate of co-morbidity between depression and some other illnesses, as well as substantial personal, family, and public health burden, major depression among Detroit residents warrants research and intervention. Another finding of particular interest is the higher rate of depression among residents of racially mixed neighborhoods.

F. Implications for Policy and Interventions

Policies and interventions to address a public health problem are most effective when targeted to the causes of the problem. However, this investigation raised many unanswered questions about how and why particular patterns of neighborhood structure influence mental health. Nevertheless, current thinking and practice in public health and urban planning suggest that efforts to promote health in older industrial cities must enhance and rebuild neighborhoods in ways that support existing residents, attract new middle income residents, and foster a balance of in and out migration. The findings of this dissertation on the effects of neighborhood stability and middle income composition on depression suggest the need for policy and intervention in five areas:

- preserve and protect existing moderate, middle, and mixed income neighborhoods;
- regenerate poor and moderate income neighborhoods, while protecting against involuntary displacement;
- provide economic and housing supports to reduce individual financial vulnerability;
- develop neighborhood environments that foster social support and community engagement; and
- target mental health services to neighborhoods experiencing structural stress.

Middle income neighborhoods are rapidly declining in Detroit, as in other older cities across the nation, due to the broader issues of economic disinvestment and population loss described earlier. Preserving and reinvesting in neighborhoods with substantial proportion middle income residents may benefit mental health. Reinvestment strategies that target stable neighborhoods include updating deteriorating infrastructure and providing supports for elderly homeowners to stay in their homes. High turnover neighborhoods may already be experiencing signs of disinvestment, such as foreclosures, vacancies, and rising crime, that may account for the high rate of depression observed in this study. Identifying and addressing these issues may prevent further loss of middle income residents that would tip the neighborhood into lower economic standing. For example, neighborhoods with high rates of predatory lending can be targeted with interventions that reduce the threat of home foreclosures, thus stabilizing neighborhoods and preventing individual financial vulnerability.

The role of housing is crucial in all neighborhoods but may be especially important in low and moderate income neighborhoods. Regeneration of such neighborhoods will require rehabilitation of older housing stock and housing subsidy programs that neither concentrate nor isolate impoverished residents. Mixed income housing development, inclusionary zoning, affordable housing, and scattered site public housing prevent further concentration of impoverished residents and provide means for economically mobile residents to stay in the neighborhood.

New housing development may be essential for attracting middle income families or encouraging upwardly mobile families to remain in neighborhoods. However, strategies that encourage middle income "resettlement," should include policies that protect against gentrification, which is the involuntary displacement of existing residents with more affluent newcomers. If the overall economic standing of the neighborhood is improved without commensurate limits on costs, such as increased property taxes, replacement of local businesses with chain stores, or less affordable amenities, longtime low income residents and small businesses will be forced to leave. Some types of gentrification may be detrimental to the mental health of the "gentrifiers" as well as existing residents. For example, high income housing developments in the midst of poor neighborhoods may increase both isolation (gated communities) and social conflict, and generate depression unless broader structural issues are addressed.

At the individual level, lower income residents need the means to maintain adequate incomes, including opportunities to ensure their movement within the mainstream economy. The finding that higher financial vulnerability increases the likelihood of depression indicates the need for individual and family economic supports, particularly in times of acute economic stress, such as loss of employment. In addition, current residents must have access to affordable services to treat existing mental health problems.

Persons in this study with higher social support were substantially less likely to be depressed, indicating the potential value of interventions that foster supportive social networks. Although this study did not find that either emotional or instrumental social support mediated the effects of neighborhood structure on depression, interventions that strengthen social support may contribute to higher residential stability. Fullilove suggests that in communities that have been uprooted by displacement, depopulation, and disinvestment, the creation of healing places that provide opportunities for relatedness and the reforming of the web of relationships can be beneficial to individual and community mental health (Fullilove 2004). Utilizing and rebuilding collective neighborhood spaces, for example through community land banks, may provide some of the health-promoting benefits of stable, resourced neighborhoods.

Finally, mental health prevention and treatment services should be directed to residential areas experiencing the structural stress described here. Policymakers and health planners need to identify neighborhoods with a higher burden of chronic stressors, depression, and illnesses associated with risk of depression, such as stroke and heart disease. Targeted strategies for both services and neighborhood reinvestment may more effectively reduce some of the high cost and suffering of depression.

In summary, many older industrial cities, such as Detroit, have a history of stable, moderate and middle income neighborhoods and community organization within poor communities that can be drawn upon as a collective resource. The findings of this study call upon us to reject policies and interventions that empty out existing poor neighborhoods, whether nationally as Urban Renewal in the 1970's or as "reconstruction" in New Orleans in 2007. Likewise, the evidence calls upon us to reject approaches that rely solely on helping individual residents to "escape," one by one, to more affluent neighborhoods, such as Moving To Opportunity. Rather, efforts to promote mental health in cities must enhance and rebuild neighborhoods so that the places in which people live provide the benefits of stable, resource rich environments with opportunities for economic mobility for people of different incomes.

CHAPTER 9.

CONCLUSION

Over the past fifty years there has been a dramatic change in the economic and demographic structure of metropolitan areas of the United States. Economic restructuring and institutionalized racial discrimination have resulted in vast inequalities in the geographic distribution of resources that are essential for health, including adequate economic and educational opportunities, safe and supportive physical environments, and strong networks of social relationships.

In this broader context, there is a substantial and growing body of research on the relationship between neighborhood residential environments and mental health, particularly for understanding racial and economic inequalities in health. Two structural aspects of neighborhoods that may be particularly consequential for residents of older urban centers are residential stability and the socioeconomic composition of neighborhoods.

There is ample evidence that more economically advantaged neighborhoods have a beneficial effect on the health of residents. Additionally, residential stability has long been considered beneficial for the health of communities and those who live in them. However, recent studies have indicated that residential stability may have different effects depending upon other structural characteristics of the neighborhood, in particular the economic standing of the neighborhood as a whole and of those who live there. In communities with a higher proportion of affluent residents, stability may enable the formation of lasting economic, social, and political ties rich in resources. In communities with few affluent residents, residential stability may limit access to economic resources, constrain mobility, and expose residents to stressful social and physical environments.

However, there has been little to no published research to date on the importance of the neighborhood proportion of middle income residents on the relationship between stability and health, and in particular the effects on mental health. In this dissertation I expanded our knowledge in this area by investigating how these two structural characteristics of neighborhoods, residential stability and middle income composition, jointly influence mental health in Detroit, Michigan, an economically disinvested older city with a high degree of economic and racial segregation. Using multilevel models, I found that neighborhood stability was beneficial to mental health in neighborhoods with a higher percentage of middle income neighbors, but was deleterious to mental health in neighborhoods with low percentage of middle income residents. I further found that a change in neighborhood middle income composition over time had similar significant effects, with a decline or no change in percent middle income predicting greater rates of depression among residents.

To explore the role of collective material resources as a pathway between neighborhood stability, advantage and depression, particularly in lower income neighborhoods, I examined whether individual financial vulnerability was a potential mediator of neighborhood effects. While the data did not support financial vulnerability as a pathway between neighborhood effects and depression, financial vulnerability was highly predictive of depression. Likewise, I found no evidence that either instrumental or emotional social support mediated neighborhood effects on depression, but each separately has a highly significant effect at the individual level.

Finally, I found that the racial composition of neighborhoods, as measured by percent African Americans, did not predict mental health or the relationship between stability and mental health, net of residents' individual socioeconomic characteristics. This contributes to our understanding of how racial sorting into residential neighborhoods of advantage or disadvantage has contributed to racial inequalities in health.

These findings indicate that efforts to improve the mental well being of residents of economically disinvested urban areas must include attention to structural factors of neighborhoods and the ways in which they interact. Policies and interventions related to housing, infrastructure, and economic development may be particularly important to prevent further loss of middle income residents, support existing residents and regenerate older neighborhoods without displacement. Future research in characteristics of different neighborhoods and how they influence depression would further contribute to reducing the disproportionately high burden of mental disorder in predominantly low income urban communities.

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