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The Relationship between Neighborhood Disadvantage Trajectories and Health Outcomes in a Large Urban US City

Sherry Owens

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The Relationship between Neighborhood Disadvantage Trajectories and Health Outcomes in a
Large Urban US City

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Dissertation Submitted to
The School of Public Health
at West Virginia University

In partial fulfillment of the requirements for the degree of
Doctor of Philosophy in
Social and Behavioral Sciences

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ABSTRACT

The Relationship between Neighborhood Disadvantage Trajectories and Health Outcomes in a Large Urban US City

Sherry Owens

Neighborhood Disadvantage is the sum of a series of socioeconomic indicators that triangulate disadvantaged living conditions in a neighborhood (i.e., poverty, unemployment, home vacancies, female headed households, educational attainment, and segregation). Associations between Neighborhood Disadvantage (ND) and health outcomes have been widely explored. However, findings on mental and behavioral health outcomes remain inconclusive, and individual-level covariates often attenuate relationships between ND and health outcomes. This inconclusive evidence has denied researchers the opportunity to focus on neighborhoods as points of intervention. A potential reason for inconclusive findings is that neighborhoods and individuals are both subject to macro-level socioeconomic events, such as segregation and deindustrialization (loss of manufacturing jobs). This may generate between-level multicollinearity issues in traditional multilevel models because both neighborhoods and individuals are subject to these macro-level events. Instead, this dissertation focused on classifying neighborhoods based on their socioeconomic trajectories. A “trajectory” was defined as the changes in ND scores that occurred in a neighborhood over time. The objective of this dissertation was to determine whether ND trajectories from 1970 to 2000 were associated with residents’ health outcomes in a 2001-2003 study of Chicago residents. This method intended to capture the types of socioeconomic influences, such as segregation and deindustrialization, which may have contributed to variation in neighborhoods’ health resources and social norms in later years. Residents’ health outcomes were compared across trajectories. This approach was compared to the traditional multilevel model used to analyze associations between ND and health outcomes.

In the first method, The Long-Term Census Tract Database (LTDB) was used to create the Neighborhood Disadvantage. I employed a latent profile analysis of ND scores across 343 Neighborhood Clusters in Chicago from 1970-2000. A multiple-regression was performed to investigate the association between Neighborhood trajectory classifications and three outcomes: depressive symptoms, smoking, and drug dependence symptoms among Chicago Community Adult Health Study (2001-2003) participants (n=3,105). The adjusted models indicated that: residents in Long-Term (LT) Very Disadvantaged and LT Inequality trajectories had significantly greater depressive symptom scores than the LT Advantaged trajectory. Residents of Declining trajectories were 1.66 (95% CI: 1.08-2.55) times more likely to smoke compared to the LT Advantaged trajectory. Residents of LT Very Disadvantaged trajectories were 3.25 times more likely to suffer from drug dependence symptoms than the LT Advantaged trajectory (95% CI: 1.32-8.05). The second method was a mixed-effects multilevel analysis of year 2000 ND and each aforementioned health outcome. ND was significantly and positively associated with depressive symptoms, not associated with drug dependence symptoms, and was negatively associated with smoking in the unadjusted and adjusted models. Overall, the Neighborhood trajectory method for identifying neighborhoods as points of intervention shows promise.

Dedication

I would like to dedicate this dissertation to my husband, Daniel Owens, parents, Kay and Mitch Finkel, and my sister, Mary Finkel. Daniel's impressive commitment to public service motivates me to do better work every day. Without his support I would have neither applied nor finished my PhD, and would I have certainly never enjoyed a cooked dinner. Thank you to my parents and sister for all of your help and encouragement through the process. I could not have done this without you.

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List of Symbols, Abbreviations, and Nomenclature

ND: Neighborhood Disadvantage

LT: Long-Term

CES-D: Centers for Epidemiological Studies—Depression 11-item Index

Chapter 1.1: Introduction

An extensive body of literature has provided compelling, but largely cross-sectional evidence of significant disparities in health outcomes across US neighborhoods.[1-4] Intervention efforts to improve health disparities across racial/ethnic groups have been hampered by a lack of insight into possible mechanisms or factors contributing to these disparities.[5] For example, interventions that have taken a neighborhood-level approach to health disparities have not shown consistently improved health outcomes across studies (e.g. Moving to Opportunity).[6-9] However, studies of programs that address neighborhood health disparities have found that temporal settings may have a previously unstudied relationship to health disparities.[10-14] Recent advances in computational methodologies now provide the opportunity to explore these temporal issues at a more fundamental level. In particular, the analyses of large datasets over time can provide unprecedented insight into spatial and temporal relationships between mental and behavioral health outcomes within and between neighborhoods.[15]

Understanding these spatial and temporal relationships between residence and health is critical because long-term patterns of residential racial and income segregation have systematically denied these groups opportunities for upward mobility, and thus the improved health outcomes that are associated with this mobility.[1] Residential racial segregation of African Americans from whites in the US has remained a stable, high levels since the 1940s. Racial health disparities have been attributed by many to the disadvantaged socioeconomic conditions that have defined areas experiencing residential segregation.[16]

Neighborhood Disadvantage (ND) is generally defined as a combination of characteristics that indicate impoverished conditions.[17] Researchers that typically study ND use the

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Neighborhood Disadvantage score, which is constructed using a series of socioeconomic indicators (i.e., poverty, unemployment, home vacancies, female headed households, educational attainment, and segregation). Given its widely accepted use in the literature, ND was the focus of this dissertation.[14, 18] Previous studies suggest that ND is associated with a variety of unfavorable health outcomes in unadjusted models, including mental health and health behaviors.[16, 19-21] In this dissertation, the percentage of African American residents (as a proxy for segregation), percentage of unemployed adults, percentage of those receiving public assistance, and the percentage of individuals living below the poverty threshold are averaged to generate a ND score.[14]

I chose to focus on ND because associations between ND and health outcomes are wellstudied, but generate variable results.[22-24] For instance, studies examining the relationship between ND and mental health outcomes often find that individual-level covariates attenuate the bivariate relationships seen between ND and the respective outcomes.[16] These findings drove the investigation longitudinal studies of ND and health outcomes. These studies investigated neighborhood-level and individual-level indicators of poverty over a specific time period to model their associations with individuals' health outcomes. Many of these studies intend to determine whether neighborhood-level or individual-level variables are the "cause" of negative health outcomes.[25, 26] The results of these studies do not provide adequate recommendations and implications for public health interventions other than to reemphasize an individual-level intervention focus, which often generates higher cost and less efficacious results than higherlevel interventions. [27]

Moreover, this longitudinal ND approach may be flawed because the multilevel interplay between macro-level predictors of health, such as deindustrialization or housing and job

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discrimination manifest in both individual-level measures of income or education and ND scores.[25] In other words, both neighborhood-level and individual-level covariates can represent decades of socioeconomic insults or advantages which can be attributed to macro-level predictors.[21, 25] Since this impact is represented in two levels of the traditionally employed multilevel model, issues with between-level multicollinearity may arise.[28] Furthermore, investigating only the timeframe through which the individuals were followed may omit important socioeconomic changes, such as deindustrialization, which can shape neighborhood and individual-level measures for extended periods of time.[23, 29] It is therefore expected that some longitudinal studies conclude that individual-level covariates attenuate relationships between ND and health.[30, 31]

This dissertation offers an alternative method for investigating temporal associations between ND and health outcomes, with an intention of identifying neighborhood-level targets for interventions.[32] This dissertation intends to further refine our understanding of ND and mental/behavioral health outcomes by determining whether individuals' health outcomes differ based on ND trajectory. Each trajectory is defined by the way its ND indicators (poverty, unemployment, home vacancies, female-headed households, educational attainment, and segregation) change from 1970-2000. This approach allows for a long-term view of the relationships between neighborhood socioeconomic changes and individual-level health outcomes without a focus on individual-level longitudinal data. The approach can also elucidate differences in neighborhoods with varying socioeconomic histories but identical year 2000 ND scores.

For example, a neighborhood that was once middle-income that declined into disadvantage may not have the same score as a neighborhood that has suffered from persistent

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disadvantage.[30] The residents in these respective neighborhood types may have different mental or behavioral health needs that were previously undiscovered by traditional methods. Neighborhoods that have experienced an increase in mean income may also have different health needs than those that have been consistently high income.[33] This particular analysis is a departure from the traditional analyses that typically treat the temporal trend as a single timepoint.[24]

The racial and socioeconomic dynamics of the city of Chicago provide the potential for its neighborhoods to serve as a well-suited model for understanding health disparities shaped by temporal and spatial variables.[34, 35] The focus of this dissertation is to elucidate the connections between Chicago's racial and socioeconomic history and its current health disparities. These health disparities have previously been quantified spatially using Neighborhood Disadvantage (ND) variables. However, these studies were unable to identify specific neighborhood-level targets of intervention to improve health outcomes.[16] The data used in this dissertation include several Census tract level socioeconomic indicators from 1970 to 2000.[36] This time period was chosen because it represents: 1) the decline from Chicago's peak in income equality (1970's), 2) massive deindustrialization (1980's), 3) a rise in employment in either high-income or low-income spectrum (1990's), 4) a further loss of middle-class jobs and rise of few high-income opportunities (2000's).[34] This dissertation is predicated on the hypothesis that the analysis of Neighborhood Disadvantage trajectories (i.e., the change in ND over time) further refines the examination of racial/ethnic health disparities driven by Chicago's complex industrial history.

Understanding Chicago's industrial history is necessary to gain insight into current racial/ethnic health disparities.[37, 38] Chicago was an industrial city which attracted a Great

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Migration of millions of African American emigrants from the South, which occurred primarily from 1915-1950.[39] Unfortunately, these southern African American job seekers were not allowed to live in white neighborhoods.[40] In fact, they were met with Jim Crow Laws and housing laws that enforced residential segregation. Redlining, the practice by which real estate agents refused to sell homes African American in white communities, also prevented integration into white areas.[23] Additionally, Jim Crow Laws allowed Chicago's unions to exclude African American workers from organizing with them, preventing African Americans from earning the same wages as whites.[40]

It was not until 1965 that the Civil Rights Act brought down institutional barriers that prevented upward mobility for African Americans.[40] Specifically, the Civil Rights Act and the Immigration Act of 1965 required that unions include individuals from all racial/ethnic backgrounds into their membership ranks. In turn, African American unemployment in Chicago fell below 8% shortly afterward, and the median household grew for every racial/ethnic group.

Unfortunately, this success was short-lived, as massive unemployment brought on by deindustrialization hit Chicago (circa 1970's-1980's). The loss of union-wage jobs in Chicago's city centers hit still segregated African American neighborhoods the hardest.[23, 40, 41] Factory jobs were mechanized, or left for locations where wages were lower. Over 37% of Chicago's nearly 1 million factory jobs were lost between 1979 and 1986.[40] As a result, Neighborhood Disadvantage increased in many areas of the city.[42] In particular, segregated African American neighborhoods saw stark increases in unemployment. This increase in unemployment was particularly harsh for the residents of segregated neighborhoods. As such, social disorganization theory suggests that unemployment disrupts health-promoting social norms that may have once operated in middle-income earning neighborhoods.[29]

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This massive loss in unionized middle-income employment was not ameliorated during the 1990's economic boom.[23, 40] During the boom, Chicago gained thousands of very high-income jobs and very-low income jobs, with few jobs gained in the middle-income spectrum.[40] Although disadvantaged neighborhoods gained employment, they grew comparatively more disadvantaged.[40, 43] On the other hand, affluent neighborhoods with very low Neighborhood Disadvantage scores spread throughout Chicago's predominately white, Northeastern neighborhoods.[34] Employment in high-skill industries that required advanced education grew in 1990's Chicago. Few residents could meet the requirements for these high salary positions, which were filled by young professionals and others from places other than Chicago.[23] Additionally, another overlooked factor of this 1990's economic boom was that 165,000 middle-income manufacturing jobs were lost between 1991 and 1998.[40] Thus, few Chicago residents were lifted from poverty during this job boom. Furthermore, these new salaries inflated the costs of housing, rent, groceries, and other living expenses that placed stress on low-income residents.[33] From the 1990's on, the rise of limited high-income employment opportunities dominated parts of Chicago's landscape while other neighborhoods fell into poverty.[44]

The data used in this dissertation came from the Chicago Community Adult Health Study (CCAHS). The CCAHS is well-suited for testing this hypothesis in the city of Chicago.[45] The CCAHS was conducted from 2001-2003 and was specifically designed to investigate racial/ethnic health disparities across neighborhoods. The CCAHS has been used widely to study associations between Neighborhood Disadvantage and a variety of health outcomes. Connecting the CCAHS to historical data in Chicago may provide additional context in which neighborhood health disparities can be understood. The CCAHS provides detailed individual-level data nested

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in 343 Neighborhood Clusters (NCs). These NCs were defined using social, institutional, and economic knowledge of the city of Chicago to create meaningful units of NCs.[18] As explained, no individual-level longitudinal data are available for the city of Chicago that covers the time period of interest. However, appending US Census neighborhood data from years 1970 to 2000 may provide novel insights into the historical trends in ND that may have a relationship to residents' mental and behavioral health. Chicago's history of industrialization (pre 1970s), segregation (1970s), deindustrialization (1980s), and revitalization (1990s-2000s) make the city an ideal model for investigating ND trajectories.[34, 43]

Chapter 1.2: Purpose Statement

The purpose of this dissertation was to illustrate the use of Neighborhood Disadvantage (ND) trajectories in identifying Neighborhood Clusters (NCs) of Chicago in which specific mental and behavioral health interventions were needed. The methods were comprised of two major components: 1) an examination of the influence of ND trajectories on the mental health and health behavior in a sample of Chicago residents, and 2) a comparison of the traditional method of multilevel modeling to the neighborhood socioeconomic trajectory technique. There were 3 studies conducted for this dissertation. **Research Question 1** (Developing ND Neighborhood Cluster (NC) trajectories for the city of Chicago from 1970-2000) developed and described ND trajectories from 1970-2000 in the city of Chicago. **Research Question 2** investigated the associations between a) ND trajectories and b) Year 2000 ND scores with depressive symptoms. **Research Question 3** investigated the associations between a) ND trajectories and b) Year 2000 ND scores with drug dependence symptoms and smoking. The dissertation begins with a literature review of ND in general, which leads into a specific discourse on longitudinal ND findings. The statement of the problem and the research goals follow the literature review. A discussion regarding the data sets used, the Long-Term Census Tract Database (LTDB) and the Chicago Community Adult Health Study (CCAHS) follows. Each study is discussed in its own chapter, which includes an introduction, methods section, discussion, and conclusion. The dissertation ends with a conclusion chapter that summarizes the main findings of all three studies, and the implications for future research regarding Neighborhood Disadvantage.

Chapter 1.3: Literature Review

Neighborhood Disadvantage

African Americans tend to disproportionately live in low-income and disadvantaged neighborhoods compared to whites and many other racial/ethnic groups.[38, 46] However, this is not merely the result of chance, or frankly, by choice among African Americans.[6, 35] From the period spanning the civil rights era to the current urban revitalization era, the history of residential segregation in the large urban cities like Chicago is quite complex and fluid.[35] Ample evidence suggests that persistent discriminatory housing and mortgage lending practices resulted in African Americans living in poorer neighborhoods with lower levels and quality of health promoting resources than whites at the same income level even after the civil-rights era.[47]

Beside overt threats of physical violence, one subtle tool of institutional discrimination was redlining.[38, 48] “Redlining” was a practice institutionalized by the banking and auto insurance industries and real estate agents to steer African Americans from buying homes in high income and mostly white neighborhoods.[47, 49] This practice was very successful in increasing and maintaining racial residential segregation.[50, 51] Despite these dogged attempts to keep African Americans out of white neighborhoods, the increase in manufacturing in northern cities like Detroit and Chicago allowed some neighborhoods to experience a higher influx of African Americans.[37] However, as noted by Bobo and others, whites’ preference against African American neighbors resulted in a large outflow of whites fleeing into the suburbs in the 1970’s and 1980’s.[52] This “white flight” created hypersegregated neighborhoods, or neighborhoods which experienced at least four of the five types of segregation severely: isolation, concentration, clustering, dissimilarity, and centralization.[36, 53]

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These historical patterns in racial segregation have persisted and have even been compounded by income segregation in more recent years.[50, 54] The combination of racial and income segregation is particularly pronounced in Chicago, where 0 of the 343 neighborhoods that were listed as high-income were majority (>50%) African American in 2000.[23] By contrast, 0 low-income neighborhoods that were majority white in 2000. Ironically, such high inequality did not exist in the 1960's when middle-income, union-jobs were more prevalent (Figure 1).[29]

Figure 1.1 Mean individual income of residents by Census tract in Chicago, IL

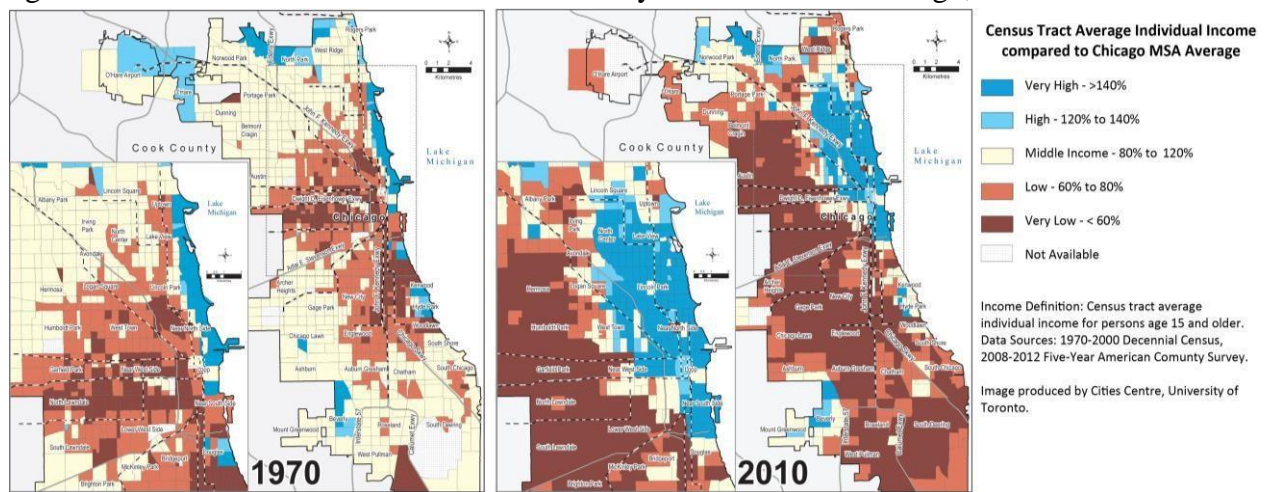


Figure 1.1 shows the dramatic change in neighborhood economic conditions from 1970 to 2010.[44] The previously middle-income (tan) areas either developed into either very high income or very low income neighborhoods.[55] While the city was still racially segregated, African American residents in the 1970's lived in neighborhoods that were higher income compared to 2010.[55] The combination of racial segregation and deindustrialization set the stage for social disorganization to flourish in some neighborhoods.[29] Massey and Denton argue that housing discrimination and loss of jobs created an underclass in isolated African American communities, which persisted and undermined success in mainstream society for residents of racially segregated neighborhoods.[36, 42, 56] Comparing neighborhoods that have endured persistent disadvantage to neighborhoods that are declining or improving may allow researchers

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to consider these historical relationships.[9, 14] The predictions made by social disorganization theory guide the hypothesis of this dissertation: variance in neighborhood mental and behavioral health outcomes can be explained by historical disadvantage trajectories.

Social Disorganization Theory

One shortcoming of Neighborhood Disadvantage research is that single time point measurements cannot capture the dynamic changes occurring in a neighborhood over time as predicted by social disorganization theory.[57] In Chicago and many other cities, deindustrialization resulted in the decline of once middle-class neighborhoods.[29, 37] The disadvantage these neighborhoods face in the 21st century are clear, but the way that decadeslong socioeconomic changes shape health is relatively unknown.[58, 59]

Social disorganization theory states that as deindustrialization results in job loss, opportunities for traditional family structures with single-earner, male heads of household are limited.[29] Sampson argues that area-level job loss is associated with higher rates of femaleheaded households because job loss resulted in disproportionately higher unemployment among men who were unable to financially support families.[60] This chain of events that occurred most frequently in racially and/or income segregated neighborhoods places high stress on women facing the stress of single motherhood and poverty.[60, 61] The theory makes two predictions that are critical for this dissertation. The first is that persistent poverty can reinforce negative social norms surrounding health behaviors.[29] The second is that persistent poverty places a disproportionate burden on women, whose mental health suffers to a greater degree than men.[29]

Social disorganization theory predicts that social norms (i.e., views toward smoking, substance use, etc.) surrounding health behaviors are more permissive toward unhealthful

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behaviors in impoverished areas.[23] For example, Karasek et al. (2012) found that neighborhoods with the most restrictive social norms toward smoking had 1.45 times greater smoking cessation rates among residents compared to residents in the most disadvantaged neighborhoods.[62] Of note, the least restrictive norms occurred in low-income neighborhoods. Stead et al.'s qualitative reports echoed similar sentiments.[63] Residents even expressed frustration that neighborhood social norms undermine smoking cessation attempts. Similarly, social acceptance toward drunkenness was associated with increased binge drinking for both men and women in a study of low-income New York neighborhoods.[64] Conversely, Ball found that healthful "contagious" behavior were spread via positive social norms in advantaged neighborhoods.[22]

Particularly pertinent to this dissertation is the paucity of data on the relationship between Neighborhood Disadvantage trajectories on these known health behaviors. Compared to a more recently declining neighborhood, areas in persistent disadvantage have fewer social institutions in place that can buffer the impacts of mass unemployment.[22, 65] Areas of persistent disadvantage may then suffer disproportionately from unhealthful social norms as compared to areas that were once considered to be middle-income. As such, analyses that rely on a single time point may confound our understanding of the potential difference between declining neighborhoods and persistently low-income neighborhoods without disentangling these trends.[26] Any variance attributed to their trajectories (changes in ND over time) may have been missed.

A second prediction of social disorganization theory is that area-level job loss places a disproportionate strain on women, who are more likely to experience additional burdens of childcare and poverty.[66-68] Sampson found that when the male unemployment rate increases,

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the likelihood of female-headed households also increases.[60] He hypothesized that a neighborhood with a high proportion of female headed households represents a neighborhood with limited informal social control over negative health behaviors. Moreover, the burden of a lack of informal social control is thought to manifest through poor mental health among women in particular.[16] For example, Ross et al., (2000) found that women who were living in disadvantaged neighborhoods were significantly more likely than men to suffer from depression. Furthermore, an assessment of pregnant African American women by Giurgescu et al. (2015) determined that women from lower quality neighborhoods were more likely to suffer from depression.[66] Mulvaney and Kendrick (2005) found that mothers in the highest quintile of disadvantaged neighborhoods were 2.42 times more likely to suffer from depressive symptoms compared to mothers in the lowest quintile of disadvantage (95% CI: 1.28-4.48).[69]

This dissertation employs both of these predictions of social disorganization theory to explain differences in health outcomes between declining neighborhoods and persistently impoverished neighborhoods. However, social disorganization theory does not offer direct explanations for the trajectories of high-income neighborhoods. Chicago, like many US cities, has some areas of persistent advantage and others that have experienced increasing advantage.[55] These neighborhoods have been traditionally analyzed using a single time-point method, which cannot distinguish between persistent and increasing advantage.[70] Evidence suggests that these two distinct subtypes of advantaged neighborhoods may have different health needs that may be identified when their trajectories are taken into account.

Neighborhood Advantage

Areas that have recently experienced an increase in advantage may have a unique set of mental and behavioral health circumstances that differ from neighborhoods that are persistently

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advantaged. For example, low-income individuals in neighborhoods with rapidly increasing income among a concentrated few may experience the added stress of relative disadvantage more acutely.[58, 59, 71, 72]

The implications for mental and behavioral health of these varying trajectories is unknown. In gentrified neighborhoods, or neighborhoods with an increase in wealth concentration among the few, low-income individuals may have fewer opportunities for affordable and quality food and housing due to rising costs of goods.[33, 73] A qualitative study of low-income residents in gentrifying San Francisco yielded disturbing results. Residents reported increasing long-term food insecurity and hunger, stealing food, and even engaging in sexual activities in order to acquire food.[73] The threat of displacement or eviction is another stressor for low-income individuals.[33] In Los Angeles, low-income residents in the downtown area were subject to the “28-day shuffle,” in which they were systematically moved into different public housing within 28 days so that they were unable to claim residence.[74] This stress was even evidenced in a study of New York City’s boroughs.[75] Low-income residents in gentrifying neighborhoods were significantly more likely to give birth to preterm and low birth weight infants. Moreover, increases in the relatively few high-income employment opportunities may have the capacity to increase the subjective psychosocial stress of inequality for low-income individuals living in these areas.[76] This subjective experience of inequality is a known chronic stressor associated with depression.[76-79]

Another individual-level stressor that complicates the relationship between Neighborhood Disadvantage and mental and behavioral health is perceived interpersonal discrimination. Perceived interpersonal discrimination (hereafter described as “discrimination”) is defined as experiencing unfair treatment based on race or ethnicity. The measure is generally reported using

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the Williams' (1997) Everyday Discrimination Scale (EDS).[80, 81] The EDS includes 9 questions about the frequency with which respondents perceive that they receive poorer service, or that they are followed in stores, are harassed, or are treated with less respect because of their race/ethnicity. Frequently enduring these discriminatory events is hypothesized to act as a psychosocial stressor that negatively impacts an individual's health over time.[82]

Empirical studies show that discrimination has well-known mental and behavioral health correlates.[82-85] Pascoe and Richman (2009) report that 110 studies have revealed 497 relationships between discrimination and health outcomes. Additionally, discrimination is also associated with substance use across several studies.[21, 86] According to reviews by Williams and others, African Americans report more frequent occurrences of discrimination than other racial/ethnic groups, with whites reporting the lowest frequency.[87] Specifically, African Americans at higher income and education levels are more likely to report discrimination.[82, 84]

Some researchers argue that higher income African Americans who experience more perceived interpersonal discrimination than members of other racial groups are more likely to live in integrated neighborhoods.[88] In contrast, low-income African Americans in segregated neighborhoods have fewer encounters with individuals from other races that could potentially perpetrate discrimination.[88] For example, the Black Women's Health Study showed that African American women living in neighborhoods that were <20% African American were 1.40 times more likely to report discrimination than women in neighborhoods that were $\geq 80\%$ African American (95% CI: 1.31-1.49).[89] Because experiences of discrimination can vary by neighborhood, this variable should be explored in greater detail.[76] For instance, African Americans in high-income neighborhoods, whose health should benefit accordingly, may endure the psychosocial stressor of discrimination more frequently. These individuals, in turn, may

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suffer from negative mental and behavioral health consequences that seem paradoxical given their neighborhood conditions.[90] Similarly, African Americans in areas rapidly becoming more advantaged may also feel the stress of discrimination as high-income and/or white individuals move in to a neighborhood.[33, 40, 91, 92]

In contrast to the stressors such as discrimination placed upon low-income residents in gentrifying areas, the high-income residents that are moving into gentrifying neighborhoods may engage in riskier health behaviors.[93, 94] A more recent increase in high-income employment often results in an influx of young professionals, whose health concerns may differ from populations living in persistently advantaged areas.[95, 96] Younger, unmarried individuals may be more likely to engage in heavy drinking or drug use than other high-income residents.[95] These differential health behaviors may be elucidated when investigating Neighborhood Disadvantage.

The temporal changes in neighborhood environments that occur as a neighborhood declines, improves, or remains persistently advantaged or disadvantaged may explain variances in the present-day mental and behavioral health outcomes of residents.[33, 97] Very few studies have investigated longitudinal ND and its associations with health.[30, 31] Those temporal studies have investigated the health risks of individuals rather than neighborhoods. This dissertation focused on the relationship between temporal Neighborhood Disadvantage trajectories and mental and behavioral health. An overview of longitudinal Neighborhood Disadvantage research is discussed next and shapes the intent of this dissertation.

Longitudinal Neighborhood Disadvantage Findings

Recently, neighborhood studies have begun to investigate longitudinal relationships between Neighborhood Disadvantage and health.[31, 98] A latent class growth-curve analysis of

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New Zealand neighborhoods showed that the most persistently disadvantaged neighborhoods had all-cause mortality rates that were 1.68 times greater than persistently moderate (reference) neighborhoods (95% CI: 1.54-1.85).[30] This odds ratio is greater than the value obtained when only current conditions were taken into account. In contrast, neighborhoods that had become moderately more disadvantaged were not significantly more likely to experience greater all-cause mortality rates. Neighborhoods with persistent advantage were 0.75 times as likely to experience the same outcome (95% CI: 0.67-0.84).[30]

An examination of the Household, Income, and Labour Dynamics in Australia Study (HILDA) investigated the relationship between Neighborhood Disadvantage and advantage and a variety of health indicators: mental health, physical activity, alcohol consumption, smoking, and self-rated health.[31] The study found that people living in disadvantaged neighborhoods were more likely to report poor indicators of mental, physical, and behavioral health than those in more affluent neighborhoods.[31] However, the main intent of this paper was to determine if exposure to Neighborhood Disadvantage over time was associated with a change in an individual's health outcomes from time 1 (2001) to time 2 (2011). The study was mainly concerned with deciphering between individual and neighborhood level correlates of health. Jokela (2015) concluded that individual-level income and education were stronger predictors of health behaviors and outcomes than neighborhood residence.[31] This conclusion was based largely on the finding that low-income residents moved frequently, and therefore they selfselected into disadvantaged neighborhoods. Among movers, the vast majority of low-income, unhealthy people moved into more disadvantaged neighborhoods over time. While not discussed by the authors, this suggests that disadvantaged neighborhoods may be receiving more people in need of

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targeted intervention. Whether or not these areas that received unhealthy individuals were persistently disadvantaged or in decline was also unknown.

Strong individual-level findings were also echoed in other studies when pairing longitudinal Census data with the Americans' Changing Lives (ACL) survey.[14] Clarke et al. (2014) showed an increased risk of mortality for every decade of living in disadvantaged conditions. The study examined four equivalent time intervals between 1986 and 2001. Residents living in disadvantaged neighborhoods through the entire duration of the study were 20% more likely to suffer from a decline in health after correcting for demographic factors. Moreover, the study found that single time-point ND was less predictive of both health declines and mortality.[14] In addition, neighborhood advantage was strongly protective against health declines over time.[14] However, when adding individual-level sociodemographic factors such as income, age, race, and education, this relationship was attenuated. It is plausible that affluent neighborhoods were not protective, and potentially harmful, for low-income individuals over time. This dissertation attempts to advance the analyses in the Clark et al. (2014) study by investigating how health outcomes vary according to the trajectories of neighborhoods, rather than simply classifying the cumulative disadvantage of individuals.

However, much of the variation in both the Jokela (2014) and Clarke et al. (2014) studies was attributed to self-selection by low-income, unhealthy people into disadvantaged neighborhoods. Self-selection theory asserts that unhealthy individuals move to disadvantaged neighborhoods because they are poor and cannot afford to live elsewhere. Many studies conclude that the neighborhood is not a significant predictor of health outcomes when selfselection theory is supported.[99] While this conclusion holds merit statistically, it is unhelpful to practitioners trying to improve these individuals' health. In fact, the findings of these studies suggest that

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disadvantaged neighborhoods act as catchments for poor, unhealthy individuals. Therefore interventionists may find that the neighborhood is an appropriate and convenient point of intervention for these individuals. Nonetheless, self-selection theory was not supported Halonen et al.'s longitudinal study of Finnish Public Sector employees. This study found that individuals were 1.23 times more likely to begin smoking (95% CI: 1.04-1.47) after moving to a 1 standard deviation more disadvantaged neighborhood.[10]

The intent of the present dissertation is to identify *neighborhoods* rather than *individuals* in need of targeted interventions. While previous longitudinal studies have focused on selfselection theory, the fact remains that unhealthy individuals inhabit disadvantaged neighborhoods. This dissertation intends to improve the understanding of how past neighborhood socioeconomic changes may be associated with current residents' health outcomes.

The CCAHS is an in-depth study designed to investigate correlates of ND and health.[45] The study has been used extensively in Neighborhood Disadvantage research.[18, 61, 100, 101] The individual data are not longitudinal. However, attaching longitudinal census data to predict health outcomes provides researchers with a novel way to contrast the changes in Neighborhood Disadvantage approach to the traditional static ND approach.[24, 32]

Chapter 2: Statement of the Problem

Neighborhood Disadvantage research has resulted in the publication of over 1170 articles.⁹⁵ Relationships between single time-point Neighborhood Disadvantage and mental/behavioral health outcomes are supported theoretically and empirically.[17, 102] However, evidence indicates that relationships between Neighborhood Disadvantage to residents' health outcomes should be explored.[38] Investigating neighborhoods spatially and temporally may uncover differences in the health needs of areas based on their trajectories, or changes in ND

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scores over time. Neighborhood Disadvantage research is only beginning to incorporate these trajectories into its analytical methods.

Thus, longitudinal ND research is in its infancy.[10, 38] Some studies indicate a strong relationship between long-term exposure to Neighborhood Disadvantage and poor health at the individual level.[13, 30, 103, 104] This is particularly true regarding mental and behavioral health.[105, 106] However, these studies have focused on examining individual health outcomes, despite the field of public health's recognition of the need for neighborhood-level interventions.[1, 6] This dissertation attempts to stratify the health disparities seen across trajectories for targeted interventions rather than individuals' responses to neighborhood exposures.

This paper examined ND trajectories in Chicago between 1970 and 2000 as a predictor of poor mental and behavioral health of residents. The dissertation was executed using data from the well-studied CCAHS data set to allow for a direct comparison of the single time-point approach to the trajectory approach on various health outcomes.

Research Aims

Three studies investigated the relationship between Neighborhood Disadvantage (ND) trajectories and various health outcomes. Each research question is comprised of several aims.

Research Question 1, Chapter 4: Developing ND Neighborhood Cluster (NC) trajectories for the city of Chicago from 1970-2000.

Research Question 2, Chapter 5: Determining the relationship between ND trajectories and depressive symptoms.

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Aim 1: To determine the association between ND trajectories and depressive symptoms.

Aim 2: To compare the association between the ND trajectories and depressive symptoms to the association between single time-point Neighborhood Disadvantage and depressive symptoms.

Research Question 3, Chapter 6: Determining the relationship between ND trajectories and substance use.

Aim 1: To determine the association between ND trajectories and drug dependency symptoms.

Aim 2: To determine the association between ND trajectories and smoking status. **Aim**

3: To compare the association between the ND trajectories and drug dependence symptoms and smoking status to their associations with single time-point Neighborhood Disadvantage.

Successful completion of the specific aims demonstrated the utility of change in Neighborhood Disadvantage as a diagnostic tool for refining the identification of high risk neighborhoods. Moreover, the magnitude of specific mental or behavioral health outcomes may differ by historical persistence or variability in Neighborhood Disadvantage. Thus, more specifically targeted interventions may result in more efficient use of limited resources focused on the most appropriate neighborhoods at the highest risk for a particular poor health outcome. The following Chapter describes the data sources and methods for addressing these research questions.

Chapter 3: Data Sources

Data Sources

Two data sources--Census data and the Chicago Community Adult Health Study (CCAHS)—were used in this section. Socioeconomic variables from each Census data year (1970, 1980, 1990, 2000) were used to create the ND score for each of Chicago's 343 NCs. The ND scores of each NC were used for two purposes. The first purpose was to generate Neighborhood Disadvantage in Research Question 4. The second purpose was to conduct traditional multilevel models between year 2000 ND and depressive symptoms (Aim 5.2), smoking, (Aim 6.3) and drug dependence symptoms (Aim 6.3).

Census Data

Census tracts are a geographic unit comprised of roughly 4,000 individuals. Each decade, Census tract boundaries are redefined in order to include as close to 4,000 individuals as possible. The data collected in the Census includes a range of socioeconomic variables, including the variables used in creating the ND score: percentage unemployed, percentage in poverty, percent of vacant homes, percent of African Americans, and the percent with a high school degree or less in each tract (Appendix, Table A.). However, using these variables in longitudinal studies is hindered by the fact that the boundaries are redefined each year.

Logan et al. (2014) generated a database of Census tract variables that can be compared across years, beginning with 1970. These data were available through Brown University's Spatial Structures in the Social Sciences Initiative's Longitudinal Tract Database (LTDB). The LTDB accounts for the spatial discrepancies in Census tract boundaries between Censuses, because the boundaries are redefined to accommodate population changes over time. Several or more tracts may be merged into one across years, or a tract may be split into two or more tracts

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across years in order to maintain a tract-level population of 4,000 individuals. These changes may make comparisons of variables across years inaccurate, because the tracts have changed locations. Thus, Logan et al. interpolated the boundaries of the 1970, 1980, 1990, and 2000 Census variables to match the boundaries of the Census year 2010 by building a “crosswalk” file. The varying boundaries across the Census years were corrected using an interpolation procedure.[107] The interpolation worked by creating proportional weights for each Census year (1970, 1980, 1990, and 2000) that allowed the variables to match 2010 boundaries. Stataformatted data were downloaded from these Census from the LTDB website. The procedure is a highly accurate and validated method for proportion and percentage data, but has demonstrated some issues with accuracy using raw counts.[107] Therefore income, which has been used as a variable in some ND scores, was excluded from this analysis. However, a per capita income variable is shown in Table 4.3 for purposes of triangulating the characteristics of Neighborhood Disadvantage. Income variables for 1970, 1980, and 1990 were corrected to reflect year 2000 income values using a Consumer Price Index calculation.

Creating Neighborhood Cluster-level Data

Since LTDB data set includes 2010 data, but the NCs are composed of Census year 2000 boundaries, data were back-interpolated to year 2000 using the “Backwards LTDB” Stata .do file macro. This method has been shown to retain high accuracy (>99%) when comparing percentage variables across multiple years, so multiple interpolations is highly unlikely to create sampling error.[107] A data set containing the 1970-2000 Census variables interpolated to 2000 boundaries was then merged with the CCAHS’s 343 NCs by year 2000 Census tract ID numbers.

Sampson and others defined Chicago’s 343 NCs based on cohesive social and institutional features of these areas, as well as local knowledge.[23] Each NC has an average of 2 Census

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tracts from the year 2000 boundaries. Therefore, the means of the interpolated Census tract-level ND variables were weighted based on the respective year's proportion of the population they represented and summed to generate the NC-level ND variables. This was the same procedure applied by Logan et al. (2014) in the instance when the boundaries from a previous year were combined.[107] In the majority of instances (>50%), the boundaries received equal weights.

Generating Neighborhood Disadvantage Scores

The NC Neighborhood Disadvantage (ND) scores were generated for each Census year: 1970, 1980, 1990, and 2000. The ND variable was created by summing the 6 indicator variables and standardizing the sum to a mean of 0 and standard deviation of 1.[14] The four ND scores from 1970-2000 were then imported into MPlus 7 Demo Editor to conduct the latent profile analysis, which created the Neighborhood Disadvantage. The creation of Neighborhood Disadvantage is described in greater detail in Chapter 4.

The Chicago Community Adult Health Study (CCAHS)

The Neighborhood trajectory classifications for each NC were merged with the CCAHS data. The CCAHS, conducted in 2001-2003, is a socio-epidemiological study designed to investigate the relationship between the social environment and health disparities.[45] The CCAHS was conducted from 2001-2003 and consists of 4 components. The first component was a multistage probability sample of 3,105 adults living in 343 Neighborhood Clusters (NCs) in Chicago. Face-to-face interviews and measurements of height, weight, blood pressure, leg length, and waist-to-hip ratio were conducted. The face-to-face interviews covered a broad series of 24 health topics. A high response rate of 72% was achieved in this study. The sample is comprised of 40% African Americans, 33% whites, and 27% Hispanics. The study is housed by the Inter-University Consortium of Social and Political Research (ICPSR) through the

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University of Michigan.[45] A formal restricted data access plan was required to access the CCAHS to ensure the data set remains confidential because sensitive health information was included from participants. The access plan was completed through the ICPSR, and data access was granted on January 15, 2016. The latent profile analysis technique used to generate Neighborhood Disadvantage was then used to generate weighted descriptive statistics for the CCAHS. For Research Questions 2 and 3, the CCAHS was used as the source of individual-level health data.

Individual-Level Covariates:

Studies 2 and 3 used the following individual-level covariates in each of the adjusted models performed. Based on previous research, individual-level covariates were included to control for confounding in all of the analyses.[18, 108] Age was measured as a continuous variable. Gender is coded as 1=female and 0=male. Race/ethnicity was recoded/coded in a 4-category variable with non-Hispanic white as the referent group compared to African American, non-white Hispanic, and other races/ethnicities. Education was coded as a 3-category variable including 4-year degree as the referent compared to high school degree and less than high school degree. Income was a 6-category variable ranging from <\$5,000 (ref), \$5,000-\$9,999, \$10,000-\$29,999, \$30,000-\$49,999, ≥\$50,000, and Missing. Years of residence in the current neighborhood was a continuous variable. Finally, the Williams' Everyday Discrimination Scale (EDS) 9-item scale was used to capture discrimination. The ask how often "You are treated with less courtesy," "You are treated with less respect," "People act as if you are not smart," "You receive poorer service," "People act as if they are afraid of you," "People act as if you are

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dishonest,” “People act as if they are better than you,” and “You are insulted” or “You are harassed.” Each item has a response ranging from 0 (never) to 6 (everyday), and the mean of these scores was taken to calculate the discrimination score for individuals.[80] The presence or absence of health insurance was dichotomized as 1=yes and 0=no. I use these data sets and variables in Chapter 4 to develop the neighborhood trajectories.

Chapter 4: Study 1: How do Neighborhood Disadvantage trajectories vary across the city of Chicago?

Introduction

While it is well-known that residence in a disadvantaged area is associated with poor health, rigorous studies in the field of Neighborhood Disadvantage (ND) and health outcomes have generated trajectories outcomes. Unadjusted models of associations between ND and various outcomes are often statistically significant.[16] However, adjusting for individual-level covariates often attenuates these relationships. These findings have led to the investigation of longitudinal ND and health studies, whose focus has largely been on elucidating the relationships between individual socioeconomic status and the ND score of the residents. In particular these studies have investigated individuals as they move from more advantaged to disadvantaged neighborhoods.[13] In other words, the current focus of longitudinal ND studies has been to determine whether unhealthy people at low socioeconomic positions simply move to disadvantaged neighborhoods. Many studies have concluded that the relationship between ND and various health outcomes occurs as a secondary consequence of low-income individuals living in or moving to disadvantaged neighborhoods.[30] This focus and conclusion has not provided community-level interventionists with helpful recommendations.

Unfortunately, in attempts to distinguish between individual and neighborhood determinants of health, longitudinal ND studies have disregarded two major points of systemsbased public health: 1) trajectories, defined as the change in ND over time, at the neighborhood level which provides access to resources and shapes individuals' socioeconomic positions, and 2) interventions targeting neighborhoods rather than individuals may be more efficacious.[109-111] The trajectories of many cities, which endured a dramatic decline in union-

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wage, middle-income employment followed by an influx of few, high-income opportunities, may explain how individuals fell into low socioeconomic status.[41, 60] Given this possibility, an alternative method of investigating the relationship between ND and health is to incorporate neighborhoodlevel socioeconomic trajectories into the analysis, as these trajectories may be likely to shape the health of current residents.

Identifying the Neighborhood Disadvantage where residents suffer disproportionately from negative health outcomes may be useful because systems-based public health approaches can benefit from implementing more targeted, cost-effective interventions.[112] Furthermore, analyzing neighborhoods to target for interventions is an efficient approach for addressing lowincome, vulnerable, and transient populations that can be difficult to contact at the individual level.[113]

Study 1 of this dissertation categorized 343 Neighborhood Clusters (NCs) in the city of Chicago into Neighborhood Disadvantage based on their ND scores from the years 1970-2000. The time period chosen represents a time when Chicago, as with much of the US, experienced union-wage manufacturing job loss and growth in few, high-income jobs.[23] The trajectory classifications provide a novel way to incorporate the socioeconomic histories that have led to current ND conditions. These trajectories were then used to assess mental and behavioral health outcomes across the city using the Chicago Community Adult Health Study (CCAHS). The CCAHS gathered health data from Chicago residents, who are nested within NCs, from 2001-2003. The outcomes of Study 1 of the dissertation were used to inform Study 2 and Study 3 of this dissertation.

Methods

The classification derived from this Research Question was applied to Research

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Questions 2 and 3 as well. Therefore, the methods listed in this section are referred to in later studies. The methods of this dissertation were divided into several sections. A description of the data sources was provided in Chapter 2. The statistical analysis used in Research Question 1 provides an in-depth description of the analyses for Research Question 1 (Chapter 4), and a cursory description of Research Questions 2 and 3 (Chapters 5 and 6).

Analysis Plan

Part 1, Research Question 1: Latent Profile Analysis: Latent profile analysis (LPA) is a structural equation modeling technique that classifies variables into groups of similar classes, known in this dissertation as trajectories. This method allowed a complex analysis of 343 NCs to several groups that can be labeled based on their similarities. The LPA assigned each NC a trajectory class based on the way that the ND score changed over time. The LPA was run five times to test whether a 3-class, 4-class, 5-class, 6-class, 7-class, or 8-class solution had the best model fit statistics. Model fits for each class were compared to determine which number of trajectory class assignments would be used in the second part of the analysis (Table 4.1). The model fit statistics investigated were the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), adjusted BIC (a-BIC), Entropy, and the Vuong-Lo-Mendell-Rubin test.[114, 115] The AIC measures the tradeoff between the model's goodness of fit and complexity, because goodness of fit inherently increases with model complexity. The AIC ensures that a balance between fit and parsimony is achieved. The Bayesian Information Criterion is similar to the AIC but incurs a larger penalty to more complex models. The Adjusted BIC provides an adjustment for sample size. Finally, entropy indicates the amount of "noise" explained in the model.[116] The values range from 0 to 1, with values of >0.8 indicating a good fit and 1 indicating a perfect fit.[114] The Vuong-Lo-Mendell-Rubin test

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determines whether including an additional class improves the model fit. A p-value of <0.05 for the VLMR indicates that an additional class (k classes) may explain more variance than the null hypothesis of k-1 classes. Each of these five indicators were compared across each class solution. The solution with the smallest AIC, BIC, and a-BIC values and the largest entropy was chosen. Specifically, larger entropy emphasized to ensure that NCs were classified with the highest probability of their inclusion in the respective class being accurate.

Part 2, Research Questions 2 and 3: Regression Analysis: The health outcomes of each aim were analyzed using the trajectory classes created in the LPA. The trajectory assignments for each NC were saved in the MPlus output file, imported into Stata 14, and merged with the CCAHS data. Multiple regression procedures with trajectories as categorical predictors were chosen as the most parsimonious model for the first component of each aim. These models were run using covariates listed in Chapter 3.

LPA Model Specification

The LPA was completed using a minimum of 1 class and a maximum of 8 classes. The maximum of 8 was chosen because of a dramatic decrease in Entropy values between the 7-class and 8-class solutions. Each model was run with start values of 20 and 40 random starts as to ensure that the best likelihood values were still reached and avoid local maxima from generating invalid solutions. The 3- and 4-class solutions generated increasingly better fit statistics, but showed poor model fit statistics compared to the 5-, 6-, and 7-class solutions (Table 4.1). Although the AIC, BIC, and a-BIC were lowest in the 8-class solution, the 5-class solution was chosen for several mathematical and theoretical reasons. First, the entropy values were high (>0.8) for all classes, indicating strong fits. However, the entropy value decreased from the

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5-class to 6-class solution, indicating that the 6- and 7-class solutions generated higher class uncertainty. The Vuong-Lo-Mendell-Rubin Likelihood ratio test (VLMR) decreased from the 6 to 7 class solution as well. Entropy was prioritized in this analysis because the classes developed in the LPA were used to predict each aim's outcomes. This approach renders low class certainty a threat to validity.[114, 115] Accordingly, maximizing the probability that NCs belonged in their respective classes improved the predictive ability of the classes in the second part of the analysis. While some studies recommend the VLMR as the most reliable test and others recommend the BIC, the goal of Study 1 was to generate NCs classifications that were useful for addressing the subsequent Research Questions. The VLMR favored a solution in which some classifications contained fewer than 15 NCs, which would not have been a favorable unit of analysis for the subsequent portion of this dissertation. This limitation which would potentially violate assumptions of sample size in the multivariable regression to analyze each aim in Step 2. Finally, Henson et al. (2007) argued that model fit statistics should not be prioritized over the probabilities that each NC was accurately categorized, also known as the probability of class membership.[116] Given that the probability of class membership was between 96%-100% for each class in the 5-class solution, this solution was chosen as the best fit for the data.[116] Classes are hereafter referred to as trajectories or Neighborhood Disadvantage trajectories.

Table 4.1 Model fit statistics used to determine the most appropriate number of Neighborhood Cluster Classes, hereafter known as trajectories

LPA Fit Indices by Class	3-Class	4-Class	5-Class*	6-Class	7-Class	8-Class
Entropy	0.956	0.957	0.968	0.965	0.966	0.938
AIC	2032.043	1714.925	1441.041	1327.465	1192.689	1050.671
BIC	2101.122	1803.193	1548.497	1454.110	1338.522	1215.694
Adjusted BIC	2044.022	1730.232	1459.675	1349.426	1217.977	1079.287
VLMR Test p-value	0.004	0.082	0.002	0.008	0.078	0.213

*Chosen as best solution. The 1 and 2 class solutions are not shown.

Results

The means of each variable in the 5-class LPA are shown in Table 4.2. Mean values shown in Table 4.2 represent Neighborhood Disadvantage (ND) scores, a sum of 6 socioeconomic indicators that are standardized to a mean of 0 and a standard deviation of 1. Positive values represent neighborhood clusters that are more disadvantaged than the mean. Negative values represent neighborhood clusters that are more advantaged than the mean. The class variable is hereafter also referred to as trajectory. The trajectories generated in the 5-class LPA solution are depicted in Figure 1. The trajectories were given the following names: LongTerm (LT) Advantaged, Declining, Decreasing (Dcr.) Disadvantage, LT Very Disadvantaged, and LT Inequality.

The LT Advantaged contained 149 neighborhoods whose mean negative ND values become more negative from 1970 to 2000 (Figure 4.2). These negative ND scores indicates that trajectory is more advantaged across all years than the standardized mean neighborhood (ND=0). This trajectory began in 1970 with a value that is within 1 standard deviation of the mean (0.710) in 1970 and approaches, but did not exceed, 1 standard deviation below the mean ND score (-0.930) in 2000.

The Declining trajectory contained 42 neighborhoods whose mean 1970 ND score indicated slight advantage (-0.359). However, these neighborhoods experienced a large increase in ND scores between 1970 and 1980, reaching a ND score of 0.722. This increase in ND continued in 1990 and 2000 which indicates a socioeconomic decline that corresponds to an increase in ND scores over time.

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The Dcr. Disadvantage trajectory included 65 neighborhoods whose mean ND score improved from 1.393 in 1970 to 1.074 in 2000, yet remained 1 standard deviation above the mean ND score. While this trajectory's values indicated persistent disadvantage, the LT Very Disadvantaged consisted of the smallest group of neighborhoods (n=21) with the highest ND scores in each year. The 1970 value for the LT Very Disadvantaged trajectory was 2.122, over 2 standard deviations above the mean ND score. This trajectory improved slightly to 1.852 in 1980, but remained very high in 1990 (2.003) and 2000 (1.952).

Finally, the 66 neighborhoods in the LT Inequality trajectory have mean ND values that were close to, but slightly below, the overall mean ND score of 0. This trajectory class began with a score of -0.255 in 1970 and gradually increased to -0.128 in 2000. This slight increase in disadvantage in the LT Inequality trajectory class was consistent with the overall mean ND scores from 1970 to 2000.

Table 4.2 Mean Neighborhood Disadvantage Score by year for each Trajectory, 1970-2000

Trajectories	Neighborhood Clusters (n)	ND Score 1970	ND Score 1980	ND Score 1990	ND Score 2000
LT Advantaged*	149	-0.71	-0.89	-0.93	-0.93
Declining*	42	-0.34	0.73	0.82	0.86
Dcr. Disadvantage*	65	1.41	1.22	1.08	1.07
LT Very Disadvantaged*	21	2.13	1.86	2.04	1.94
LT Inequality	66	-0.25	-0.25	-0.14	-0.13

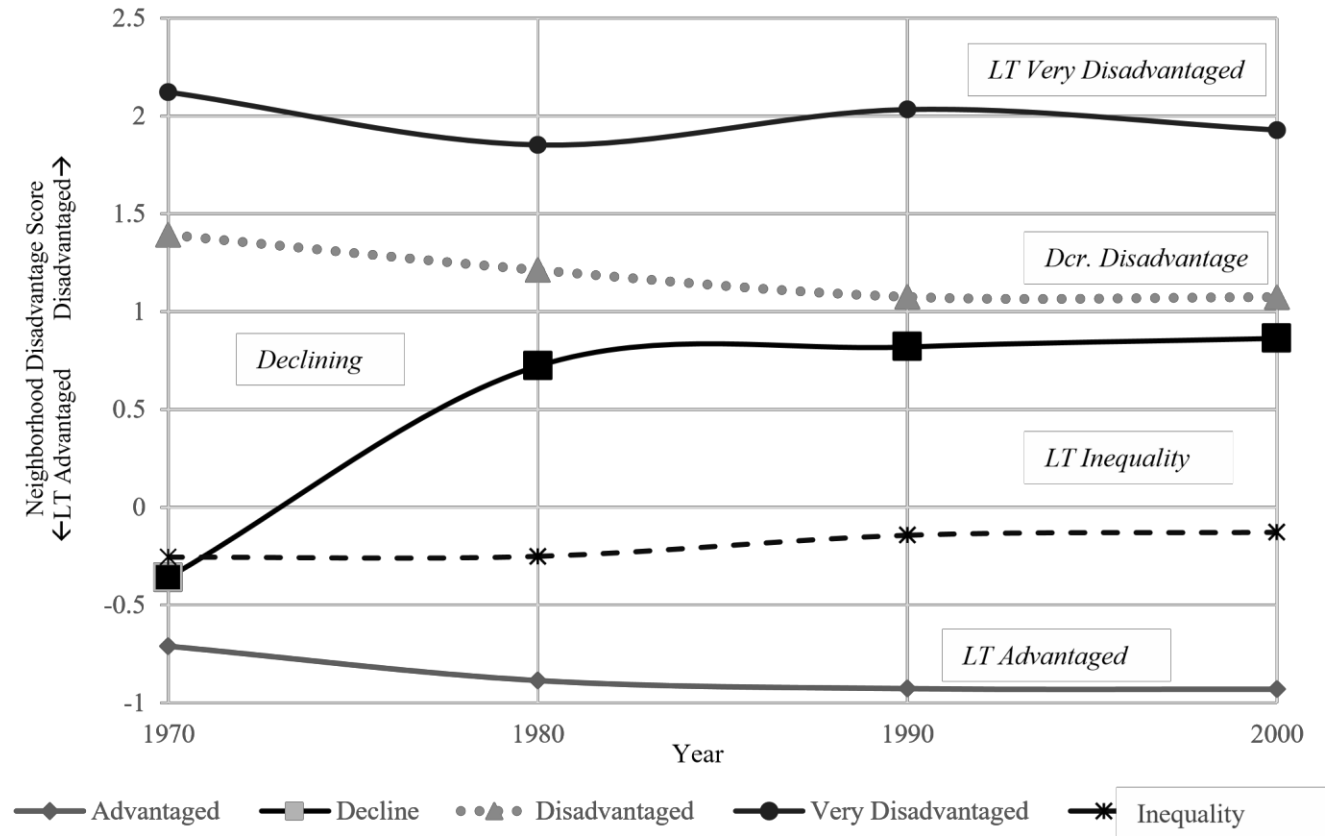
ND: Neighborhood Disadvantage

*T-test indicated significant change in ND scores between 1970 and 2000

Figure 4.2 Standardized Neighborhood Disadvantage Scores of each Neighborhood trajectory charted across Census years 1970-2000. Positive scores indicate greater disadvantage, and negative scores indicate greater advantage.

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Chicago Neighborhood Cluster Mean Disadvantage Scores by Trajectory, 1970-2000



Trajectory Statistics

The results of the latent profile analysis (LPA) resulted in the generation of Neighborhood Disadvantage (ND) trajectories. The five trajectories indicated various socioeconomic paths that Neighborhood Clusters (NCs) in Chicago underwent from 1970 to 2000. Table 4.3 shows the ND variable statistics for the year 2000, and Table 4 shows the percent change in each variable from the year 1970 to 2000. The percentage of African Americans was investigated as a proxy for measuring segregation across trajectories. Analyses with and without this variable revealed that the classification of NCs into trajectories did not change with the inclusion or exclusion of this variable. Therefore, the statistics for the percentage of African Americans are shown for discussion purposes in later sections.

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The Neighborhood Disadvantage (ND) variable means are shown for each neighborhood trajectory in Table 4.3. The LT Advantaged trajectory had the lowest percentages of poverty, unemployment, female heads of household, vacant homes, and percentage of African Americans. The Declining trajectory had the third highest percentages of poverty, unemployment, female headed households, and the same number of residents with a high school degree or less as the LT Advantaged trajectory. The Declining trajectory had twice the poverty rate of the LT Advantaged trajectory (26.1% vs. 13.8%). The Dcr. Disadvantage trajectory had the second highest rate of all indicators and the second-lowest income per capita, while the LT Very Disadvantaged trajectory had the highest-rates of all indicators with less than half of the income per capita of the Dcr. Disadvantage trajectory (\$7,100 vs. \$14,400). The LT Inequality trajectory had higher percentages of poverty, unemployment and female heads of household than the LT Advantaged trajectory. However, the LT Inequality trajectory also had the highest income and education rates.

Table 4.3 Year 2000 Neighborhood Disadvantage Scores

Trajectories	% In Poverty	% Unemployed	% Female Headed Households	% Vacant Homes	Income per capita*	% with ≤HS Education	% African American
LT Advantaged	13.8	7.1	11.6	5.7	\$22,000	58.3	4.5
Declining	26.1	18.5	34.7	9.7	\$15,000	58.3	90.2
LT Disadvantage	29.9	19.0	38.9	11.3	\$14,000	57.7	96.6
LT Very Disadvantaged	54.0	31.4	58.0	30.3	\$7,000	70.6	96.7
LT Inequality	19.7	9.7	19.3	10.0	\$35,000	42.7	30.7
Total	22.0	12.7	23.9	9.6	\$21,000	55.9	43.1

* Due to potential validity issues, Income per capita was **NOT** used in the Neighborhood Disadvantage calculation

Table 4.4's results show that the Declining, Disadvantaged, and LT Very Disadvantaged trajectories' ND scores worsened significantly from 1970 to 2000, while the LT Advantaged

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trajectory experienced a significant improvement in ND scores. The LT Inequality trajectory saw no significant change over time. All indicators of ND increased significantly from 1970 to 2000, with the exception of education. Additionally, corrected income per capita dropped significantly for all trajectories except the LT Inequality trajectory. Education levels significantly increased across Chicago and in each trajectory, as evidenced by over 20% decreases in the percentage of people with high school degrees or less across all trajectories. Though including the segregation proxy in the analysis had no impact on the way neighborhoods were classified, all trajectories saw an increase in the percentage of African Americans with the exception of the Disadvantaged trajectory.

Table 4.4 Change in Neighborhood Disadvantage (ND) variables between 1970 and 2000

Trajectories	Poverty Rate	% Unemployed	%Female Headed Households	% Vacant Homes	Income per capita**	% with ≤HS Education	% African American
LT Advantaged	6.2*	3.9*	6.8*	2.1*	-\$3,000*	-27.9*	4.9*
Declining	17.2*	14.8*	28.3*	5.5*	-\$7,000*	-26.4*	74.4*
Dcr.	12.0*	12.6*	22.1*	5.6*	-\$4,000*	-26.1*	6.2
Disadvantage							
LT Very	17.3*	21.1*	27.2*	21.8*	-\$4,000*	-23.0*	-0.6
Disadvantaged							
LT Inequality	6.8*	5.5*	12.6*	2.9*	\$4,000	-34.2*	25.6*
Total	9.5*	8.3*	14.7*	4.5*	\$2,000*	-28.3*	16.8*

*T-test p-value<0.05, indicating significant change between 1970 and 2000

Adjusted to 2000 values. Income per capita was **NOT used in the ND calculation

CCAHS Sample Statistics

Table 4.5 shows the weighted descriptive statistics for each individual-level covariate for the overall CCAHS sample (Panel A) and by trajectory (Panel B). Overall, respondents were a mean age of 42.2 years and 51.6% female. The weighted sample was 34.1% African American,

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46.6% white, 13.3% Hispanic, and 6.03% Other races/ethnicities. College graduates comprised 27.9% of respondents, with 23.4% having earned less than a high school degree and 48.7% having earned a high school degree. Residents had lived in their current locations for an average of 9.8 years. The mean frequency of everyday discrimination due to race or ethnicity was 1.5 out of a possible 20.

The mean age of the LT Advantaged trajectory's respondents was 42.6, with the highest proportions of male (43.7%) respondents. This trajectory was 65.0% white and 4.5% African American with the highest proportions of Hispanic (22.2%) and other race/ethnicity residents (8.3%). In addition, 24.5% of the LT Advantaged trajectory's respondents were college graduates, 49.4% had graduated high school, and 26.1% had no high school degree. Residents had lived in their locations for 10.1 years, and the mean everyday discrimination score was 0.94

The mean age of the Declining trajectory's respondents was 45.2, with 42.0% male and 58.0% female respondents. Only 7.7% of respondents were white, 88.6% were African American, 2.0% Hispanic, and 0.2% other races/ethnicities. 16.4% of residents held college degrees, 56.4% held at least high school degrees, and 27.2% had less than a high school degree. Residents had lived in their current locations for 12.2 years and had the highest mean everyday discrimination score at 2.6.

The Disadvantaged trajectory had a mean age of 45.9. Respondents were 42.0% male and 58.0% female. This trajectory had the highest percentage of African Americans at 98.2%, with 1.7% white residents, 0.0001% Hispanic, and 0% other races/ethnicities. Just under a fifth of residents were college graduates (19.2%), 56.9% had at least a high school degree, and 23.9% had less than a high school degree. Moreover, this trajectory had the longest duration of residency at 13.4 years. The mean everyday discrimination score was 2.3.

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The mean age for the LT Very Disadvantaged trajectory was 41.1 years. This trajectory had the lowest proportion of male respondents (34.6%) and highest proportion of female respondents (65.1%). White respondents comprised 6.2% of the sample. Also, 91.8% of respondents were African American, 2.0% were Hispanic, and 0% were other races/ethnicities. The LT Very Disadvantaged trajectory had the lowest college graduation rate (8.7%), while 55.1% had at least a high school degree. Another 36.2% had not graduated high school. The average residency was 8.0 years, and mean everyday discrimination score was 2.11.

Finally, the LT Inequality trajectory had the lowest mean age of 38.8. Overall, residents were 46.4% male and 53.6% female, 59.2% white, 23.7% African American, 8.1% Hispanic, and 9.0% other races/ethnicities. The percentage of college graduates was 49.5%, with 37.1% of residents obtaining at least a high school degree, and 13.4% had no high school degree. This trajectory had the shortest average residency at 6.1 years, while the mean everyday discrimination score was 1.48.

Table 4.5 Descriptive Statistics of the CCAHS Sample Overall and by Neighborhood Trajectory.*

	Panel A		Panel B			
Variable	CCAHS Sample	LT Advantaged	Declining	Disadvantaged	LT Very Disadvantaged	LT Inequality
	Mean (SE) or Percent	Mean (SE) or Percent	Mean (SE) or Percent	Mean (SE) or Percent	Mean (SE) or Percent	Mean (SE) or Percent
Depressive Symptoms	1.81 (0.01)	1.74 (0.02)	1.90 (0.03)	1.90 (0.03)	2.07 (0.05)	1.85 (0.03)
Drug Dependence (1+ symptom)	5.7	3.9	5.9	6.2	14.3	7.9
Current Smoker	25.3	22.7	36.2	29.6	35.0	21.8
Age	42.5 (0.39)	42.6 (0.56)	45.2 (1.1)	45.9 (1.0)	41.1 (1.5)	38.8 (0.79)
Gender						
Male	47.4	48.4	42.0	42.0	34.6	46.4
Female	52.6	51.6	58.0	58.0	65.1	53.6
Race/Ethnicity						
White	46.6	65.0	7.7	1.7	6.2	59.2
African American	34.1	4.5	88.6	98.2	91.8	23.7
Hispanic	13.1	22.2	2.0	4x10 ⁻⁴	2.0	8.1
Other	6.3	8.3	0.2	0.0	0.0	9.0
Education						
< High School	23.4	26.1	27.2	23.9	36.2	13.4
>HS< College	48.7	49.4	56.4	56.9	55.1	37.1
≥College	27.9	24.5	16.4	19.2	8.7	13.4
Income						
<\$5,000	3.0	2.1	5.2	4.6	6.8	2.4
\$5,000-\$9,999	6.8	3.4	6.5	11.2	24.7	8.8
\$10,000-\$29,999	26.1	24.8	32.0	30.4	38.5	21.5
\$30,000-\$49,999	18.3	18.3	18.0	18.3	4.0	20.6
≥\$50,000	27.0	28.7	16.2	21.5	14.4	33.9
Missing	18.8	22.8	22.2	14.1	11.6	12.7
Years of Residence	9.8 (0.27)	10.1 (0.39)	12.2 (0.79)	13.4 (0.83)	8.0 (1.08)	6.1 (0.39)

Everyday Discrimination	1.46 (0.07)	0.94 (0.07)	2.57 (0.24)	2.29 (0.19)	2.11 (0.34)	1.48 (0.16)
Health Insurance (yes)	79.9	77.4	82.9	85.0	74.4	81.6

*A trajectory was defined by a latent profile of Chicago Neighborhood Clusters, using Neighborhood Disadvantage Data from years 1970-2000.

Means and standard errors are provided for continuous variables. Frequencies as percentages are provided for categorical variables.

Discussion

The results of the latent profile analysis (LPA) provided an opportunity to classify Chicago's Neighborhood Clusters (NCs) based on their Neighborhood Disadvantage (ND) indicators between 1970 and 2000. Overall, a 9.5% increase in poverty, 8.3% increase in unemployment, 14.7% increase in female headed households and a 4.5% increase in vacant homes occurred between 1970 and 2000 despite a 28.3% increase in educational attainment. These changes were significant at the $p < 0.001$ level. Additionally, socioeconomic changes at the trajectory level were highly significant ($p < 0.001$) as well.

Trajectory Labeling

Two trajectories, the LT Advantaged and LT Inequality, maintained ND scores below 0 for the duration of the study period. The LT Advantaged trajectory was named as such because its values remained continuously below the mean ND score of 0 that continuously approached -1. These NCs were primarily located in Northwestern Chicago in what has been characterized by others as middle class suburbs (Figure 4.3).[44] Additionally, the LT Advantaged trajectory was distinguished from the LT Inequality trajectory which had slightly negative ND scores for several reasons. First, the LT Advantaged trajectory had both lower overall poverty, unemployment, female heads of household, and vacant home rates across all years than the LT Inequality trajectory. Moreover, the LT Inequality trajectory had higher levels of income and

educational attainment as well as all other variables. The LT Inequality trajectory is characterized by high levels of both affluence and poverty indicators. This information combined with the fact that the majority of LT Inequality NCs are in Chicago's Northeast lakeshore coast, the area that experienced the high-income employment boom in the 1990's, led to the classification of this trajectory as LT Inequality (Figure 4.3).[40]

Three more trajectories, the Declining, Dcr. Disadvantage, and LT Very Disadvantaged, had ND scores greater than 0 at the end of the study period. The Declining trajectory had a slightly negative ND score in 1970, which increased by approximately 1 standard deviation between 1970 and 1980. Its ND score continued to approach 1 through 2000. The Declining areas were generally located on the periphery of the clusters of Dcr. Disadvantage NCs. For example, Declining NCs formed the perimeter of what is commonly known as "Southside" Chicago (Figure 4.3). In addition to its overall ND score and locations, the Declining trajectory received its label from the most dramatic increases in other indicators, including poverty (17.2%), unemployment (14.8%), female headed households (28.3%) and percentage of African Americans (74.4%) between 1970 and 2000. The Declining trajectory began with similar metrics to the LT Advantaged trajectory in 1970, but experienced similar metrics to the Dcr. Disadvantage NC in 2000.

In contrast, the Dcr. Disadvantage and LT Very Disadvantaged trajectories remained relatively stable at slightly over 1 and 2 standard deviations above the mean ND score, respectively. Both trajectories had the highest percentages of African Americans at over 96% which had not changed significantly from 1970. These NCs comprise Chicago's Southside, with many of the 65 Dcr. Disadvantage NCs surrounding the 21 LT Very Disadvantaged NCs. The LT Very Disadvantaged trajectory saw the most severe increases in poverty of all categories.

These increases in poverty indicators did not significantly increase the ND score for either of these trajectories across years because the variables were standardized in every year. Therefore,

the increases in poverty may have reflected increases in overall poverty of the city that manifested most severely in the already disadvantaged neighborhoods.

Long-Term (LT) Advantaged Trajectory

Despite having the lowest Neighborhood Disadvantage (ND) scores across all years, the LT Advantaged trajectory experienced significant increases across all disadvantage indicators with the exception of education.

Another important feature of the LT Advantaged trajectory was that it had a significantly lower mean income than the LT Inequality trajectory (Table 4.3). Despite the potential for skew in the raw income values, the difference between the mean incomes was greater than \$12,000 (42.9% difference), indicating that it was unlikely that this occurred by chance. However, the LT Advantaged trajectory's income dispersion was much less skewed. This greater "equality" of incomes, in addition to favorable ND indicators, such as low poverty rates, low percentage of female headed households, low unemployment rates, and low home vacancy rates may have beneficial implications for residents' health outcomes.[42, 92, 102, 117, 118]

The LT Advantaged trajectory was also the most racially diverse of all the trajectories, with a particularly high percentage of Hispanics (22% of the CCAHS sample) and Other races/ethnicities (8.3% of the CCAHS sample). While this trajectory benefits from the lowest poverty rate, unemployment rate, percentage of female-headed households, and vacancy rates, the improved health of residents may also be reflected by the "healthy immigrant paradox." The paradox has been observed among first-generation immigrants to the US, who consistently report positive health outcomes despite lower incomes and education levels.[65, 119]

Declining Trajectory

The Declining trajectory began with a negative ND score which indicated slight advantage in 1970. Unemployment was at 3.7% in 1970 and the population was 15.5% African

American. However, unemployment rose to 14.1% and the percentage of African Americans rose to 77.6% in 1980. Both unemployment and percentage of African Americans continued to rise, eventually reaching 18.5% and 90.2% in 2000, respectively. Demographic theories outlined by Massey and Denton may help to interpret these findings. The argument developed by Mary Denton and Douglas Massey states that 1970's and 1980's deindustrialization, or manufacturing job loss, was concentrated within city centers with high percentages of African Americans.[39, 120-122] With few job opportunities, these places declined socioeconomically and remained segregated because people did not move to them.[37] The second component of their framework, "white flight" (in addition to African American flight), left behind African Americans in city centers when deindustrialization occurred, partly as a product of housing discrimination that barred them from fleeing to suburban areas.

Their explanation for these changes was that much of the population, which was 83.0% white in 1970, moved to seek employment. This is an example of "white flight" cited as an explanation for the concentration of poverty in city centers.[123] white flight corresponded to, but did not cause, increases in poverty, female headed households, and decreases in income per capita due to loss of manufacturing and other middle-income employment.[35]

The Declining trajectory's attributes would not otherwise be identified in classic Neighborhood Disadvantage (ND) literature because these NCs had a mean disadvantage score of 0.862. This score indicates a better socioeconomic situation compared to the Dcr. Disadvantage and LT Very Disadvantaged trajectories. Thus, the latent profile analysis has provided an instance to examine the health correlates of neighborhood decline without requiring longitudinal individual-level data.

Decreasing Disadvantaged (Dcr.) Trajectory

The Dcr. Disadvantage trajectory's mean disadvantage score has remained at 1 standard deviation above the mean since 1970, although slightly, but not significantly, improving between 1970 and 2000. Poverty rose by 12.0% between 1970 and 2000 to 29.9%. Additionally, unemployment rose from 6.8% to 19.0% in 2000, while female headed households increased by 22.1%. The percentage of vacant homes was the second highest of all trajectories at 11.3%, while educational attainment increased by 26.1%. The proxy for segregation did not change significantly between 1970 and 2000. However, the Dcr. Disadvantaged was named as such because its ND scores improved *relative to the other trajectories* over time. The entire city saw increases in raw ND score variables, such as poverty and unemployment, but this area's comparative standing actually improved. The 65 Dcr. Disadvantage NCs were also clustered in two areas of Chicago—the South, or “Southside,” and in between two clusters of LT Advantaged NCs.

The characteristics of the Dcr. Disadvantage trajectory are contextualized when this trajectory is compared to the Declining trajectory. For instance, the Declining trajectory experienced greater increases in poverty, unemployment, and female heads of households than the Declining trajectory, despite the fact that the Declining ND had a lower ND score than the Disadvantaged in the year 2000. Determining differences in health outcomes between the Declining and Dcr. Disadvantage trajectories is an important point of this dissertation. Declining NCs are considered to be more advantaged than the Dcr. Disadvantage trajectory in single timepoint multilevel models, which may not accurately depict the characteristics of these neighborhoods.

LT (Long-Term) Very Disadvantaged Trajectory

In addition to describing the Declining trajectory, the latent profile analysis provided in

Study 1 of this dissertation supports Massey & Denton's framework as also evidenced by the LT Very Disadvantaged trajectory. The LT Very Disadvantaged areas were persistently segregated from 1970-2000, ranging from 96.7% to 98.1% African American. However, unemployment was at 10.0% in 1970. Unemployment rose from 10.0% in 1970 to 22.7% in 1980, peaking at 37.5% in 1990. These high unemployment rates were coupled with the highest rates of all disadvantage indicators, particularly poverty and percentage of female headed households (both >50%). Deindustrialization occurred in the 1970's and 1980's according to Massey and Denton, which corresponded to increased unemployment in the 1980's.[37] Furthermore, the rise in unemployment was followed by increases in other ND indicators.[29] These results indicate that the LT Very Disadvantaged trajectory experienced the framework outlined by Massey and Denton.

Additionally, the LT Very Disadvantaged and Declining trajectory's ND indicators provide support for both Massey and Denton's explanation of health disparities associated with segregation and poverty. The LT Very Disadvantaged trajectory is comprised of the smallest number of NCs (n=21), which is predicted by Massey and Denton. This concentration of poverty among LT Very Disadvantaged NCs has been theorized as a mechanism by which health-damaging social norms may develop.

However, the differences seen between the LT Very Disadvantaged and Dcr. Disadvantage trajectories cannot be satisfactorily explained using Massey and Denton's framework. The Dcr. Disadvantage trajectory, with 65 NCs, fared much better than the LT Very Disadvantaged trajectory in terms of unemployment, education, vacant homes, female headed households, and educational attainment. While the Dcr. Disadvantage and LT Very

Disadvantaged areas had the same instances of segregation, the Dcr. Disadvantage trajectory fared better economically. Thus, it is possible that the Dcr. Disadvantage trajectory does not suffer disproportionately from negative health outcomes in the way that the LT Very Disadvantaged trajectory may.[23, 29] The reasons for this discrepancy are unknown, and warrant an investigation of health behaviors in each trajectory.

This study was the first to identify differences between the Dcr. Disadvantage and LT Very Disadvantaged Neighborhood Disadvantage in Chicago. Because of such stark differences between the Dcr. Disadvantage and LT Very Disadvantaged trajectory, this analysis may provide useful insights into differences in health outcomes between the two trajectories that may focus intervention efforts.[41]

LT Inequality Trajectory

The LT Inequality trajectory describes a series of NCs which have remained slightly advantaged but have slightly worsened between 1970 and 2000. The LT Inequality trajectory had the highest mean income, however, poverty and the other ND indicator scores were higher than the LT Advantaged trajectory's. Thus, the abundance of both affluence and poverty justified naming the trajectory "LT Inequality." Although these measures, in addition to the Northeast location of the LT Inequality NCs indicate that this area may be experiencing gentrification, no official measure of gentrification could be obtained or validated using the current variables. Despite this limitation, the qualitative and quantitative studies which investigate the health correlates of gentrification may offer insights into the psychosocial stressors that residents endure.

Education

One positive finding of this analysis was that the percentage of individuals with a high school education or less decreased across all trajectories. However, early disparities may account for this. For instance, the LT Very Disadvantaged trajectory had the smallest increase in education levels (23.0% increase between 1970 and 2000). This trajectory still ranks far behind the others with 70.6% having had a high school degree or less. The change was still dramatic in that 93.6% of the population had a high school degree or less in 1970.

An unfortunate reality of educational attainment findings is that increases in high school graduation rates do not directly correlate with other NC socioeconomic improvements. The earning potential for a high school graduate compared to a college graduate has declined dramatically in the US since 1970. Therefore, residents of a NC with a high percentage of high school graduates would not necessarily live in an area with high employment and stable family structures. On the other hand, low high school graduation rates may correlate with a higher ND score.

Limitations

The major limitation of this analysis was that it included only years 1970-2000. The year 2010 was excluded because the remaining aims of this dissertation were conducted using individual-level data from the CCAHS, conducted from 2001-2003. Therefore, the Census data that were previously interpolated to Census year 2010 boundaries were interpolated back to Census year 2000 boundaries. Subsequently, the NC-level ND was generated by taking a weighted average of the tract-level ND indicators. Thus, the number of boundary manipulations prevented raw count variables from being used because of the potential for skewed counts.

Conclusions

The findings of Study 1 indicated that Chicago's NCs have endured varying socioeconomic trajectories. While all NCs saw improvements in high school graduation rates, all NCs also endured increases in poverty, unemployment, female-headed households, and vacant homes. The rate of increase in these ND indicators varied dramatically across trajectories. The LT Advantaged and LT Inequality trajectories saw very slight increases in these indicators, while the Declining, Dcr. Disadvantage, and LT Very Disadvantaged trajectories saw dramatic increases. The variation across trajectories may offer support for Massey and Denton's theories describing the concentration of poverty due to segregation based on the changes in segregation (% African Americans).[36]

I use the trajectories generated in Chapter 4 as predictor variables for CES-D symptoms (Chapter 5), current cigarette smoking (Chapter 6) and symptoms of drug dependence (Chapter 6).

Chapter 5: Study 2: What is the relationship between Neighborhood Disadvantage trajectories and depressive symptoms?

Introduction

Depression is the most common, yet treatable, mental illness in the US and worldwide and the world's second leading cause of years living with a disability (YLD).[124] The National Institute of Mental Health reports that 15.7 million Americans experienced an episode of depression lasting two weeks or more in 2014.¹¹² Those with depression are more likely to suffer from a heart attack, develop diabetes, or commit suicide, among other complications.[125] Associations between ND and depression are well-documented.[61, 126] However, studies often find that the associations between depression and ND are attenuated after adjusting for

individual-level covariates.[16] Nonetheless, the common attenuation of this relationship may be explained by investigating Neighborhood Disadvantage. For instance, neighborhood mechanisms predicted by social disorganization theory have maintained associations with depression.[61, 127] In particular, studies of ND and depression note that low-income and unemployed individuals are more likely to be depressed due to various psychosocial and financial strains.[128-130] For example, Galea et al. (2007) showed that residents of low-income neighborhoods were 2.19 times more likely to suffer from depression than those in high-income neighborhoods (95% CI: 1.04-4.59).[130]

The stress of low- or no income is particularly salient for individuals in disadvantaged neighborhoods.[97] For example, social disorganization theory predicts that women in areas of high-unemployment are disproportionately burdened with both the financial and emotional stress of child-rearing.[67] Another financially stressed group are senior citizens. While depression is generally more frequent among younger individuals,[125] Kubzansky et al. (2005) found a significant relationship between ND and depression in a community sample of senior citizens (65+).[131]

Similarly, a study of the Medical Expenditure Panel Survey found that those with zero depressive symptoms had a mean income over \$16,000 greater than those with 6 depressive symptoms.[132]

Thus, the evidence linking income and depression is clearly supported. However, the tendency to treat income and employment as inherent attributes of the individual, such as age or gender, has disadvantages in regards to identifying and targeting populations for intervention.[109] Denying the neighborhood socioeconomic processes that increase or decrease individuals' incomes may prevent interventions from identifying upstream correlates of

depressive symptoms.[5] Moreover, longitudinal ND studies that correct for changes in income alongside neighborhood socioeconomic changes may risk high multicollinearity between the two variables. For example, Can et al. (2015) found that between-level multicollinearity prevented multilevel models from reaching admissible solutions in a Monte Carlo simulation. Likewise, Clark (2013) found similar problems with multicollinearity when investigating model fit statistics.[28] As such, Research Question 2 investigates the socioeconomic processes foremost, while only adjusting for current (year 2000) income as a covariate. I therefore posit that the relationship between low income, gender, and ND is predicted by two socioeconomic frameworks that, in turn, predict depressive symptoms.

First, the processes of massive job loss and increases in poverty outlined in social disorganization theory may predict individuals' incomes and ND levels. These, in turn, predict depressive symptoms.[133] Secondly, the finding that low-income individuals are at higher risk for depression may be further exacerbated by increases in high-income employment for a small number of residents.[102, 118] Unequal conditions place many, especially low-income individuals, at a higher risk of developing depression.[117] For example, as suggested by Marmot, earning a low income or no income among high income earners can operate as a psychosocial stressor.[8] Pabayo et al. (2014) additionally found that women in the top quintile of inequality were 1.37 (95% CI: 1.01-1.88) times more likely to develop depression between 2001 and 2005 in the US.[77] These processes of neighborhood decline and increases in inequality are not identified using single time-point measures of ND, although evidence suggests that they are particularly predictive of depressive symptoms.[8]

To date, I am unaware of studies that have investigated how ND trajectories are related to depressive symptoms. These changes can reflect job loss in some areas and increasing

advantage in others, resulting in the unequal conditions that are present in all analyses of the CCAHS.[45] The purpose of Study 2 of this dissertation was to investigate ND trajectories to determine whether they are significantly predictive of depressive symptoms.

Methods

The analyses in Study 2 addressed the following question:

Research Question 2: What is the relationship between ND trajectories and depressive symptoms?

The question is addressed by investigating two research aims:

Aim 5.1: To determine the association between ND trajectories and depressive symptoms.

Aim 5.2: To compare the association between the ND trajectories and depressive symptoms to the association between single time-point (ND) and depressive symptoms.

Study Measures

Independent Variables:

The trajectory variables generated and described in Chapter 3 (Study 1) were used in Study 2. The latent profile analysis of Chicago's Neighborhood Clusters (NCs) yielded five trajectories: LT Advantaged, Declining, Dcr. Disadvantage, LT Very Disadvantaged, and LT Inequality. These trajectories were used as a categorical predictor of depressive symptoms in Study 2.

Outcome Variables:

The Center for Epidemiological Studies Depression 11-item inventory is a well-known indicator of depression symptoms.[134] The CES-D 11 displays high internal consistency

(Cronbach’s alpha=0.851) in the CCAHS data set.[45] The response option to each item has 4 categories (1: never, 2: hardly ever, 3: some of the time, 4: most of the time) that describe the frequency with which the respondent experiences symptoms in the past 30 days. An item marked as never having experienced the symptom was scored as a 1, and very often was scored as a 4. The mean of all items provides the respondent’s final score. Scores ranged from 1.00 (no depressive symptoms) to 3.82 (frequent depressive symptoms). The variable was analyzed as a continuous variable.

Table 5.1 Description of the Centers for Epidemiologic Studies—Depression 11-item Index used as the outcome of each Aim’s analysis

Outcome	Variable Name	Survey Item	Variable Type
Depressive Symptoms	CES-D-11 Index. 11 item. Imputed	V770-V780 I felt depressed I felt that everything I did was an effort. My sleep was restless. I was happy. (reverse coded) I felt lonely. People were unfriendly. I enjoyed life. (reverse coded) I did not feel like eating. My appetite was poor. I felt sad. I felt that people disliked me. I could not get “going.”	Continuous Measured as a mean score ranging from 1 (lowest) to 4 (highest)

Analysis Plan

The analytic plans for Aims 5.1 and 5.2 are shown below.

Aim 5.1: The latent profile analysis described in Chapter 3 was used to predict depressive symptoms by NC trajectory. An intraclass correlation value of 0.0008 revealed that a multilevel model was not the most parsimonious. Therefore, a multivariable regression using the trajectory

classifications as a categorical independent variable with the LT Advantaged trajectory as the referent group was conducted. The mean score of the Centers for Epidemiological Studies—Depression (CES-D) scale for each individual was used as the outcome variable. The individual-level covariates used in the adjusted model were also listed in Chapter 3, and included age, gender, race/ethnicity, education, income, years living in the current residence, discrimination, and the presence or absence of health insurance.

Aim 5.2: A multilevel, mixed-effects regression of ND in the Census year 2000 and depressive symptoms was conducted. Level 1 of the multilevel analysis was derived from the same CES-D variable used in Aim 5.1 in the unadjusted model. The adjusted model included the same covariates used in Aim 5.1. The level 2 independent variable for Aim 5.2 was the standardized Neighborhood Cluster (NC) score for the year 2000.

All analyses were conducted in Stata 14, Statacorp, Houston, TX. A weighting variable was calculated using a multiplicative combination of several weights: a centered household weight and a centered individual-level post-stratification weight. The weight was standardized to a mean and standard deviation of 1. The overall findings and model fit statistics of Aims 5.1 and 5.2 were compared qualitatively to develop a recommendation for which method provided the most applicable information for neighborhood-level interventions.

Results

Weighted demographic characteristics of the study sample overall and by trajectory are shown in Table 4.5, Panels A and B. The overall mean CES-D score in the CCAHS sample was 1.81 out of a possible 4. The LT Advantaged trajectory's mean CES-D score was the lowest at 1.74, followed by the LT Inequality (1.85), Declining and Dcr. Disadvantage (1.90) and LT Very

Disadvantaged (2.07).

Results of the weighted bivariate regressions between CES-D and each covariate are shown in Table 5.2, Panel B. Age was not significantly associated with CES-D scores ($p=0.095$), nor was having health insurance ($p=0.578$). However, female gender, African American race, and lower educational attainment were significantly associated with higher mean CES-D scores compared to their counterparts ($p<0.001$ for all outcomes). Having a household income greater than \$30,000 per year or not reporting income was associated with decreased CES-D scores ($p<0.001$). Years of residence was negatively associated with depressive symptoms ($p=0.003$), while discrimination was positively associated ($p<0.001$).

Table 5.2 Bivariate relationships between CES-D scores and covariates

	Panel A	Panel B	
	Mean (SE)	β (SE)	p-value*
Overall Mean CES-D Score	1.81 (0.01)		
Trajectories			
**LT Advantaged	1.74 (0.02)		
Declining	1.90 (0.03)	0.169 (0.04)	<0.001
LT Disadvantage	1.90 (0.03)	0.166 (0.03)	<0.001
LT Very Disadvantaged	2.07 (0.05)	0.334 (0.05)	<0.001
LT Inequality	1.85 (0.03)	0.118 (0.03)	<0.001
Age		-0.001 (.0008)	0.095
Gender (Female)	1.75 (0.03)	0.125 (0.03)	<0.001
Race/Ethnicity (White)	1.75 (0.02)		
African American	1.92 (0.02)	0.172 (0.03)	<0.001
Hispanic	1.75 (0.03)	-0.008 (0.04)	0.840
Other	1.82 (0.07)	0.061 (0.07)	0.370
Education (College)	1.72 (0.02)		
> HS <College	1.84 (0.02)	0.125 (0.03)	<0.001
Less than HS	1.88 (0.03)	0.160 (0.03)	<0.001
Annual Income (<\$5,000)	2.01 (0.06)		
\$5,000 to \$9,999	2.07 (0.05)	0.060 (0.08)	0.444
\$9,999 to \$29,999	1.95 (0.03)	-0.058 (0.06)	0.358
\$30,000 to \$49,999	1.78 (0.03)	-0.227 (0.06)	<0.001
\$50,000 or more	1.69 (0.02)	-0.318 (0.06)	<0.001

Missing	1.73 (0.03)	-0.277	(0.06)	<0.001
Years of Residence		-0.003	(0.001)	0.003
Everyday Discrimination		0.024	(0.004)	<0.001
Health Insurance (yes)	1.82 (0.01)	0.017	(0.03)	0.578

Significant values are bolded

*significance tests determined by linear regressions for continuous variables and

regressions with categorical predictors for categorical variables

**Referent group

Results of the unadjusted, weighted multivariable regression between Neighborhood Disadvantage and the mean CES-D questionnaire score were described in Table 5.2, Panel B. Compared to the LT Advantaged (referent) trajectory, respondents of the Declining trajectory experienced a 0.169 unit increase in CES-D scores ($p < 0.001$). Respondents living in the Dcr. Disadvantage trajectory reported a 0.166 unit increase in CES-D scores than the referent ($p < 0.001$), while the LT Very Disadvantaged trajectory's respondents saw an increase of 0.334 units in CES-D scores ($p < 0.001$). Finally, the LT Inequality trajectory's residents had 0.118 units higher CES-D scores on average compared to the LT Advantaged.

In the adjusted model, mean CES-D scores of the Declining and Dcr. Disadvantage trajectories were no longer significantly different from the referent (Table 5.3). However, the LT Very Disadvantaged trajectory residents reported a 0.181 unit increase in depressive symptom scores ($p = 0.004$), and residence in the LT Inequality trajectory was associated with a 0.100 unit increase in CES-D scores compared to the LT Advantaged trajectory after adjusting for covariates ($p = 0.003$). Age was not a significant predictor of CES-D symptoms ($p = 0.914$), although female gender was associated with a 0.120 units higher CES-D symptom score compared to male gender ($p < 0.001$). Hispanics reported significantly fewer depressive symptoms than whites ($p = 0.049$).

Compared to a college education, having a high school education was associated with a 0.086 unit increase in CES-D scores (p=0.005). Earning less than a high school education corresponded to a 0.118 unit increase in CES-D scores (p=0.003). Reporting an income above \$30,000 or not reporting income was significantly associated with a lower CES-D score. An additional year of residence in the current location was associated with a 0.004 unit decrease in CES-D scores (p=0.003). A standard deviation increase in everyday discrimination frequency corresponded to a 0.022 unit increase in CES-D scores (p<0.001), while having health insurance was associated with a 0.082 unit increase in CES-D scores (p<0.001).

Table 5.3 Adjusted weighted multivariable regression of the relationship between Neighborhood Disadvantage and Depressive Symptoms

CES-D Score	β (SE)	p-value
Trajectories		
**LT Advantaged		
Declining	0.081 (.05)	0.088
Dcr. Disadvantage	0.084 (.05)	0.093
LT Very Disadvantaged	0.181 (.06)	0.004
LT		
Inequality	0.100 (.03)	0.003
Covariates:		
Age	-1.0x10 ⁻⁴ (.0009)	0.914
Gender (Female)	0.120 (.02)	<0.001
Race/Ethnicity (White)		
African American	-0.019 (.04)	0.653
Hispanic	-0.081 (.04)	0.050
Other	-0.015 (.06)	0.808
Education		
(College) > HS	0.086 (.03)	0.005
<College		
Less than HS	0.118 (.04)	0.003
Annual Income (<\$5,000)	0.048 (.08)	
\$5,000 to \$9,999		0.526
\$9,999 to \$29,999	-0.028 (.06)	0.643
\$30,000 to \$49,999	-0.182 (.06)	0.003

\$50,000 or more	-0.260 (.06)	<0.001
Missing	-0.225 (.06)	<0.001
Years of Residence	-0.004 (.001)	0.003
Everyday Discrimination	0.022 (.004)	<0.001
Health Insurance (yes)	0.082 (.03)	0.011

*Referent group

Significant values are bolded

Aim 5.2 Results

Results from the Aim 5.2 multilevel model, mixed-effects regression of year 2000 Neighborhood Disadvantage (ND) and Centers for Epidemiologic Studies—Depression (CES-D) scores are shown in Table 5.4. In the unadjusted model, a one unit increase in ND score was associated with a 0.036 unit increase in CES-D scores (95% CI: 0.017-0.040). After adjusting for covariates, one standard deviation increase in ND was associated with a 0.015 unit increase in CES-D scores (95% CI: 0.009-0.026). As in Aim 1, age was not significantly associated with CES-D scores (p=0.691). Hispanic race corresponded to a 0.093 unit decrease in CES-D scores (p=0.018). Compared to a college education, a high school education was related to a 0.071 unit increase in CES-D scores (p=0.022), while less than a high school education was associated with a 0.102 unit increase in CES-D scores (p=0.006). An income greater than \$30,000 or not reporting income was associated with a significantly lower CES-D score. An additional year of residence corresponded to a 0.003 unit increase in CES-D scores (p=0.006), while a unit increase in the frequency of everyday discrimination was associated with a 0.023 unit increase in CES-D scores (p<0.001). Health insurance was positively associated with depressive symptoms (p=0.018).

Table 5.4 Adjusted and unadjusted multilevel model, mixed-effects regression of the relationship between Neighborhood Disadvantage and Depressive Symptoms

CES-D	β (SE)	(95% CI)	β (SE)	p-value (95% CI)
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Year 2000 ND Score	0.036 (0.006)	(.017, .040)	0.015 (0.004)	(.009, .026)
Covariates:				
Age			-0.003 (.0009)	0.704
Gender (Female)			0.118 (.02)	<.0001
Race/Ethnicity				
(White)				
African American			0.040 (.03)	0.155
Hispanic			-0.093 (.04)	0.019
Other			-0.024 (.06)	0.679
Education (College)				
> HS <College			0.071 (.03)	0.022
Less than HS			0.102 (.04)	0.006
Income (<\$5,000)				
\$5,000 to \$9,999			0.053 (.08)	0.496
\$10,000 to \$29,999			-0.050 (.06)	0.430
\$30,000 to \$49,999			-0.196 (.06)	0.002
\$50,000 or more			-0.278 (.07)	<.0001
Missing			-0.233 (.07)	<.0001
Years of Residence			-0.003 (.001)	0.005
Everyday			0.023 (.004)	<.0001
Discrimination				
Health Insurance			0.083 (.04)	0.018
(yes)				

Significant values are bolded

The model fits for Aims 5.1 and 5.2 are shown in Table 5.5. The model r-squared values are used to assess the amount of variance explained by the multivariable regression used in Aim 5.1 to assess the association between Neighborhood Disadvantage and CES-D symptoms. The unadjusted model explained 2.4% of the variance in CES-D symptoms, while the adjusted model explained 9.9% of the variance in overall CES-D scores. The Intraclass Correlation Coefficients (ICC) presented in the table measured the amount of variance in CES-D scores which can be explained by the higher-level Neighborhood Cluster (NC) variable. The unadjusted multilevel model indicated that the 343 NCs explained 8.2% of the variance in CES-D scores, while the adjusted model indicated that the NCs explained 5.3% of the variance in CES-D scores.

Table 5.5 Qualitative Comparison of Model Fits between regression and multilevel model techniques

Model	Unadjusted Model R-Squared	Adjusted Model R-Squared	Unadjusted Intraclass Correlation Coefficient	Adjusted Intraclass Correlation Coefficient
CES-D Symptoms				
Aim 5.1	0.024	0.099		
Aim 5.2			0.082 (0.054-0.12)	0.053 (0.031-0.088)

Discussion

The first aim of this study was to determine whether individuals' Centers for Epidemiological Studies Depression (CES-D) scores varied significantly by Neighborhood Disadvantage (ND) trajectory. Compared to the LT Advantaged trajectory, all other trajectories had significantly greater mean CES-D scores prior to adjustment for covariates. However, only the LT Very Disadvantaged and LT Inequality trajectories' associations remained significant after adjusting for covariates. Residents of the LT Very Disadvantaged trajectory had a 0.334 unit increase depressive symptom score compared to the LT Advantaged trajectory. LT Inequality trajectory residents had an average of 0.100 unit greater CES-D scores than the LT Advantaged trajectory. Female respondents, people residing in their current NC for more time, and people experiencing more discrimination were significantly more likely to report higher CES-D scores. Additionally, having a college education and having an income greater than \$30,000 or not reporting income was inversely associated with CES-D scores.

It was expected that residents in the LT Advantaged trajectory would have lower CES-D scores because they live in more advantaged areas.[102] The correction due to individual-level covariates seem to be consistent with self-selection theories reported in other ND studies.[99]

This theory states that low-income residents are unhealthy and happen to live in disadvantaged conditions, which confounds ND research findings.

The finding that the LT Very Disadvantaged trajectory residents had higher mean CES-D scores was also expected.[77] However, the presence of a trajectories' low-income population only somewhat explains why the LT Inequality trajectory has elevated CES-D scores after correcting for individual-level covariates.

The elevated CES-D scores seen in LT Inequality trajectory residents were particularly unexpected when investigating the covariates.[8] The LT Inequality trajectory had the highest education levels, which were negatively associated with CES-D scores. This may be explained by the fact that the LT Inequality trajectory has a diverse range of incomes and education levels.[118] Although this value should be interpreted with caution, the LT Inequality trajectory had a significantly higher mean income than the LT Advantaged group. However, the LT Inequality trajectory had higher unemployment (9.7%), female headed household (19.3%), and poverty (19.7%) rates than the LT Advantaged trajectory despite having a higher proportion of educated individuals. This was not the case in 1970. Unemployment rose by 5.5%, poverty by 6.8%, and female headed households by 12.8% between 1970 and 2000. The mean income also rose, but mean income was highly skewed by a small number of high-income earners. The changes in this trajectory's ND variables indicate a growing gap between the wealthy and disadvantaged, commonly described as income inequality.[92] In fact, the NCs in this LT Inequality trajectory are clustered in the predominantly "wealthy" Northeast Chicago.[23] The growth and presence of such high income inequality may explain higher depressive symptom scores in this trajectory.[8]

Several studies suggest that an increase in income inequality may have the capacity to increase subjective experiences of inequality, which is a known chronic stressor.[135] LT Inequality conditions place many, in this case men, at a higher risk of developing depression. Wilkinson et al. (2006) found that income inequality is a stronger predictor of mortality than income per capita, showing that black men in the US live nine fewer years than black Costa Rican men, despite having a five-fold greater average income.[136] While mortality is a different outcome than depression, Wilkinson et al. suggests that the psychosocial stressor of relative deprivation may explain their findings.[136] This stress of inequality has been cited in qualitative studies as an explanation of poor mental health by low-income respondents.[8]

Additionally, stratification of the analyses by gender revealed that men's, but not women's mean CES-D scores were significantly greater in the LT Inequality trajectory. The stratification determined that men in the LT Inequality trajectory reported a 0.124 increase in CES-D scores compared to the LT Advantaged ($p=0.016$) (Appendix, Table B). Moreover, men in the LT Very Disadvantaged trajectory reported a 0.269 unit increase in CES-D scores compared to the LT Advantaged trajectory. ($p=0.007$). Despite the LT Very Disadvantaged residents living in different NCs than the LT Advantaged and LT Inequality NCs, they may still feel the psychosocial burden of inequality. As Prins (2015) found, the ability of inequality to predict depressive symptoms improves as larger area units are incorporated. In other words, social hierarchies arrange themselves at the national level, and can be perceived acutely among those who live in concentrated disadvantage.[57] Thus, it is intuitive that men in the LT Very Disadvantaged trajectory report an increase in depressive symptoms in accordance with their deprivation relative to others in Chicago and the nation.[136]

Overall, the finding that the LT Very Disadvantaged and LT Inequality trajectory residents, and specifically low-income men in these trajectories suffer disproportionately from depressive symptoms is consistent with the works of Wilkinson and Marmot.[8, 137] However, the women's depressive symptoms did not differ significantly across trajectories. The trajectories may not have captured the burdens that women face as well as it may have for men. For instance, deindustrialization may have been a greater psychosocial burden on men who relied on or hoped to rely on factory employment than it did on women. Another possible explanation is that other variables not investigated in ND research, such as biological differences, macrolevel policies, or cultural norms, may be responsible for such high rates of depressive symptoms in women.[77] Generally, variation in men's depressive symptoms are difficult to identify [12, 127, 128], but the results of this study should serve as an impetus for further investigation into the associations between inequality and depressive symptoms among men. Furthermore, future investigations into women's depressive symptoms may incorporate other predictors and approaches.

This study also found that lower education, greater discrimination, and the presence of health insurance were positively associated with CES-D symptoms. Several studies support the findings that both lower education and greater discrimination are associated with higher depression rates and depressive symptoms.[138-140] However, the associations between having health insurance is less easily explained.[125] It is possible that since CES-D symptoms occurred more frequently in the lowest-income bracket, respondents receiving public insurance accounted for the positive association. [57]

However, the fact that years of residence is negatively associated with CES-D symptoms is inconsistent with one other study of moving patterns and depressive symptoms.[141]

Airaksinen (2015) found that depression had no association with moving patterns in a Finnish population.[141] It may be possible that experiencing Chicago's socioeconomic history is correlated with increased depressive symptoms.[23] Whether the variation in methods or outcomes between this study and the Airaksinen study accounts for differences in outcomes remains to be examined.

Limitations

This nature and conduct of this study imposed some limitations. Most notably, the study lacks individual-level longitudinal data. Despite this limitation, the analyses did not find a significant association between years of residence in a neighborhood and drug dependence symptoms.

Conclusions

The relationship between Neighborhood Disadvantage and depressive symptoms has been inconsistent across studies.[61, 127, 131, 142, 143] However, using the Neighborhood trajectory method to classify neighborhoods appears to have offered new insights into this unclear relationship. More specifically, the experience of growing inequality across Chicago may have contributed to differences between the LT Advantaged trajectory and other, less egalitarian trajectories.[78] Unadjusted models revealed that residents of all other trajectories have significantly higher CES-D scores than the LT Advantaged trajectory's residents (all relationships were significant at the $p < 0.001$ level). Individual-level covariates could attenuate some of these relationships. However, this was not true for the LT Very Disadvantaged and LT Inequality trajectories. In fact, it may be that the LT Very Disadvantaged and LT Inequality trajectories' residents feel the psychosocial burden of inequality most poignantly, so much so that correcting for individual-level covariates cannot attenuate the relationship.[42, 102, 118]

Chapter 6: Study 3: What is the relationship between Neighborhood Disadvantage trajectories and substance use?

Introduction

Substance use is a major predictor of many causes of death in the US including several types of cancer, heart disease, respiratory infections, and accidental deaths.[144] Smoking in particular accounts for over 480,000 preventable deaths annually, and accidental poisonings due to drug use have ascended into the top 15 causes of death in the US in the past decade.[145]

A systematic review by Pickett and Pearl (2003) revealed evidence that smoking is more frequent in disadvantaged neighborhoods.[16] According to general strain theory, individuals engage in delinquent coping behaviors to alleviate high level of strain, particularly when faced with disadvantaged neighborhood conditions.[146, 147] Individuals living in high Neighborhood Disadvantage (ND) are more likely to start smoking as well as less likely to quit smoking than residents of more advantaged neighborhoods.[63, 148] Additionally, Businelle et al. (2010) found that the relationship between ND and smoking is mediated by higher levels of stress experienced by residents of disadvantaged neighborhoods.[149] Moreover, disadvantaged neighborhoods have higher concentrations of tobacco outlets and advertising, with predominantly African American neighborhoods being targeted most intensely.[150, 151]

Substance dependence is not limited to legal substances, however.[152] Illicit substance dependence is more likely to be adjudicated in disadvantaged neighborhoods as well.[153] The 1995 Detroit Area Study revealed that residents in disadvantaged neighborhoods were more likely to report abusing illicit drugs even after correcting for individual-level disadvantage.[19] Similarly, respondents from disadvantaged neighborhoods in the Healthcare for Communities (HCC) study were more likely to report symptoms of drug dependence.[154]

The incidence of drug dependence in disadvantaged neighborhoods appears to be higher than in less disadvantaged neighborhoods.[152, 155] However, more nuanced inferences about the relationship between ND and substance use have not been explored. Some evidence exists that living in neighborhoods that are experiencing decline or an increase in unequal conditions can act as a psychosocial stressor (Chapter 5), which elicits two potential causal pathways for linking these Neighborhood Disadvantage (Chapter 4) to substance use. The first, in accordance with general strain theory, is that the conditions of each trajectory act as a psychosocial stressor for residents, in comparison to the LT Advantaged trajectory.[146, 156] In turn, residents may smoke or rely on drug use to cope with such stressful conditions.[111, 156] The second pathway would be predicted by social disorganization theory: dramatically increased unemployment over time in the Declining trajectory or a comparative decline of status in the LT Inequality trajectory.[60]

Two historical incidents specifically justify the need for researching neighborhood trajectories and their relationship to substance use. The first is the crack cocaine epidemic, which occurred in inner cities in the 1980's.[60] This increase in drug dependence occurred after deindustrialization in the 1970's which generated a dramatic increase in unemployment seen across trajectories.[23] In particular, the Declining and LT Very Disadvantaged trajectories were severely impacted, with unemployment increasing by 14.8% and 21.1%, respectively between 1970 and 1980 (Table 4.3). However, studies examining associations between the crack cocaine epidemic and deindustrialization refer to a general "inner city" socioeconomic shift which was related to increases in drug dependence.[6, 60] Additionally, few studies have examined if or where drug dependence remains across cities, despite the fact that NCs socioeconomic paths varied dramatically. This study is the first to classify Neighborhood Clusters (NCs) in Chicago

according to socioeconomic trajectories, and to use these trajectories to predict differences in substance use and dependence.

A second socioeconomic phenomenon occurred in Chicago after deindustrialization. In the city center, a growth of few high-paying jobs with advanced educational qualifications in conjunction with a loss of union-wage employment defined the LT Inequality trajectory. The LT Inequality trajectory's socioeconomic character aligns with definitions of gentrification, which has been the focus of some drug dependence research.[58, 73] For instance, gentrification may disrupt drug markets and lessen the availability of some drugs.[58] Additionally, the social norms and local policies surrounding activities such as smoking may change in these areas such that smoking is less tolerated.[148] On the other hand, negative consequences of living in the LT Inequality trajectory may occur as well. Specifically, the psychosocial stress of comparatively low status may result in increased drug dependence among low-income individuals.[145]

Given the expanse of associations between neighborhood conditions and substance use and dependence, I hypothesize that varying Neighborhood Disadvantage may have differential associations with reported drug use and smoking.[145] This study addressed whether Neighborhood Disadvantage are associated with current smoking use or drug dependence symptoms.

Methods

The analyses in Study 3 of this dissertation addressed the following question:

Research Question 3: What is the relationship between ND trajectories and substance use?

The question was addressed by investigating two research aims:

Aim 6.1: To determine the association between ND trajectories and smoking.

Aim 6.2: To determine the association between ND trajectories and drug dependence symptoms.

Aim 6.3: To compare the association between the ND trajectories and smoking and drug dependence to their associations with single time-point Neighborhood Disadvantage (ND) scores.

Study Measures

Independent Variables:

Aims 6.1 and 6.2: The latent profile analysis technique described in Chapter 4 was used to generate the Neighborhood Disadvantage (ND) trajectory variables for this study. The trajectories were used in Aims 6.1 and 6.2 as a categorical predictor of smoking and drug dependence, respectively in a logistic regression procedure.

Aim 6.3: Two multilevel, mixed-effects logistic regression of ND in the Census year 2000 and 1) current cigarette smoking and 2) the presence of drug dependence symptoms were conducted. The same CES-D variable used in Aim 5.1 in the unadjusted model was used in the multilevel analysis. The adjusted model included the same covariates used in Aim 5.1. The level 2 independent variable for Aim 5.2 was the standardized Neighborhood Cluster (NC) score for the year 2000.

All analyses were conducted in Stata 14, Statacorp, Houston, TX. A weighting variable was calculated using a multiplicative combination of several weights: a centered household weight and a centered individual-level post-stratification weight. The weight was standardized to a mean and standard deviation of 1. The overall findings and model fit statistics of Aims 5.1

and 5.2 were compared qualitatively to develop a recommendation for which method provided the most applicable information for neighborhood-level interventions.

Outcome Variables:

Drug dependence symptoms were measured through the Composite International Diagnostic Interview (CIDI) short-form drug dependency questionnaire.[134] The CIDI is an interview structure supported by the World Health Organization and is used to assess mental health disorders according to DSM-IV criteria. It was scored on a scale from 0-7, with 0 being no indication of drug dependence and 7 indicating strong dependence. Drug dependence was not specific to a single drug. Therefore, this variable represents dependence to any illicit drug. This variable was analyzed as a binary variable with 0=no symptoms, 1=at least 1 symptom so that sub-threshold dependence could be identified across neighborhoods. Current smoking was treated as a 2-category variable (yes/no) (Table 6.1).

Table 6.1 Description of the outcome variables used in Aims 6.1-6.3

Outcome	Variable	Survey Items	Variable Type
Drug Dependence Symptoms	V2142 CIDI Short-Form Drug Dependence Index Score	<ol style="list-style-type: none"> 1. Have you often been under the effects of this substance/any of these substances or suffering its/their after-effects while at work or school, or while caring for children (in the past 12 months)? 2. Were you ever under the effects of this substance/any of these substances or feeling its/their after-effects in a situation which increased your chances of getting hurt (in the past 12 months)? 3. Did you have any emotional or psychological problems from using this substance/any of these substances- such as feeling uninterested in things, feeling depressed, suspicious of people, paranoid, or having strange ideas (in past 12 months)? 4. Did you have a strong desire or urge to use this 83.6% substance/any of these substances that you could not resist or could not think of anything else (in the past 12 months)? 5. Did you have a period of a month or more when you spent a great deal of time using this substance/any of these substances or getting over any of its/their effects (in the past 12 months)? 6. Did you often use much larger amounts of this 83.6% substance/any of these substances than you intended when you began, V830 or did you use it/them for a longer period of time than you intended (in the past 12 months)? 7. Did you ever find that you had to use more of this substance/any of these substances than usual to get the same effect or that the same amount had less effect on you than before (in the past 12 months)? 	Binary 0: No symptoms 1: At least 1 symptom
Smoking	V2445 3Category Smoking Status	Do you smoke any cigarettes now?	Binary 0: Non-Smoker 1: Current Smoker

Analysis Plan

The analytic plans for Aims 6.1 and 6.2 are shown below.

Aim 6.1: The latent profile analysis described in Chapter 3 was used to predict smoking by Neighborhood Cluster (NC) trajectory. An intraclass correlation (icc) value of 0.02 revealed

that a multilevel model was not the most parsimonious analytic method. Therefore, a logistic regression using the trajectory classifications, a categorical independent variable, with the LT Advantaged trajectory as the referent group, was conducted. Current smoking (yes/no) was used as the outcome variable. The individual-level covariates used in the adjusted model were also listed in Chapter 3, and included age, gender, race/ethnicity, education, income, years living in the current residence, discrimination, and the presence or absence of health insurance.

Aim 6.2: The latent profile analysis described in Chapter 3 was used to predict drug dependence symptoms by NC trajectory. An intraclass correlation value of 0.04 revealed that a multilevel model was not the most parsimonious analytic method. Therefore, a logistic regression using the trajectory classifications as a categorical independent variable with the LT Advantaged trajectory as the referent group was conducted. A binary measure of drug dependence symptoms (yes/no) was used as the outcome variable. The individual-level covariates used in the adjusted model were also listed in Chapter 3, and included age, gender, race/ethnicity, education, income, years living in the current residence, discrimination, and the presence or absence of health insurance.

Aim 6.3: Two multilevel, mixed-effects regression of ND in the Census year 2000 were conducted ($icc=0.04$). Smoking was the outcome variable of the first equation, and drug dependence was the outcome of the second. Level 1 of the multilevel analyses used the same smoking and drug dependence variables used in Aims 6.1 and 6.2 in the unadjusted model. The adjusted models included the same covariates used in Aims 6.1 and 6.2. The level 2 independent variable for Aim 6.3 was the standardized ND score for each NC the year 2000.

All analyses were conducted in Stata 14. A weighting variable was calculated using a multiplicative combination of several weights: a centered household weight and a centered

individual-level post-stratification weight as defined by Morenoff et al (2007).[18] The weight was standardized to a mean and standard deviation of 1. The overall findings and model fit statistics of Aims 6.1 and 6.2 were compared to their respective analyses in Aim 6.3 to develop a recommendation for which method provided the most useful information for neighborhood-level interventions.

Results

Aim 6.1: Smoking

Descriptive Statistics

Weighted demographic characteristics of the study sample overall and by trajectory are shown in Table 4.5. The percentage of CCAHS respondents who smoked was 25.3%. In the LT Advantaged trajectory, 22.7% of respondents smoked, while 36.2% of respondents in the Declining trajectory did. With regards to the two disadvantaged groups, 29.6% of the Dcr. Disadvantage trajectory respondents smoked while 35.0% of those in the LT Very Disadvantaged trajectory smoked. On the other hand, only 21.8% of individuals in the LT Inequality trajectory smoked.

Bivariate correlations between smoking and each covariate were reported from logistic regression equations (Table 6.2). Younger age was significantly associated with smoking ($p < 0.001$), as was male gender ($p < 0.001$). African Americans were 1.44 times more likely to smoke than whites ($p = 0.001$), and Hispanics were 0.61 times as likely to smoke as whites ($p = 0.007$). Compared to those with a college degree, individuals with at least a high school degree were 2.34 times more likely to smoke ($p < 0.001$), while those with less than a high school degree were 1.65 times more likely to smoke ($p = 0.001$). Earning an income of at least \$50,000 per year was negatively associated with smoking compared to those who made less than \$5,000

per year ($p=0.001$). Finally, those with health insurance were nearly half as likely to smoke as those without insurance ($p<0.001$).

Main Analysis

The unadjusted results of Aim 6.1, which investigated the relationship between neighborhood trajectories and smoking, are shown in Table 6.3. Compared to the LT Advantaged trajectory, residents of the Declining trajectory were 1.94 times more likely to smoke (95% CI: 1.42-2.64, $p<0.001$). The Dcr. Disadvantage trajectory's residents were 1.43 times more likely to smoke (95% CI: 1.09-1.89, $p=0.010$) than the LT Advantaged trajectory's residents. Additionally, the LT Very Disadvantaged trajectory residents were 1.84 times more likely to smoke than the LT Advantaged trajectory residents (95% CI: 1.19-2.84, $p=0.006$).

The adjusted results are shown in Table 6.4. Individuals in the Declining trajectory were 1.66 times more likely than those in the LT Advantaged trajectory to smoke cigarettes (95% CI: 1.08-2.55, $p=0.020$). Younger age was significantly associated with smoking ($p=0.007$). Women were 0.59 times as likely as men to report smoking (95% CI: 0.68-1.23). Compared to whites, Hispanics were 0.44 times as likely to smoke (95% CI: 0.30-0.63) and members of the "Other" race were 0.54 times as likely to smoke (95% CI: 0.32-0.904). Educational attainment was negatively associated with smoking. Individuals with at least a high school degree were 2.25 times more likely to smoke (95% CI: 1.69-3.00) and those without a high school degree with 1.68 times more likely to smoke than those with a college degree (95% CI: 1.19-2.40). Neither income nor years of residence in the adjusted model were associated with smoking. Discrimination was negatively associated with smoking (OR: 0.97, 95% CI: 0.93-1.00). Having health insurance was also negatively associated with smoking (OR: 0.67, 95% CI: 0.52-0.87).

Aim 6.2: Drug Dependence

Table 6.2 Bivariate correlations between Drug Dependence Score, Smoking, Trajectories, and covariates using a logistic regression procedure.

	Smoking Prevalence (%)	Smoking (yes)	p-value	Drug Dep. Prevalence (%)	Drug Dependence (yes)	pvalue
Trajectories	22.7	1.00		3.9	1.00	
*LT Advantaged						
Declining	36.2	1.94 (1.42-2.64)	<0.001	5.8	1.52 (0.83-2.81)	0.061
LT Disadvantage	29.6	1.43 (1.09-1.89)	0.010	6.2	1.61 (0.93-2.79)	0.060
LT Very Disadvantaged	35.0	1.84 (1.19-2.84)	0.006	14.3	4.05 (2.03-8.09)	<0.001
LT Inequality	21.8	0.95 (0.73-1.25)	0.725	7.9	2.10 (1.29-3.41)	0.004
Covariates						
Age		0.99 (0.98-0.99)	<0.001		0.95 (0.94-0.97)	<0.001
Gender (Female)	29.6	0.65 (0.53-0.79)	<0.001	8.4	0.37 (0.25-0.54)	<0.001
Race/Eth (White)	24.2			5.7		
African American	31.6	1.44 (1.17-1.79)	0.001	7.1	1.26 (0.85-1.89)	0.250
Hispanic	16.3	0.61 (0.42-0.87)	0.007	3.3	0.56 (0.28-1.15)	0.114
Other	17.1	0.665 (0.40-1.04)	0.076	3.5	0.61 (0.22-1.70)	0.342
Education (College)	16.1			5.7		
> HS <College	31.0	2.34 (1.79-3.06)	<0.001	6.6	1.16 (0.73-1.83)	0.526
Less than HS	24.1	1.65 (1.22-2.25)	0.001	3.8	0.55 (0.36-1.18)	0.162
Income (<\$5,000)	38.5			8.1		
\$5,000 to \$9,999	29.9	0.68 (0.38-1.22)	0.196	15.3	2.07 (0.80-5.31)	0.132
\$9,999 to \$29,999	27.7	0.61 (0.37-1.02)	0.059	6.8	0.83 (0.36-1.92)	0.659
\$30,000 to \$49,999	28.1	0.62 (0.37-1.05)	0.076	5.0	0.60 (0.24-1.49)	0.268
\$50,000 or more	20.2	0.40 (0.24-0.68)	0.001	5.2	0.63 (0.26-1.51)	0.303
Missing	22.6	0.47 (0.28-0.79)	0.005	1.7	0.20 (0.08-0.53)	0.001
Years of Residence		0.98 (0.98-1.00)	0.003		0.95 (0.93-0.97)	<0.001
Everyday		1.00 (0.97-1.03)	0.995		1.09 (1.04-1.14)	0.001
Discrimination						
Health Insurance (yes)	23.1	0.59 (0.47-0.75)	<0.001	5.0	0.59 (0.39-0.89)	0.012

*Referent group

Significant values are bolded.

Descriptive Statistics

Weighted demographic characteristics of the study sample overall and by trajectory are shown in Table 4.5. A total of 5.7% of the overall CCAHS sample reported having symptoms of

drug dependence. Only 3.9% of the LT Advantaged trajectory reported drug dependence symptoms, while 5.9% of the Declining residents did report drug dependence symptoms. Additionally, 6.2% of individuals in the Dcr. Disadvantage, 14.3% in the LT Very Disadvantaged, and 7.9% of those in the LT Inequality trajectory reported drug dependence symptoms.

The bivariate correlations between drug dependence symptoms and the other covariates are shown in Table 6.2. Younger individuals and females were significantly more likely to have drug dependence symptoms ($p < 0.001$), although race/ethnicity and educational attainment were not. Compared to individuals with a household income of less than \$5,000, those who did not report their income were 0.20 times as likely to report drug dependence ($p = 0.001$). Fewer years living in the current residence was associated with decreased reporting of drug dependence symptoms, as well ($p < 0.001$). A one standard deviation increase in the frequency of everyday discrimination was associated with a 9% increased odds of drug dependence symptoms ($p = 0.001$). Having health insurance was associated with 0.59 times lower likelihood of reporting drug dependence symptoms ($p = 0.012$).

Main Analyses

The unadjusted results of the Aim 6.2 logistic regression analysis, which investigated Neighborhood Disadvantage's association with drug dependence symptoms, are also shown in Table 6.2. In the unadjusted model, individuals in the NCs characterized by the LT Very Disadvantaged trajectory were 4.05 times more likely to have at least one symptom of drug dependence (95% CI: 2.03-8.09), while those in the LT Inequality trajectory were 2.10 times more likely compared to the LT Advantaged trajectory (95% CI: 1.29-3.41).

After adjusting for covariates, residents of the LT Very Disadvantaged trajectory were 3.25 times (95% CI: 1.32-8.05) more likely to suffer from symptoms of drug dependence compared to the LT Advantaged trajectory (Table 6.3). Younger age and male gender were significantly associated with drug dependence symptoms ($p < 0.001$; $p < 0.001$). Compared to whites, Hispanics were 0.44 times as likely to report drug dependence symptoms (95% CI: 0.21-0.92). Annual incomes between \$5,000-\$9,999 increased the odds of drug dependence symptoms by 4.25 times (95% CI: 1.36-13.3) compared to incomes below \$5,000. Education, discrimination, years of neighborhood residence, and health insurance status were not significantly associated with reporting symptoms of drug dependence.

Table 6.3 Adjusted Logistic Regressions of the relationship between Drug Dependence and Neighborhood Disadvantage

	Smoking OR (95% CI)	p-value	Drug Dependence OR (95% CI)	p-value
Trajectories				
*LT Advantaged				
Declining	1.66 (1.08-2.55)	0.020	1.81 (0.86-3.79)	0.116
LT Disadvantaged	1.20 (0.79-1.82)	0.400	1.75 (0.83-3.68)	0.140
LT Very Disadvantaged	1.30 (0.75-2.25)	0.358	3.25 (1.32-8.05)	0.011
LT Inequality	0.91 (0.68-1.23)	0.544	1.36 (0.82-2.25)	0.238
Age	0.99 (0.98-1.00)	0.007	0.96 (0.95-0.98)	<0.001
Gender (Female)	0.59 (0.68-1.23)	<0.001	0.37 (0.25-0.56)	<0.001
Race/Eth (White)				
African American	1.11 (0.77-1.60)	0.571	0.74 (0.38-1.42)	0.361
Hispanic	0.44 (0.30-0.63)	<0.001	0.44 (0.21-0.92)	0.029
Other	0.54 (0.32-0.90)	0.018	0.36 (0.12-1.07)	0.067
Education (College)				
> HS <College	2.25 (1.69-3.00)	<0.001	1.03 (0.62-1.71)	0.915
Less than HS	1.68 (1.19-2.38)	0.003	0.68 (0.36-1.27)	0.228
Income (<\$5,000)				
\$5,000 to \$9,999	0.86 (0.47-1.57)	0.613	4.25 (1.36-13.3)	0.013
\$9,999 to \$29,999	0.82 (0.48-1.40)	0.477	1.52 (0.53-4.33)	0.435
\$30,000 to \$49,999	0.95 (0.55-1.65)	0.863	1.12 (0.38-3.35)	0.836
\$50,000 or more	0.67 (0.39-1.18)	0.165	1.10 (0.37-3.28)	0.867
Missing	0.69 (0.40-1.21)	0.195	0.47 (0.15-1.55)	0.217

Years of Residence	0.99 (0.98-1.00)	0.051	0.98 (0.96-1.00)	0.104
Everyday Discrimination	0.97 (0.93-1.00)	0.056	1.06 (1.00-1.12)	0.061
Health Insurance (yes)	0.67 (0.52-0.87)	0.002	0.74 (0.45-1.20)	0.223

*Referent group

Significant values are bolded.

Aim 6.3 Results

Smoking

The unadjusted and adjusted results of the multilevel model, in which single time-point (year 2000) Neighborhood Disadvantage (ND) predicts smoking is shown in Table 6.4 and 6.5, respectively. In the unadjusted model, increasing ND is protective against smoking (OR: 0.18, 95% CI: 0.095-0.34). This relationship between ND and smoking remains protective in the adjusted model (OR: 0.088, 95% CI: 0.27-0.28). Younger age was significantly associated with smoking ($p=0.015$, $p<0.001$, respectively). Female respondents were 0.59 times as likely to smoke as men. Compared to whites, Hispanics were 0.43 times as likely to smoke and those of “Other” non-white races/ethnicities were 0.54 times as likely to smoke. Annual income, years of residence, and discrimination were not associated with smoking, although those with health insurance were less likely to smoke ($p=0.002$).

Drug Dependence Symptoms

Results of the multilevel model predicting the association between single time-point year 2000 Neighborhood Disadvantage (ND) and drug dependence symptoms are shown in Tables 6.4 and 6.5. No significant association between drug dependence symptoms and ND was observed in the unadjusted or adjusted models. In the adjusted model, younger age and male gender were

significantly associated with drug dependence ($p < 0.001$; $p < 0.001$). Race/ethnicity and education were not significant predictors of drug dependence symptoms. An annual income of \$5,000 to \$9,999 increased the odds of drug dependence symptoms by 4.43 times ($p = 0.016$). Years of residence and health insurance were not significantly associated with drug dependence symptoms. A one standard deviation increase in everyday discrimination increased the odds of reporting drug dependence symptoms by 7% ($p = 0.027$).

Table 6.4 Unadjusted Multilevel Model of the Association between Drug Dependence, Smoking, and Year 2000 Neighborhood Disadvantage Scores

	Smoking OR (95% CI)	Drug Dependence OR (95% CI)
Year 2000 ND Score	0.18 (0.095-0.34)	0.84 (0.47-1.49)

Significant Values are Bolded

Table 6.5 Adjusted Multilevel Model of the Association between Drug Dependence, Smoking, and Neighborhood Disadvantage

Drug Dependence	Smoking OR (95% CI)	p-value	Drug Dependence OR (95% CI)	p-value
Yr 2000 ND Score	0.088 (0.03-0.28)		0.70 (0.37-1.34)	
Covariates:				
Age	0.99 (0.98-1.00)	0.015	0.96 (0.94-0.97)	<0.001
Gender (Female)	0.59 (0.48-0.73)	<0.001	0.35 (0.23-0.53)	<0.001
Race/Ethnicity (White)				
2	1.39 (1.11-1.76)	0.005	1.17 (0.70-1.96)	0.539
3	0.43 (0.30-0.63)	<0.001	0.44 (0.20-0.97)	0.042
4	0.54 (0.31-0.91)	0.021	0.36 (0.10-1.30)	0.119
Education (College)				
2	2.28 (1.69-3.06)	<0.001	1.05 (0.60-1.81)	0.873
3	1.72 (1.21-2.45)	0.003	0.72 (0.38-1.39)	0.334
Income (<\$5,000)				
\$5,000 to \$9,999	0.81 (0.43-1.50)	0.498	4.43 (1.32-14.9)	0.016
\$10,000 to \$29,999	0.80 (0.47-1.36)	0.416	1.46 (0.49-4.39)	0.499
\$30,000 to \$49,999	0.93 (0.54-1.61)	0.794	1.01 (0.32-3.19)	0.981
\$50,000 or more	0.65 (0.38-1.12)	0.120	1.02 (0.32-3.22)	0.979
Missing	0.68 (0.40-1.15)	0.150	0.44 (0.13-1.55)	0.202
Years of Residence	0.99 (0.98-1.00)	0.068	0.98 (0.95-1.01)	0.122
Everyday Discrimination	0.97 (0.93-1.00)	0.066	1.07 (1.01-1.13)	0.027
Health Insurance (yes)	0.67 (0.52-0.87)	0.003	0.74 (0.48-1.13)	0.165

Significant Values are Bolded

The model fits for Aims 6.1-6.3 are shown in Table 6.6. The model r-squared values are used to assess the amount of variance explained by the multivariable regression used in Aim 6.1 to assess the association between Neighborhood Disadvantage and smoking. The unadjusted model explained 1.1% of the variance in smoking habits, while the adjusted model explained 6.7% of the variance. For Aim 6.2, the Intraclass Correlation Coefficients (ICC) presented in the table measure the amount of variance in smoking which can be explained by the higher-level Neighborhood Cluster (NC) variable. The unadjusted multilevel model indicated that NC ND scores explained 5.2% of the variance, while the adjusted model explained 2.6% of the variance

in smoking across NCs after adjusted for individual-level covariates. Aim 6.3 investigated the association between Neighborhood Disadvantage and drug dependence symptoms. The unadjusted model explained 2.0% of the variance while the adjusted model explained 15.0% of the variance. The unadjusted multilevel model in Aim 6.4 showed that NC-level ND explained 21.0% of the variance in drug dependence symptoms across NCs, while 18.0% of the variance of drug dependence symptoms was explained by NC-level ND after adjusting for individual-level covariates.

Table 6.6 Qualitative Comparison of Model Fits between regression and multilevel model techniques

Model	Unadjusted Model R-Squared	Adjusted Model R-Squared	Unadjusted Intraclass Correlation Coefficient	Adjusted Intraclass Correlation Coefficient
Smoking				
Aim 6.1	0.011	0.067		
Aim 6.2			0.052 (0.028-0.094)	0.026 (0.008-0.080)
Drug Dependence				
Aim 6.3	0.020	0.15		
Aim 6.4			0.21 (0.13-0.31)	0.18 (0.10-0.29)

Discussion

Aim 6.1: Smoking

The primary aim of this study was to investigate the associations between Neighborhood Disadvantage (ND) trajectories and current smoking. In the unadjusted model, residents in the Declining neighborhoods were 2.05 times more likely to smoke and LT Very Disadvantaged neighborhoods were 1.98 times more likely to smoke compared to those in LT Advantaged neighborhoods. However, only the Declining trajectory remained significant after adjusting for individual-level covariates.

Younger age and male gender were associated with increased likelihood of smoking.

Additionally, Hispanic or “Other” non-white ethnicity was associated with decreased odds of smoking. Compared to respondents with a college education, those with a high school degree were 2.56 times more likely to smoke, while individuals without a high school degree were 2.00 times more likely to smoke. Increasing reports of everyday discrimination were significantly negatively associated with smoking, while having health insurance significantly decreased the odds of current smoking.

These individual-level covariates were responsible for attenuating the relationship between LT Very Disadvantaged neighborhood residence and current smoking. One potential reason for this attenuation was that the LT Very Disadvantaged trajectory has a high prevalence of low overall educational attainment, which was significantly predictive of smoking. In contrast, the Declining trajectory’s association was strengthened when covariates were added to the model, indicating that the neighborhood conditions may disproportionately contribute to smoking prevalence in this neighborhood.[63]

The Declining trajectory NCs were labeled as such because ND scores worsened by one standard deviation between 1970 and 2000. The trajectory’s most dramatic increase in ND occurred between 1970 and 1980, which corresponds to the time in which Chicago experienced an overall decline in union-wage employment.[23] Union-wage factory employment was largely responsible for the employment of men without college degrees. In accordance with general strain theory, smoking may serve as a coping mechanism for these particular individuals who may have lost employment.[156] This finding is also consistent with many other findings that rank men as more frequent smokers.[157] Stratification of the results revealed that male smoking accounted for the differences in smoking rates by ND trajectory (Appendix, Table C).

Moreover, social disorganization theory may offer some insight into why men in the Declining trajectory were particularly vulnerable to smoking. As the Declining trajectory's ND measures increased, such as unemployment, female headed households, vacant homes, etc., neighborhood conditions may have become a greater stressor. In these conditions, smoking may provide a legal and affordable source of stress relief. For instance, unemployment in Declining neighborhoods rose from 3.7% in 1970 to 18.2% in 2000. This dramatic change may act as a stressor in itself. This may be particularly true when compared to an area that has experienced long-term disadvantage, such as the Dcr. Disadvantage and LT Very Disadvantaged trajectories. The Declining trajectory experienced the largest increase in female headed households of all trajectories, increasing from 6.3% to 34.7% between 1970 and 2000. Female headed households serves as a proxy for the availability of men who can support families, indicating that this number dramatically decreased between 1970 and 2000 in the Declining trajectory. By contrast, female headed households in the LT Advantaged trajectory only rose from 4.9% to 11.9% over the same time period. It may follow that men who are disproportionately stressed by growing unemployment are more likely to smoke.

A potential limitation to this study is that long-term smoking trends were not studied. Therefore, determining whether smokers chose to move to declining neighborhoods in accordance with self-selection theory is not possible. However, results from Halonen et al.'s longitudinal study of Finnish Public Sector employees found that individuals who moved to more disadvantaged neighborhoods were 1.23 times more likely to begin smoking (95% CI: 1.04-1.47 per 1 standard deviation increase in disadvantage score) than those who did not move to more disadvantaged neighborhoods.[10] These results do not support self-selection

theory.[99] Rather, the study indicates that declining neighborhood conditions preceded the advent of smoking.

The purpose of this study was not to determine the importance of individual attributes compared to neighborhood attributes in predicting smoking habits. Instead, the goal of this study was to profile the relationship between Neighborhood Disadvantage from 1970 to 2000 and smoking habits in 2000. The finding that residents of the Declining trajectory were 2.13 times more likely to smoke than those in the LT Advantaged trajectory was useful to identify these neighborhoods for neighborhood-level interventions.

Aim 6.2: Drug Dependence

The second primary aim of this study was to determine whether Neighborhood Disadvantage (ND) trajectories were significantly associated with symptoms of drug dependence. Prior to adjusting for covariates, the LT Very Disadvantaged and LT Inequality trajectories were significantly more likely than the LT Advantaged trajectory residents to report drug dependence symptoms. Based on the adjusted findings, residence in the LT Very Disadvantaged NCs was associated with increased reporting of drug dependence symptoms. Residents in LT Very Disadvantaged neighborhoods were 3.25 times more likely to report at least one drug dependence symptom. Younger age was predictive of drug dependence symptoms, as was male gender. Hispanics and those of “Other” races were significantly less likely to report drug dependence symptoms than whites. No significant difference between African Americans and whites was found.

While drug dependence symptoms were more frequent among men, the relationship between the LT Very Disadvantaged trajectory and drug dependence was only significant in women (Appendix, Table D). While men have an overall higher rate of drug dependence,

women in the LT Very Disadvantaged trajectory were 4.97 times more likely to report drug dependence symptoms than the LT Advantaged trajectory after stratifying by gender. Gender differences in drug dependence have often been attributed to biological sex differences.[20] However, this study lends evidence to the potential for a gender interaction with sociological conditions which may disproportionately impact women.

The finding that residents of LT Very Disadvantaged neighborhoods had the highest odds of reporting drug dependence symptoms was consistent with both theoretical predictions and empirical models. The LT Very Disadvantaged trajectory consisted of persistently disadvantaged neighborhoods from 1970 to 2000 with ND scores over 2 standard deviations above the mean. The underlying causes of this persistent disadvantage may be a product of residential racial segregation, as these neighborhoods had the highest percentage of African Americans for all time points.[49] Sociological works by Wilson, Massey, and others suggest that histories of Redlining and other discriminatory housing practices may have shaped the socioeconomic outcomes of these areas.[1, 158] Massey and Denton (1989 & 2004) reported that African Americans in Chicago were segregated across five dimensions of segregation, indicating that Chicago was “hypersegregated” through all years.[35] The results of this study built on these sociological frameworks by demonstrating that disparities in Neighborhood Disadvantage (ND) can be temporally linked to segregation. Moreover, the trajectories developed by investigating segregation revealed that residents of persistently segregated, LT Very Disadvantaged neighborhoods were 3.25 times more likely to suffer from drug dependence symptoms.

ND has been linked to drug use, but not dependence, in one other study. Boardman et al. (2001) found that ND was associated with drug use at the $p < 0.10$ level and cited availability as a

reason for elevated drug use.[159] This same rationale was echoed in a community study of 1416 adolescents, which found that adolescents from the highest tertile of ND were 5.6 times more likely to have been offered cocaine ($p=0.001$).[160] These findings suggest that treating ND as a continuous variable may attenuate the strong association between ND and drug use in the most disadvantaged neighborhoods. In other words, a threshold level of ND may occur in which mainstream institutions and social norms break down, leaving residents highly vulnerable to drug availability.[41] In the case of this study, living in a LT Very Disadvantaged trajectory captured a degree of social breakdown that allowed drug dependence to flourish.

Inferences from the sociology literature further suggest that hypersegregation and persistent disadvantage may have shaped the drug dependence outcomes of the LT Very Disadvantaged neighborhoods by shaping illicit drug markets. The decline of post WW-II factory employment in city centers was commonly credited as a reason that drug markets could gain traction by offering an alternative source of income. Further inspection of the results revealed that residents of LT Very Disadvantaged neighborhoods were 10.1 times more likely to report past year cocaine/crack cocaine/free base use compared to the LT Advantaged neighborhoods ($p=0.004$) (Appendix, Table E), supporting the hypothesis that drug markets may play a role in LT Very Disadvantaged drug dependence symptoms. Addressing the significance of illicit drug markets is beyond the scope of this dissertation, although the results warrant further investigation into this topic. Future research may address the associations between persistent disadvantage and drug dependence by gender as a corollary of illicit drug markets.

Summary

Overall, this study found that LT Very Disadvantaged trajectory residents are over 3 times more likely to report drug dependence symptoms than LT Advantaged trajectory residents.

Moreover, Declining trajectory residents were significantly more likely to both smoke than LT Advantaged trajectory residents. Evidence of socioeconomic decline as a correlate of substance use problems was also seen in a natural experiment in the USSR. When the USSR dissolved in the 1990's, formerly communist countries were exposed to capitalism.[136] The result was upward mobility for some groups and decline for others. The former USSR countries that experienced economic decline saw dramatic decreases in life expectancy and increases in accidental overdoses due to substance use.[136] This decline may reflect the events occurring in the Declining neighborhoods. It is unclear whether increasing unemployment, decreasing wages, or a comparative loss in status can explain this association.[136] However, uncovering the relationship between Declining neighborhoods and smoking that has previously gone undetected should generate opportunities for intervention in these neighborhoods and early intervention among areas that experience economic decline.[57]

Limitations

This nature and conduct of this study imposed some limitations. Most notably, the study lacks individual-level longitudinal data. Despite this limitation, the analyses did not find a significant association between years of residence in a neighborhood and drug dependence symptoms. Secondly, drug use and dependence were self-reported to live interviewers, which may introduce reporting bias.[32] Finally, the ND index was a standardized mean of 6 variables which were equally weighted.[18] Researchers have yet to address whether each of the socioeconomic variables contribute equally to ND.

Conclusions

The trajectories created using latent profile analysis (Chapter 4) were successful in predicting substance use patterns across the city of Chicago. Smoking was significantly more

frequent in the Declining trajectory, and drug dependence symptoms were significantly more frequent in the LT Very Disadvantaged trajectory. Additionally, this analysis provides compelling evidence that a) the impacts of segregation should still be considered when approaching drug dependence in persistently disadvantaged neighborhoods, particularly among women; and b) the strong correlation between neighborhood decline and smoking warrants further investigation.[37]

Chapter 7: Discussion

Main Findings

The intent of this dissertation was to determine whether incorporating neighborhood socioeconomic trajectories when predicting resident health outcomes provided additional information over and above traditional single-time point ND studies. The results partially support this hypothesis: the single time-point analysis did not identify the high prevalence of smoking in the Declining trajectory, the high prevalence of depressive symptoms in the LT Inequality trajectory, or the high prevalence of drug dependence symptoms in the LT Very Disadvantaged trajectory. However, the mixed-effects regression models consistently explained more variance in the outcomes than their respective trajectory analyses. A summary by Chapter is followed by an in-depth discussion of the dissertation's findings.

Chapter Findings

The purpose of Chapter 4 was to classify Chicago's 343 NCs by their ND scores from 1970-2000 using a latent profile analysis. Five NCs trajectories were derived and labeled as LT Advantaged (n=149), Declining (n=42), Dcr. Disadvantage (n=65), LT Very Disadvantaged (n=21), and LT Inequality (n=66). These trajectories were used in Chapters 5 and 6 to investigate the health outcomes of interest.

In Chapter 5, I investigated associations between ND and depressive symptoms. Specifically, in Aim 5.1 I examined the relationship between Neighborhood Disadvantage and depressive symptoms using a multivariable regression. In the unadjusted model, the Declining, Disadvantaged, LT Very Disadvantaged, and LT Inequality trajectories had significantly higher depressive symptoms than the LT Advantaged trajectory ($p < 0.001$). After adjusting for individual-level covariates, the LT Very Disadvantaged and LT Inequality trajectories had 0.181 and 0.100 unit greater depressive symptom scores than the LT Advantaged trajectory ($p = 0.004$, $p = 0.003$, respectively). The relationships observed between Neighborhood Disadvantage and CES-D symptoms were significant in males but not females when stratified by gender. Aim 5.2 was used to investigate the relationship between year 2000 ND and depressive symptoms using a multilevel, mixed-effects regression model. In the unadjusted model, a one unit increase in ND was associated with a 0.036 unit increase in CES-D scores (95% CI: 0.017-0.040). In the adjusted model, a unit increase in ND was associated with a 0.015 unit increase in depressive symptom scores (95% CI: 0.009-0.026).

In Chapter 6, the associations between Neighborhood Disadvantage and two outcomes were explored: current cigarette smoking (Aim 6.1) and the presence or absence of drug dependence symptoms (Aim 6.2) using logistic regressions. I investigated the association between the year 2000 ND and each outcome using a multilevel, mixed-effects logistic regression model in Aim 6.3. In the Aim 6.1 unadjusted model, residents of the Declining trajectory were 1.94 times more likely to smoke (95% CI: 1.42-2.64), residents in the Dcr. Disadvantage trajectory were 1.43 times more likely to smoke (95% CI: 1.09-1.89), and individuals in the LT Very Disadvantaged trajectory were 1.84 times more likely to smoke than the LT Advantaged trajectory's residents (95% CI: 1.19-2.84). Adjusting for covariates

attenuated the Dcr. Disadvantage and LT Very Disadvantaged trajectories' associations with smoking. However, individuals in the Declining NCs were 1.66 times more likely to smoke (95% CI: 1.08-2.55) than the LT Advantaged trajectory residents after adjusting for covariates. The relationship between the Declining trajectory and smoking was significant for males but not females when stratified by gender. In the Aim 6.3 unadjusted multilevel model, residents were 0.18 times as likely to smoke with a one unit increase in ND score (95% CI: 0.10-0.34). In the adjusted model, residents were 0.09 times as likely to smoke with a one standard deviation increase in ND score (95% CI: 0.03-0.28) such that increasing ND was deemed to have a protective association against smoking.

In Aim 6.2, the unadjusted regression revealed that residents in LT Very Disadvantaged NCs were 4.05 (95% CI: 2.03-8.09) and LT Inequality trajectory residents were 2.10 (95% CI: 1.29-3.41) times more likely to report at least one symptom of drug dependence than individuals in the LT Advantaged trajectory. After adjusting for covariates, residents of the LT Very Disadvantaged trajectory were 3.25 times more likely to report drug dependence symptoms (95% CI: 1.32-8.05) than those in the LT Advantaged trajectory. The relationship between the LT Very Disadvantaged trajectory and drug dependence scores was significant in females but not males when stratified by gender. In the Aim 6.3, reporting drug dependence symptoms was not significantly associated with the unadjusted or adjusted multilevel models.

A Comparison of Neighborhood Trajectory and Multilevel Modeling Approach

The purpose of this study was to identify neighborhoods in which residents suffer from disproportionately worse health outcomes. Two approaches to investigating neighborhoods were used: the neighborhood trajectory approach in which neighborhoods were classified based on socioeconomic changes from 1970-2000, and the traditional multilevel modeling approaching

using year 2000 Neighborhood Disadvantage (ND) scores as the predictor. The approaches were compared to investigate which method provides more information for intervention purposes.

A potential barrier to this comparison is that comparing model fits between multivariable regressions and multilevel models would not provide useful or valid information.[161] Instead, comparing indices that describe the same phenomenon—that is, fit indices that are used to measure the amount of variance explained—were compared qualitatively. Thus, the intraclass correlation coefficient (icc) for each multilevel model was compared to the r-squared value for the multivariable regressions to see how much variance each model explained. When individuallevel covariates are added to the model, the r-squared value of the multivariable regression models are expected to increase, while the icc values of the multilevel model are expected to decrease.[161] This is because the r-squared provides an approximation of the entire model's ability to predict outcomes, while the icc provides an approximation of how much variation is explained by including spatial variation (NCs) in the model. Therefore, two approaches for comparing these models were used.

First, a comparison of the percent changes that occurred between the unadjusted and adjusted models was investigated. This comparison intends to describe the impact that the inclusion of covariates had on the respective model fit statistics. In the Chapter 5 analysis of depressive symptoms, the r-squared changed 312.5% in the regression (r^2 : 0.024 unadjusted, 0.099 adjusted) and 100% in the multilevel model (icc: 0.052 unadjusted, 0.026 adjusted). In the Chapter 6 smoking analyses, the r-squared value increased by 509.1% (r^2 : 0.011 unadjusted, 0.067 adjusted) with the addition of covariates while the icc was 100.0% without covariates (icc: 0.052 unadjusted; 0.026 adjusted). The drug dependence analyses revealed that the r-squared changed from 0.02 to 0.15 (650%) in the regression analysis, while the icc changed from 0.21 to

0.18 (16.7%) with the addition of covariates.

Second, a comparison of the unadjusted model r-squared and icc values was conducted because they provide an analysis of how much variance was explained by the ND variables (trajectories vs. traditional NCs). Each unadjusted multilevel model yielded higher icc values than its respective multivariable model's r-squared value, meaning that the multilevel models explained a greater percentage of the variance in each health outcome investigated.

Regardless, evidence suggests that model fit statistics should not be regarded with utmost importance.[115, 116] It may be more useful to recognize that the multilevel ND analyses significantly predicted depressive symptoms but not smoking or drug dependence symptoms in the adjusted analyses. However, the ND trajectory analyses yielded significant associations with all three variables in both unadjusted and adjusted analyses. Moreover, the latent profile analysis responsible for classifying the trajectories yielded excellent model fits, further providing evidence as this approach as a useful analytic technique.[28]

A potential point of concern in this comparison is that multivariable regression techniques may have the potential for type I errors when estimating multilevel data. In other words, the Neighborhood trajectory was modeled as an inherent property of the individual, which can overinflate the statistical significance of the finding. Comparisons of multivariable regressions and multilevel models in several studies have concluded that the traditional regression found more significant relationships than the multilevel models. However, no researchers discussed the possibility that the multilevel model underestimates the significance of relationships across levels, particularly when between-level multicollinearity exists.[162, 163] Additionally, the multilevel models and multivariable regressions in this study did not examine the same measures.

Because of these factors, considering the results of both techniques may provide the most complete information. For instance, Aims 6.1 and 6.3 investigated cigarette smoking status. The multilevel model found that ND was inversely associated with cigarette smoking, while the Neighborhood trajectory regression found that residents in the Declining trajectory NCs were significantly more likely to smoke than those in the LT Advantaged trajectory. The findings from the regression contextualize the multilevel model findings in a way that would not have been because the Declining trajectory's year 2000 ND score likely drove the inverse association between smoking and ND. Finally, the analyses of drug dependence symptoms found no significant association in the multilevel model but elevated odds of drug dependence in the LT Very Disadvantaged trajectory. Even if the regression technique inflated the odds ratios in this instance, the fact remains that individuals who are more likely to suffer from drug dependence symptoms can be found and intervened upon in the LT Very Disadvantaged trajectory. Thus, using both techniques may offer the most useful information for targeting neighborhoods most efficiently and efficaciously.

Findings from the Neighborhood Trajectory Method

Despite their ability to explain more variance, some issues arose with the multilevel models. For instance, the multilevel model predicting smoking found ND to have a protective association with smoking. Such a counterintuitive finding was seemingly clarified by the Neighborhood trajectory multivariable approach in that the Declining trajectory, which has the second-highest mean ND score for the year 2000, had the highest odds of smoking compared to the LT Advantaged trajectory.

Contrary to the multilevel model, it was a novel finding that the Declining trajectory's residents were significantly more likely to smoke.[148] These outcomes were not previously

identified using the single time-point census data. The Declining trajectory's year 2000 ND scores were 0.2 standard deviations lower than the Dcr. Disadvantage trajectory. However, the Dcr. Disadvantage trajectory had no significant associations with the investigated health outcomes after adjusting for covariates.

Socioeconomic decline as a health-related phenomenon has received little attention in public health.[120, 164] However, further inquiry may find that it has strong associations with various health outcomes. For instance, when the USSR dissolved, formerly communist countries were exposed to capitalism. The result was upward mobility for some groups and decline for others.[136] The former USSR countries that experienced economic decline and a growth in inequality saw dramatic decreases in life expectancy and increases in accidental overdoses due to substance use—the largest in recorded peacetime history. The fall in life expectancy was particularly evident among men. This socioeconomic transition may reflect the events occurring city-wide, which impact various neighborhoods in different ways. It is unclear whether increasing unemployment, decreasing wages, or a comparative loss in status can explain this association.[136] However, uncovering the relationship between Declining, LT Very Disadvantaged, and LT Inequality neighborhoods and health outcomes that has previously gone undetected should generate opportunities for intervention after socioeconomic changes have begun to occur.

Overall, the field of public health has been slow to identify and meet the needs of areas experiencing socioeconomic transitions. In addition to a focus on individual-level behaviors and interventions, public sentiment to act in the face of public health crises has been tempered by the racial segregation and isolation of communities experiencing persistent disadvantage or decline. For example, the crack cocaine epidemic of the 1980's occurred in primarily segregated African

American neighborhoods.[47] The epidemic coincided with deindustrialization and job loss. However, an overall reluctance to treat victims of drug dependence stemmed from a paradigm which desired to punish drug offenders. The majority of the US, namely white Americans, were unfamiliar with the structural predictors of drug dependence.[4, 47, 49] In more recent times, however, drug dependence has risen dramatically in rural, predominately white areas.[165] Future research may investigate whether this rise in drug dependence in rural areas is associated with socioeconomic trajectories, so that areas experiencing decline may be targeted specifically for structural interventions.

A second important socioeconomic transition that occurred in this study was the increase in economic inequality in Northeast Chicago.[40] The socioeconomic outcomes of the LT Inequality trajectory reflect burgeoning literature in the field of gentrification. However, labeling this trajectory as “Gentrifying” may be inaccurate, as gentrification has been traditionally measured using building codes and variables that were unavailable in the current study.[166] Nonetheless, the rapid increase in wealth alongside an increase in poverty defined the LT Inequality trajectory. Moreover, this trajectory’s residents reported a 0.100 unit increase in mean depressive symptoms, which was significant among males only when stratified by gender. This association between unequal conditions and depressive symptoms was not seen in the traditional, multilevel model of ND in the year 2000. Thus, future research may investigate whether a growth in unequal conditions is associated with other poor mental health outcomes. It should be acknowledged that the Disadvantaged trajectory residents, whose ND scores remained near 1 standard deviation above the mean from 1970-2000, were not significantly more likely than the LT Advantaged trajectory to suffer from the negative health outcomes

investigated after adjusting for covariates. The Disadvantaged trajectory residents' disproportionately good health should be further investigated. The Disadvantaged 65 Neighborhood Clusters (NCs) are have been highly segregated across all years.[158] Given that these NCs have faced discrimination and isolation from mainstream economies, these areas may have developed alternative social structures that have positive impacts on health.[164] This potential explanation is in opposition to predictions of social disorganization theory, which suggests that alternative social systems may negatively impact health.[29, 167]

Despite the discrimination and segregation that the Disadvantaged trajectory endured, its residents have not suffered from depressive symptoms, smoking, or drug dependence symptoms in the same way that the Declining, LT Very Disadvantaged, and LT Inequality trajectories did compared to the LT Advantaged trajectory. These findings lend support for the trajectory analysis of neighborhoods when investigating health outcomes. Moreover, the results offer insights into inconsistencies seen in assessing cross-sectional ND associations with health.

Finally, it was of potential importance to identify the LT Advantaged trajectory as such. Previously, measures of ND have used raw income values. Areas with very high mean incomes may obscure the inequalities that exist in a neighborhood.[18] Income measures were omitted from the ND calculations out of necessity, because the use of raw numbers was deemed to be a threat to validity by the authors of the Long-Term Census Tract Database (LTDB).[107] In omitting income values, I found that the most advantaged neighborhoods were in fact those that may be considered to be "middle-income," as they had the lowest poverty, unemployment, female headed household, and vacant home rates, the highest racial/ethnic diversity, and the second-highest incomes (Table 4.2). Traditional ND calculations may have scored the LT Inequality trajectory's NCs as the most advantaged.[16] Thus, the high rates of depressive

symptoms and drug dependence symptoms uncovered in this trajectory would have gone undetected. Future research may investigate whether affluence is a valid measure of advantage, particularly when investigating psychosocial health outcomes.[117, 118]

Identifying Neighborhoods as Targets for Interventions

The goal of this dissertation was to determine whether ND trajectories could be used to identify neighborhoods as potential targets for interventions. Therefore, identifying health disparities across trajectories prior to adjusting for covariates may be just as useful, if not more useful, for planning neighborhood-level interventions. For example, all four trajectories' residents reported significantly greater depressive symptoms than the LT Advantaged trajectory ($p < 0.001$). This information may be used to provide mental health services to these areas, regardless of whether individual-level covariates may correct for this association.[1] Since the outcome is more frequent in these trajectories, they should be targeted for intervention. Individual-level covariates may help to target low-income individuals, women, or men in the LT Inequality and LT Very Disadvantaged trajectories, but both unadjusted and adjusted findings may provide important translational information to practitioners.

Theoretical Analysis and Support

The tenets of the traditionally criminological-focused social disorganization theory were only partially supported as a potential theory for predicting health outcomes.[29] The original intent of social disorganization theory was to explain high crime rates in segregation cities as a product of neighborhood-level job loss (i.e., deindustrialization) in the 1970's and 1980's. It explained that increased crime was a product of increased unemployment, which also had a direct correlation to decreases in the ratio of marriageable (employed) men to women. Therefore, the dramatic increase in crime and economically stressed female-headed households among segregated communities was strongly associated with deindustrialization. The theory

only captured the processes that occurred in the Declining trajectory. The Declining trajectory was scored as slightly advantaged in 1970. However, a rapid increase in unemployment in the 1980s was followed by the greatest increase in segregation and female headed households compared to all other trajectories. This trajectory did not recover economically during the investigated time frame.

While social disorganization theory did explain the processes that occurred in the Declining trajectory, it is less obvious how the theory explains other Chicago trajectories. For instance, the LT Advantaged, Disadvantaged, and LT Very Disadvantaged trajectories endured positive or negative long-term socioeconomic trends, such as long-term advantage or disadvantage. However, the ND scores developed compared relative disadvantage by year. In other words, the city-wide 8.3% increase in unemployment between 1970 and 2000 was not accounted for across years of the ND score because it is merely a within-year comparison of disadvantage. Thus, the entire city experienced an increase in poverty, unemployment, home vacancies, and female headed households between 1970 and 2000 in what can be interpreted as absolute decline. As such, the Disadvantaged and LT Very Disadvantaged trajectories experienced 12.6% and 21.1% increases in unemployment, respectively between 1970 and 2000 but remained stable in socioeconomic position relative to the rest of the city. While social disorganization theory accounts for this decline and the relationship between unemployment to the rest of the ND variables, it does not account for relative forms of disadvantage.

Instead, research into inequality by scholars such as Wilkinson and Marmot offer insights. Relative disadvantage has been observed as a stressor across several studies. The Declining trajectory faced such a dramatic increase in relative inequality that it outpaced the city's overall decline. This trajectory had the highest proportion of male smokers, the second

highest percentage increase in unemployment (14.8%), and the most rapid growth in female headed households (28.3% increase from 1970 to 2000). It is plausible that the once fullyemployed workforce of men in this trajectory experienced this decline very acutely, using cigarette smoking as a method of coping. In contrast, the LT Advantaged trajectory experienced slight but significant increases in poverty, unemployment, female headed households, and home vacancies, but its residents enjoyed the best health across the three outcomes studied. This may have been due to the LT Advantaged trajectory's relative socioeconomic position compared to the rest of the city. A similar comparative disadvantage may have been conferred to low-income residents in the LT Inequality group. A highly right-skewed income distribution along with greater disadvantage indicators than the LT Advantaged trajectory may have contributed to the high depressive symptom scores in the LT Inequality trajectory.

It is plausible that social disorganization theory partially supports the findings of this dissertation because it describes a single component of the larger association between economic inequality and health.[8] The deindustrialization and job loss described in social disorganization theory occur within the overarching city-wide and nation-wide growth in economic inequality that occurred between 1970 and 2003.[40, 42] Future efforts to understand relationships between long-term socioeconomic trajectories and health outcomes should incorporate macrolevel changes in economic inequality into their theoretical methodological frameworks.

Limitations

The following limitations of this study may be considered when interpreting the results. First, the results contain information from years 1970 to 2003.[45] However, the general socioeconomic patterns of deindustrialization and growing inequality may tend to be repeated across places and eras.[136] Secondly, the individual-level data were not longitudinal, making

the overall study cross-sectional. Finally, interpolating between Census Tract boundaries may introduce some unavoidable error. This error was minimized by using only percentage variables rather than raw numbers.[107] Overall this dissertation has identified geographic points of intervention for psychosocial and behavioral health outcomes, which may generate further research into the associations between socioeconomic change and health outcomes.

Conclusions

The Neighborhood trajectory method has successfully identified new neighborhoods as points of intervention based on their socioeconomic histories. Specifically, higher depressive symptom rates were seen in the LT Inequality and LT Very Disadvantaged trajectories, particularly when comparing men in these trajectories to the LT Advantaged trajectory. Smoking was significantly more likely to occur among residents in the Declining trajectory, and drug dependence symptoms were significantly more likely to be reported in the LT Very Disadvantaged trajectory, compared to the LT Advantaged. While the trajectory variable may not explain as much variance as the NC-level ND score, it was able to provide useful information for interventions as well as suggest that the socioeconomic histories of place deserve greater attention in the field of public health. Future endeavors may classify trajectories across other cities and time points to uncover previously undetected health disparities.

One potentially applicable use of the trajectory method may be used in addressing the heroin and opioid crisis in rural US areas. Investigations and interventions have centered on the opiate prescribing behaviors of doctors and hospitals.[168, 169] However, to my knowledge, investigations have not focused on the association between opioid injuries with rural socioeconomic decline. In fact, a systematic review of urban-rural differences in opioid use only cited neighborhood disadvantage studies in its theoretical discussion of how rural economic

changes may influence drug use.[170] Deindustrialization of rural employment, such as in the mining and manufacturing sectors, has led to dramatic increases in unemployment in these areas. According to the USDA, 183 US counties are defined as economically mining-dependent and 351 as factory-dependent.[171] On average, these counties experienced dramatic socioeconomic declines during the recession and have not recovered. In the same timeframe, opioid injuries have risen to epidemic levels in the predominantly rural, mining-dependent states of West Virginia and Kentucky.[170] Future studies may better determine points of intervention by studying the associations between socioeconomic trajectories and opioid injuries in rural counties.

Recommendations

The present dissertation used data from the city of Chicago, whose history and demographics differ from other geographic units. Continuation and expansion of the Neighborhood Disadvantage method to other geographic areas may allow for recommendations that inform public health interventions. Tentatively, the findings generated in the city of Chicago found that neighborhood conditions of persistent disadvantage, decline, and inequality, as evidenced by the LT Very Disadvantaged, Declining, and LT Inequality trajectories, have associations with health behaviors and outcomes. Replications of the findings in other areas can determine the generalizability of the results found in this dissertation.

Given the current findings, some recommendations are provided. The findings of this dissertation are congruent with findings in public health that employment has a strong, positive influence on various health outcomes of individuals.[1] Moreover, residing in a neighborhood with high unemployment rates may negatively impact the health of all residents regardless of employment status.[60] Therefore, public health officials may consider working with legislators

to encourage investment in public works employment opportunities in these persistently disadvantaged and declining areas. This “New Deal” approach was taken on a much larger scale to employ citizens during the Great Depression.[172] The investments into public works and defense projects were deemed to be pivotal in generating the post-World War II growth of the US middle class. This post-war middle class had the highest median salaries and union membership in US history.[173]

Unfortunately, the benefits of the New Deal were not extended fully to African Americans. Aside from the ills of slavery, threats of violence, and segregation, partial exclusion from the New Deal prevented African American families from entering the middle class in the US at the same rate as whites. For example, the Social Security Act was not extended to jobs (i.e., agriculture) filled most frequently by African Americans. As such, 65% of African American workers were excluded from the Social Security Act while only 27% of whites were, in addition to African Americans exclusion from home ownership loans.[172] It is reasonable to consider that African Americans, who suffer disproportionately from segregation, poverty, unemployment, and the associated negative health consequences, should be candidates for public works employment as an extension of the New Deal today. These opportunities can be placed strategically in LT Very Disadvantaged and Declining neighborhoods by using the latent profile analysis technique described in this dissertation. This recommendation is made both necessary and possible due to the persistence of racial segregation in US cities and especially in Chicago. Aside from a moral debt owed to residents in these neighborhoods, the proportion of government funds devoted to Medicaid and Medicare, particularly for impoverished individuals, provides an economic incentive to taxpayers for this investment.[27]

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Appendix

Table A Variables Utilized from the National Historical Geographic Information System: Version 2.0.

Census Year	Percent of Persons in Poverty	Percent Female Headed Households**	Percent of Vacant Homes	Percent Unemployed	Percent African American***	Percent with High School Degree or Less
1970	X	X	X	X	X*	X
1980	X	X	X	X	X	X
1990	X	X	X	X	X	X
2000	X	X	X	X	X	X

*Note: Percentage of African American Individuals was generated by counting all those identifying as “Black” in the 1970 Census. This differs from other years, which identified “African American” individuals.

** Proxy for Male Marriage Pool Index [173]

***Proxy for Segregation

Table B Adjusted multivariable regressions predicting the relationship between trajectories and CES-D scores.**

	β (SE)	p-value
Mean CES-D Score		
Men		
*LT Advantaged Declining	0.127 (.07)	0.055
LT Disadvantaged	0.099 (.07)	0.157
LT Very Disadvantaged	0.282 (.10)	0.005
LT Inequality	0.120 (.05)	0.019
Women		
*LT Advantaged Declining	0.024 (.07)	0.838
LT Disadvantaged	0.053 (.07)	0.536

LT Very Disadvantaged	0.098 (.08)	0.360
LT Inequality	0.069 (.05)	0.174

*Referent group

Adjusted for age, race/ethnicity, education, income, years in residence, discrimination, and health insurance **Table C Adjusted multivariable regressions predicting the relationship between trajectories and Smoking.**

	OR (95% CI)	p-value
Current Cigarette Smoking		
Men		
*LT Advantaged Declining	1.97 (1.05-3.70)	0.034
LT Disadvantaged	1.46 (0.76-2.83)	0.252
LT Very Disadvantaged	1.05 (0.41-2.69)	0.924
LT Inequality	0.79 (0.52-1.20)	0.269
Women		
*LT Advantaged Declining	1.57 (0.91-2.72)	0.105
LT Disadvantaged	1.05 (0.62-1.79)	0.854
LT Very Disadvantaged	1.61 (0.82-3.15)	0.165
LT Inequality	1.16 (0.74-1.67)	0.597

*Referent group

**Adjusted for age, race/ethnicity, education, income, years in residence, discrimination, and health insurance

Table D Adjusted multivariable regressions predicting the relationship between trajectories and drug dependence symptoms.**

	OR (95% CI)	p-value
Drug Dependence Symptoms		
Men		
*LT Advantaged Declining	2.26 (0.85-6.03)	0.103
LT Disadvantaged	1.84 (0.69-4.96)	0.226
LT Very Disadvantaged	2.28 (0.66-7.89)	0.192
LT Inequality	1.25 (0.65-2.39)	0.501
Women		
*LT Advantaged Declining	1.65 (0.47-5.72)	0.433
LT Disadvantaged	1.93 (0.59-6.30)	0.274
LT Very Disadvantaged	4.97 (1.27-19.6)	0.022
LT Inequality	1.71 (0.78-3.76)	0.181

*Referent group

**Adjusted for age, race/ethnicity, education, income, years in residence, discrimination, and health insurance

Table E Adjusted logistic regressions predicting the relationship between trajectories and cocaine/crack cocaine/free base use.**

	OR (95% CI)	p-value
Used Crack/Crack Cocaine/Free Base in the past 12 months		
*LT Advantaged		
Declining	1.56 (0.30-8.14)	0.595
LT Disadvantaged	5.94 (1.25-28.2)	0.025
LT Very Disadvantaged	10.1 (2.05-49.7)	0.004
LT Inequality	3.47 (1.13-10.6)	0.030

*Referent group

**Adjusted for age, gender, race/ethnicity, education, income, years in residence, discrimination, and health insurance