

2007

Community context and health disparities among older adults

Helen M. Zayac
University of South Florida

Follow this and additional works at: <https://digitalcommons.usf.edu/etd>



Part of the [American Studies Commons](#)

Scholar Commons Citation

Zayac, Helen M., "Community context and health disparities among older adults" (2007). *USF Tampa Graduate Theses and Dissertations*.
<https://digitalcommons.usf.edu/etd/2427>

This Dissertation is brought to you for free and open access by the USF Graduate Theses and Dissertations at Digital Commons @ University of South Florida. It has been accepted for inclusion in USF Tampa Graduate Theses and Dissertations by an authorized administrator of Digital Commons @ University of South Florida. For more information, please contact digitalcommons@usf.edu.

Community Context and Health Disparities Among Older Adults

By

Helen M. Zayac

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
School of Aging Studies
College of Arts and Sciences
University of South Florida

Co-Major Professor: Jennifer R. Salmon, Ph.D.
Co-Major Professor: David A. Chiriboga, Ph.D.
Larry Polivka, Ph.D.
Steven Reader, Ph.D.
Sandra Reynolds, Ph.D.

Date of Approval:
June 27, 2007

Keywords: ethnic disparities, neighborhood, geographic information systems, health,
depression

© Copyright 2007, Helen M. Zayac

Note to Reader: The original of this document contains color that is necessary for understanding the data. The original dissertation is on file with the USF library in Tampa, Florida. In addition, although the heart of the dissertation (chapters 2-5) is four distinct manuscripts to be submitted to peer reviewed journals, they use a common reference list found at the end of the dissertation.

Dedication

This dissertation is dedicated to my grandparents, Grandma Joan, Grandpa Kurt, Grammy, and Poppy, who first taught life begins at 50. Their devotion to our family, enthusiasm for life, and the strength they have shown when confronted with the challenges of growing older have been inspiring. They have taught me that there is unconditional, life-long love and I have been blessed to have them in my life.

Acknowledgements

This research was funded by the University of South Florida Presidential Doctoral Fellowship and in part through a grant from the U.S. Administration on Aging (Grant #90AM2750).

I want to acknowledge with deep gratitude the assistance of my co-authors for each of the four articles (chapters 2-5): Dr. Jennifer R. Salmon, Dr. David A. Chiriboga, and Dr. Steven Reader. In addition, I want to thank Dr. Sandra Reynolds for her assistance with the statistical analyses and Dr. Larry Polivka for recruiting me as project manager for the Survey of Older Floridians and for mentoring me in long-term care policy.

I would also like to acknowledge and thank my parents and brothers for their continued support throughout my life and my academic career. Many thanks to Ashlee Carter, Guy Cafri, Amy Green, and Nicole Bekman for their invaluable editorial, statistical, and moral support over the past five years. Finally, and most importantly, I would like to express my extreme gratitude to Stephen Lamont and Madison, who believed in me even when I did not and whose love supported me throughout the entire dissertation process.

TABLE OF CONTENTS

LIST OF TABLES	v
LIST OF FIGURES	vii
ABSTRACT	viii
CHAPTER 1: INTRODUCTION	1
Community Context and Health	1
The Need for Theory	2
Use of Spatial Data to Define Community Context	4
Objectives	4
CHAPTER 2: THE COMMUNITY CONTEXT AND HEALTH DISPARITIES MODEL	8
Introduction	8
Community Context, Health, and Health Disparities	9
Residential Segregation	10
Environmental and Social Conditions	10
Limitations of Previous Research	11
Social and Environment Health Promotion Model	12
Recent Methodological Developments	13
Community Context and Health Disparities: A New Model	14
Measures of Community Context	17
Physical Environment	18
Built Environment	18
Social Environment	19
Economic Environment	20
Healthcare Environment	23
Measures of Individual Context	24
Demographics	25
Socioeconomic Status	25
Health Related Behaviors	26
Social Support	27
Stressors	27
Measures of Individual Outcomes	28
Potential Interactions	29
Discussion	30
Conclusion	33
CHAPTER 3: MEASURING HEALTHCARE AVAILABILITY AND ACCESSIBILITY	34
Introduction	34
Healthcare System	35

Provider Availability.	36
Healthcare Accessibility	39
Objectives	40
Method	42
Sample	42
Physicians	42
Hospitals With Emergency Departments	43
U.S. Census Population Data	44
Measures	45
Physician Availability (Intensity)	45
Physician Availability Comparison Variables	47
Distance to Closest ER Hospital	49
Euclidean Distance to Nearest ER Hospital	50
Evaluation	50
Results	51
Physician Availability	52
Road Network-based ER Hospital Distance	54
Physician Intensity vs. Physician Density	56
Spatial Resolution Comparison	57
Euclidean vs. Road Network-based ER Hospital	
Accessibility	60
Racial and Ethnic Disparities in Healthcare	61
Physician Availability	61
ER Hospital Accessibility	64
Discussion	66
Evaluation of New Measures	66
Racial and Ethnic Healthcare System Disparities	67
Limitations	68
Validity	69
Conclusion	69
 CHAPTER 4: COMMUNITY CONTEXT AND PHYSICAL HEALTH DISPARITIES	 71
Introduction	71
Community Context and Health Disparities Model	72
Community Context	73
Individual Context	74
Older Adults	75
Research Questions	75
Method	76
Sample	76
Communities	76
Individuals	77
Measures	79
Community Measures	79

Physical Environment	79
Built Environment	80
Social Environment	81
Economic Environment	81
Healthcare Environment	81
Individual Measures	82
Demographics	82
Socioeconomic Status	83
Health Behaviors	83
Social Support	83
Stress	83
Dependent Variable	85
Statistical Analyses	85
Results	91
Characteristics of Communities and Individuals	91
Community Characteristics	91
Individual Characteristics	92
Research Question 1	94
Research Question 2	94
Research Question 3	95
Research Question 4	97
Research Question 5	100
Discussion	102
Adequacy of the Community Context and Health	
Disparities Model	103
Possible Causes of Health Disparities Among Older Racial	
and Ethnic Minorities	104
Recommendations	105
Public Policy	105
Practice	106
Limitations	107
Future Research	108
Conclusion	108
 CHAPTER 5: COMMUNITY CONTEXT AND MENTAL HEALTH	
DISPARITIES	109
Introduction	109
Community Context and Health Disparities Model	111
Research Questions	113
Method	114
Sample	114
Communities	114
Individuals	116
Measures	117
Community Measures	117

Physical Environment	118
Built Environment	119
Social Environment	119
Economic Environment	120
Healthcare Environment	120
Individual Measures	121
Demographics	121
Socioeconomic Status	121
Health Behaviors	121
Social Support	122
Stress	122
Dependent Variable	122
Statistical Analyses	124
Results	130
Characteristics of Communities and Individuals	130
Community Characteristics	130
Individual Characteristics	131
Research Question 1	133
Research Question 2	133
Research Question 3	136
Research Question 4	138
Discussion	139
Adequacy of the Community Context and Health Disparities Model	140
Community Context as an Explanation for Mental Health Disparities	141
Limitations	141
Implications for Policy and Practice	142
Conclusion	143
CHAPTER 6: CONCLUSION	144
REFERENCES	149
ABOUT THE AUTHOR	End Page

LIST OF TABLES

Table 1.	Racial and Ethnic Composition of the United States, Florida, and Central Florida, 2000	51
Table 2.	Physician Intensity and Network-based ER Hospital Distance in Central Florida	52
Table 3.	Comparison of physician availability as measured by physician-to-population ratio (density) and kernel-density estimated intensity for zip codes in Central Florida.	55
Table 4.	Comparison of physician intensity for census block groups between unit of mean aggregation (zip code vs. block group) in Central Florida	57
Table 5.	Comparison of distance estimates (in miles) from census block group centroids to nearest ER hospital in Central Florida.	59
Table 6.	Differential physician intensity between racial and ethnic populations in Hillsborough and Orange Counties in Central Florida.	62
Table 7.	Average miles to ER hospital between racial and ethnic populations in Hillsborough and Orange Counties in Central Florida.	64
Table 8.	Correlations between community (level 2) predictors.	82
Table 9.	Correlations between individual (level 1) predictors and self-rated health.	84
Table 10.	Community (Level 2) Characteristics.	92
Table 11.	Individual (Level 1) Characteristics.	93
Table 12.	Self-rated health between communities (Model 1).	94
Table 13.	Community characteristics and self-rated health (Model 2).	98

Table 14.	Individual characteristics and self-rated health (Model 3).	99
Table 15.	Community characteristics net of individual characteristics on self-rated health and cross-level interactions (Models 4 and 5).	101
Table 16.	Correlations between community (level 2) predictors.	120
Table 17.	Correlations between individual (level 1) predictors and CES-D score.	123
Table 18.	Community (Level 2) Characteristics.	131
Table 19.	Individual (Level 1) Characteristics.	132
Table 20.	CES-D score between communities (Model 1).	133
Table 21.	Community characteristics and CES-D score (Model 2).	135
Table 22.	Individual characteristics and CES-D score (Model 3).	137
Table 23.	Community characteristics net of individual characteristics on CES-D score (Model 4).	139

LIST OF FIGURES

Figure 1.	The Community Context and Health Disparities Model	16
Figure 2.	Physician intensity per 1000 population by census block group for Central Florida	53
Figure 3.	Road network distance to closest emergency room hospital by census block group for Central Florida	55
Figure 4.	Difference in rank between physician density (negative) and physician intensity (positive) ratios.	56
Figure 5.	Variation of physician intensity by census block group within four illustrative urban zip codes of Pinellas County, Florida.	59
Figure 6.	Difference between Euclidean and road network distance to the closest emergency room hospital by census block group for Central Florida.	60
Figure 7.	Variation in physician intensity among block groups with high concentrations of four racial/ethnic populations in Hillsborough and Orange Counties, Florida.	63
Figure 8.	Variation in road network distance to nearest emergency room hospital among block groups with high concentrations of four racial/ethnic populations in Hillsborough and Orange Counties, Florida.	65
Figure 9.	Relationship between community poverty rate and self-rated health: Hispanics vs. Non-Hispanics.	102

Community Context and Health Disparities Among Older Adults

Helen M. Zayac

ABSTRACT

African Americans, Hispanics, and other minorities in the U.S. continue to face conditions of residential and educational segregation, lower socioeconomic status, and higher rates of mortality than whites. Better theory-based research that uses community and individual level factors to explain how health disparities are created and perpetuated is needed. The *Community Context and Health Disparities Model*, which extends the work of Schulz and Northridge (2004) with elements described by Williams and Collins (2001), is described. This framework identifies the pathways by which characteristics of the physical, built, social, economic, and healthcare environments impact health and are mediated by individual traits. Two measures of the healthcare environment, physician density and emergency room hospital accessibility, are created using Geographic Information Systems (GIS), compared to traditional measures of these concepts, and contrasted across racial and ethnic populations. The *Community Context and Health Disparities Model* is implemented to understand physical and mental health disparities among a sample of older adults in Miami-Dade County who were participants in the Survey of Older Floridians using hierarchical linear modeling (HLM). Exogenous measures of each community domain, including the healthcare measures created, are used as community-level predictors of self-rated health and number of depressive symptoms. The results show that community poverty rate predicts self-rated health, but is no longer

significant after individual attributes are controlled. There is a significant interaction between Hispanic ethnicity and community poverty associated with self-rated health. Hispanics are negatively impacted by community poverty but other ethnic groups are not. Depressive symptoms are found to be primarily explained by individual characteristics. Future research, practice recommendations and policy implications of these findings are described.

CHAPTER 1: INTRODUCTION

Reducing racial and ethnic health disparities has been a research and policy priority since the 1985 Report of the Secretary's Task Force on Black and Minority Health (U.S. Department of Health and Human Services [US DHHS], 1985). Over the past 20 years, racial health inequalities have most often been attributed to differential socioeconomic conditions (Mutchler & Burr, 1991; Williams, 1999; Williams & Collins, 1995). Although statistically controlling for socioeconomic measures such as education and income reduces differences in health status, older African Americans and Hispanics remain significantly more likely than whites to report poor self-rated health (Hayward, Miles, Crimmins, & Yang, 2000; Hummer, Benjamins, & Rogers, 2004). Researchers from a variety of disciplines have documented the existence and persistence of health disparities and recognize that theory is needed to guide studies which expose the mechanisms that create and perpetuate these inequalities (Krieger, 1994; Krieger, 2001; Potvin, Gendron, Bilodeau, & Chabot, 2005; Snowden, 2005). This dissertation addresses these issues in four articles (chapters 2-5) which are introduced below.

Community Context and Health

Differential neighborhood contexts in residential communities offer a potential explanation for the persistent differences in health between whites, African Americans, and Hispanics (Browning, Cagney, & Wen, 2003; Cagney, Browning, & Wen, 2002; LeClere, Rogers, & Peters, 1997; Oakes, 2004; Robert & Lee, 2002). The geographic

distribution of older minorities is not uniform across the country (Rogerson, 1998). At all personal income levels African Americans are more likely than whites to live in poorer, more disadvantaged neighborhoods (Diez Roux et al., 2001; Jargowsky, 1996; Robert & Lee, 2002; Sampson & Wilson, 1995), making this a plausible explanation for the additional variation in health between racial groups after individual socioeconomic status has been taken into account. When both individual and community socioeconomic variables are controlled statistically, there are no longer significant differences in self-rated health or number of chronic conditions between African Americans and Whites, although there are inconsistent findings among Hispanics (Browning, et al., 2003; Robert & Lee, 2002).

The community context may have a particularly strong influence on the health of older adults because they have lived in the community for a longer time, have a greater need for services, and spend less time at work and hence more time in the residential community than younger adults (Robert & Lee, 2002; Robert & Li, 2001). On the other hand, differential mortality effects may actually reduce the ability to detect the influence of these conditions (Robert & Li, 2001; Waitzman & Smith, 1998). Individuals most impacted by neighborhood conditions may be more likely to die earlier resulting in an older population of survivors who are resilient to these effects.

The Need for Theory

The elements of community context and the mechanisms by which they influence health are not clear. Convenience and availability of socioeconomic indicators from the U.S. Census have made attributes such as unemployment, poverty, deprivation, and income inequality the most often utilized measures of context, although it is unlikely that

these factors directly impact health outcomes. Instead, these indicators are, at best, proxies for neighborhood conditions such as presence of environmental toxins and pollutants, availability of social services and recreational facilities, and social mobility, which have been shown to influence health (Jones & Duncan, 1995; MacIntyre, Ellaway, & Cummins, 2002; Robert, 1998; Robert & Li, 2002; Wallace & Wallace, 1990). Additional linkages, including neighborhood strain (Feldman & Steptoe, 2004; Steptoe & Feldman, 2001), collective efficacy and social capital (Cagney, et al., 2002; Franzini, Caughy, Spears, & Esquer, 2005), health behaviors (Robert, 1999; Ross, 2000), and neighborhood disorder (Ross & Mirowsky, 2001) have also been examined.

Rather than using socioeconomic measures as proxies for the vague concept of “community context,” the specific aspects of the neighborhood and pathways by which they impact racial and ethnic health inequalities need to be outlined in a theoretical model. This framework would guide research and shape practice and policy. In the past, atheoretical research has led to inconsistent findings and made it difficult to identify what role, if any, community plays in determining an individual’s health (Sloggett & Joshi, 1994). The conceptualization of context, variables used to measure it, and statistical analyses must be theoretically guided (MacIntyre, et al., 2002; Mitchell, Gleave, Bartley, Wiggins, & Joshi, 2000; O’Campo, 2003). Theoretically-based research will also identify causal factors and pathways so that public health policies and practices can be most effective in reducing disparities. This research will help to identify specific aspects of the community that can be modified, and may increase the effectiveness of individual-level public health interventions, such as anti-tobacco campaigns and exercise interventions (Oakes, 2004).

Use of Spatial Data to Define Community Context

“Community” as a social or physical construct needs to be better defined so that the boundaries and spatial scale most appropriate for capturing the factors which influence health can be delineated (Mitchell et al., 2000; O’Campo, 2003; Pickett & Pearl, 2001; Sampson, Morenoff, & Gannon-Rowley, 2002). Currently community effects are measured at a variety of spatial scales ranging from Census block groups, which are theoretically socially and economically homogeneous and include 600 to 3,000 people (U.S. Census, 2001), up to counties, states and nations. Although community data are available for both U.S. Census-delineated units and U.S. Postal Service Zip Codes, and the former are constructed to be socially and economically homogeneous, these arbitrary boundaries may not correspond to true community boundaries. The results may change if the data are aggregated to larger geographic units or if different boundaries are used (Waller & Gotway, 2004).

Objectives

The goal of this study was to address the gaps in previous research, specifically by 1) developing a theoretical framework to understand the impact of community context on health disparities; 2) creating two new measures of the healthcare environment, availability and accessibility, to measure the domain that may be important to health disparities; 3) testing the proposed pathways between community context and physical health disparities; and, 4) testing the proposed pathways between community context and depression.

These goals were met by a combination of methods over the following four chapters, with a common reference list included at the end. First, literature from a variety

of disciplines was integrated into a theoretical framework. Next, innovative spatial techniques using Geographic Information Systems (GIS) technology were used to create two measures of the healthcare environment, physician availability and hospital accessibility. For the third and fourth objectives, secondary data analysis of the Survey of Older Floridians (SOF) was used to test the theoretical framework using exogenous measures of the community, including the new healthcare measures created, to explain disparities in self-rated health and depression.

In Chapter 2, the *Community Context and Health Disparities Model*, we describe a theoretical framework for understanding and researching the role of community and individual level factors on health disparities. The model extends the work of Schulz and Northridge (2004) with elements related to segregation described by Williams and Collins (2001), and draws on research from fields such as environmental justice, public health, and psychology. Available community measures which may be used to explain racial and ethnic disparities in individual physical and mental health outcomes within a community context are also identified.

The focus of Chapter 3 is the construction, validation, an implementation of two measures of the local healthcare system, physician availability and emergency room hospital accessibility. Geographic Information Systems (GIS) are used to map the geographic locations of healthcare providers and facilities in Florida. Physician availability is calculated using kernel density estimation and compared to traditional provider-to-population ratios. Hospital accessibility is measured as road network distance to the nearest hospital with an emergency department, which is compared to Euclidean, or straight-line, distance. Both measures are derived for U.S. Census block groups. They

are validated by comparing the new methodology to previous methods that use large geographic areas. Racial and ethnic differences in availability and accessibility are also examined as a further test of validity.

In Chapters 4 and 5, the hypothesized relationships between community attributes and physical and mental health outcomes proposed by the *Community Context and Health Disparities Model* in Chapter 2 are validated with secondary data analysis of the Survey of Older Floridians (SOF) data. Community measures for each of the five proposed domains were calculated from exogenous data sources including the U.S. Environmental Protection Agency (EPA), telephone directories, the U.S. Census (2000), and other sources as described in Chapter 2. Individual predictor and outcome data were drawn from a subset of participants from the SOF, a telephone survey of 1,433 older adults in Florida that focused on physical and mental health conditions, health care, and barriers to services faced by ethnic minorities in the state. We use hierarchical linear modeling (HLM), a statistical methodology that includes predictors at both the community and individual levels, to account for the potential similarity of individuals within communities, and allows us to examine interactions between conditions at both levels, to test the pathways proposed by the model. In Chapter 4, we examine the effects of predictors at both levels on self-rated health (Ware & Sherbourne, 1992). In Chapter 5, our focus turns to mental health, specifically depressive symptomology as measured by the Centers for Epidemiological Studies Depression scale (CES-D; Radloff, 1977).

This work represents the convergence of research from a number of social and medical disciplines, and uses two relatively new methodological innovations, HLM and spatial analysis. In Chapter 6, we discuss the implications of these findings for future

research across these fields as well as for practice and policy. Taken together, this work provides a foundation for understanding health disparities among older adults by testing a more complete theoretical model and developing two new measures of the healthcare environment. It demonstrates the potential of Geographic Information Systems and spatial data to measure community context in studies employing hierarchical linear modeling. In this way, it is possible to more clearly understand how these pernicious disparities are affected by place and perhaps not race, an important distinction because we can make policy changes to affect place.

CHAPTER 2: THE COMMUNITY CONTEXT AND HEALTH DISPARITIES MODEL

Introduction

Forty years after Lyndon Johnson's Great Society programs were put in place, African Americans, Hispanics, and other ethnic minorities in the United States still face conditions of residential and educational segregation, lower socioeconomic status, worse health, and higher rates of mortality than whites (Eberhardt, Ingram, & Makuc, 2001; Otten, Teutsch, Williamson, & Marks, 1990; Sorlie, Rogot, Anderson, Johnson, & Backlund, 1992). Hispanics and African Americans have increased rates of health conditions such as diabetes and HIV/AIDS (Keppel, Pearcy & Wagener, 2002) and live fewer years disability-free (Hayward & Heron, 1999). Infant mortality rates are twice as high among African Americans than whites (Keppel, et al., 2002) and higher levels of disease and mortality are seen throughout most of the life course (Fiscella & Williams, 2004; Hummer, Benjamins, & Rogers, 2004). Minorities are more likely to suffer from mental health disorders such as depression (Roberts, Roberts, & Chen, 1997), but are less likely to seek treatment and more often disabled by these disorders than whites (US DHHS, 1999).

The federal government has funded research and policy analyses to reduce these disparities since the *1985 Report of the Secretary's Task Force on Black and Minority Health* (US DHHS, 1985). A report to the Surgeon General highlighted the vast disparities in mental health among minorities (US DHHS, 1999). The Department of Health and Human Services' Healthy People 2010 campaign began in 2000, with the aim of eliminating racial health disparities in ten years. In the same year, the National Center for Minority Health and Health Disparities was added to the National Institutes of Health

(Oliver & Muntaner, 2005). These developments highlight the increasing priority placed on the elimination of physical and mental health disparities.

In order for these campaigns to be effective, better theory-based research is needed to expose how these disparities are created and perpetuated (Krieger, 1994; LaVeist, 2000). During the past 20 years, only a handful of factors have been used to varying degrees of success to explain these differences including socioeconomic status, racial-genetic differences, health behaviors, and psychosocial stress, but none have been able to adequately explain health differences between racial and ethnic minorities and whites (Dressler, Oths, & Gravlee, 2005). More recently, theories of residential segregation and community context have been offered as possible explanations for these inequalities (Krieger, 2001; Krieger, Chen, Waterman, Rehkopf, & Subramanian, 2003; LaVeist, 2005; Williams & Collins, 2001).

Community Context, Health, and Health Disparities

A community is a “social group of any size whose members reside in a specific locality, share government, and often have a common cultural and historical heritage” (Hart, 1998). Community context includes a number of factors that have been related to health disparities between minority groups and whites. For example, community environmental and social conditions are associated with health outcomes (Halpern, 1995; Jones & Duncan, 1995). The appropriate use of community context to explain health disparities is confounded by the fact that most communities are still not fully integrated. According to data from the 2000 U.S. Census, although racial residential segregation has declined from previous decades, it still exists to a great extent in many locations (Glaeser & Vigdor, 2001). We summarize the state of the art of community context research next.

Residential Segregation

Conditions of residential segregation, or separation of racial groups (Williams & Collins, 2001), have been associated with concentrated poverty and poorer health outcomes for both African Americans and whites living in predominantly African American, segregated communities (Massey & Fischer, 2000; Subramanian, Acevedo-Garcia, & Osypuk, 2005). At all individual income levels, African Americans are more likely than whites to live in poorer, more disadvantaged neighborhoods (Jargowsky, 1996). At all education levels, African Americans are highly segregated from whites (Darden & Kamel, 2000).

Environmental and Social Conditions

Environmental and social conditions are associated with physical and mental health outcomes (Curtis, 1990; Gardner, 1973). Environmental conditions such as air pollution, water quality, and climate are associated with mortality (Chinn, du, Florey, Baldwin, & Gorgol, 1981; Pocock et al., 1980; West & Lowe, 1976). Community socioeconomic conditions such as poverty rates, unemployment rates, and median family income are also related to heart disease, chronic conditions, self-rated health, and mortality (LeClere, Rogers, & Peters, 1998; Robert & Lee, 2002). Lack of access to services such as full-service grocery stores and healthcare facilities are associated with poorer diet and fewer opportunities for healthy behaviors (Ellaway & MacIntyre, 1996; Morland, Wing, & Diez Roux, 2002). Rates of mental health disorders also vary geographically and are associated with socioeconomic characteristics of the residential community (Brown et al., 1977; Ostler et al., 2001). It is clear that exposure of members

of racial or ethnic groups to poorer social and environmental conditions, and less access to services due to conditions of residential segregation, make community context a relevant explanation for the development and persistence of health disparities.

Limitations of Previous Research

Too often investigations of community context and health disparities have been driven by availability of data, rather than strong theoretical arguments. Socioeconomic indicators such as unemployment and poverty rates, deprivation, and income inequality, which are readily available from the U.S. Census, are the most often utilized measures of community context. It is unlikely, however, that these aggregated measures of the economic and social conditions of an individual's neighbors directly impacts that individual's health outcomes. Instead these indicators may be proxies for neighborhood conditions such as presence of environmental toxins and pollutants, availability of social services and recreational facilities, and social mobility, which have been shown to influence health directly (Jones & Duncan, 1995; MacIntyre, Ellaway, & Cummins, 2002).

Community context research often fails to take into account multiple co-existing community conditions identified by other disciplines. As a result, all the factors that influence health rarely are well integrated into a theoretical model. Such a model also needs to be used to test the direct and indirect impact of community conditions and the specific pathways through which socioeconomic and physical and mental health disparities exist (Krieger, 1994, 2001). It would examine the individual in the context of his community, identify domains of influential contextual conditions, and highlight the mechanisms through which they influence health. In addition, a theory of community

context would be parsimonious, measurable, supported by research, and pragmatic. And it would be useful for both prediction and intervention (Achenbaum & Bengston, 1994).

Social and Environment Health Promotion Model

One theoretical model responds to many of these concerns. The *Social Determinants of Health and Environment Health Promotion Model* was developed by urban planners and sociologists (Northridge, Sclar, & Biswas, 2003; Schulz & Northridge, 2004; Schulz, Williams, Israel, & Lempert, 2002). They posit that fundamental societal conditions impact characteristics of the built and social environments, which lead to individual stressors, health behaviors, and social relations that ultimately explain population health. Macro level factors, including the natural environment, the economic, legal, political, and historical societal conditions, and inequalities that result from these factors, determine where minorities live. This segregation, along with social and historical conditions, explain health disparities because they shape the built environment and social context of minority neighborhoods, which impact proximate level factors such as stress, health behaviors, and social integration and support. These, in turn, lead to physical and mental health disparities (Schulz & Northridge, 2004). Although this model is more complete than previous explanations for health disparities and it integrates findings from multiple disciplines, it has not been tested with population-based data as yet (Schulz, personal communication August 8, 2006).

This model also needs further development in regard to community context and segregation. For example, Williams and Collins (2001) identified three additional relationships between the community and health outcomes that are directly related to the

impact of residential segregation: education and employment, number and quality of medical facilities, and health promotion opportunities. Limited community educational and employment opportunities are associated with lower individual socioeconomic status which, in turn, leads to poorer health outcomes. Communities with medical facilities which are more likely to close or provide poorer care, have a direct effect on health outcomes (Mayberry, Mili, & Ofili, 2000). Health-promoting behaviors such as exercise, diet, and smoking are also influenced by the lack of community recreation facilities, poor quality grocery stores, and a higher prevalence of tobacco and alcohol advertisements (Williams & Collins, 2001).

The Social Determinants of Health and Environment Health Promotion Model meets the logical test for a theoretical model. It is relevant to the social issues we are addressing. In addition, it is clear, simple, consistent, and informative and many of the social determinants are supported by research. It is difficult to find reliable measures for all pieces of the model, however, so it may not be pragmatic when the goal is to make policy or practical changes in the community to decrease disparities between race and ethnic groups.

Recent Methodological Developments

Recent advances in software now make it possible to address these questions in ways that would not have been feasible in the past. Geographic Information Systems (GIS) make it possible to reference information within geographic units, such as census tracts, and there has been increasing availability of timely data on relevant community-level factors which may be studied with these systems. For example, it is now possible to map populations, individuals, and community conditions such as poverty, crime rates,

traffic incidents, or air pollutant emissions and examine trends and relationships spatially. These developments make it feasible to test existing theoretical frameworks in using comparable community data, which was not possible in the past.

Community Context and Health Disparities: A New Model

We developed a new model, *Community Context and Health Disparities* (Figure 1), that integrates the theoretical model of Schulz and Northridge (2004) with the additional elements described by Williams and Collins (2001) to explain racial and ethnic disparities in individual socioeconomic status and health outcomes within a community context. We apply the theory by suggesting better measures that are now available. The balance of this article describes the new model and how it can be validated using community and individual data.

As noted above, the previous theory (Schulz & Northridge, 2004) suggested that fundamental (macro level) factors such as the environment, sociopolitical, historical conditions and the resulting inequalities are interrelated with community factors such as the built, business, and political environments. These, in turn, may cause or be affected by environmental stressors, health behaviors, and the degree of social integration and support. All of these factors theoretically explain physical and mental health outcomes. The previous model has primarily been used to argue for the complexity of the reasons that are associated with poorer health and well-being of African Americans, but the hypotheses inherent to the model have not been tested with population data. In contrast, the *Community Context and Health Disparities Model* (Figure 1) nests individual factors within the community context and simplifies the pathways between them and health outcomes. The earlier model was proposed mainly to test health disparities between

African Americans and whites (the most pernicious disparities in the United States). The current model examines health disparities between all race and ethnic groups and within socioeconomic groups in a population-based research study.

Societal conditions such as segregation, political, historical and economic conditions, cultural and social beliefs, institutional racism, and ideologies are likely to determine and shape the characteristics of residential neighborhoods in which minorities live (Schulz et al., 2002; Collins & Williams, 1999), but it is difficult, if not impossible, to measure these aspects of society in a contemporary population-based research study, for example. Therefore, most of these macro level factors from the earlier model are not included here, although we fully recognize their importance in explaining current inequities.

The broadest unit of analysis in the new model is community context, which includes the physical, built, social, economic, and healthcare environments. Some of these factors have been shown to affect health outcomes, such as exposure to toxins, poor housing conditions, and high rates of poverty (e.g., Krieger & Higgins, 2002; Morello-Frosch & Jesdale, 2006; Waitzman & Smith, 1998). Other factors have been proposed by Schulz and Northridge (2004) and others, and are measurable, so they are included here even though the research on their relationship to health disparities is not yet established (e.g., education quality, civic participation). Nested within, and shaped by the community context, are individual factors, including demographics, health behaviors, social interactions and support, and psychological stressors. These individual level

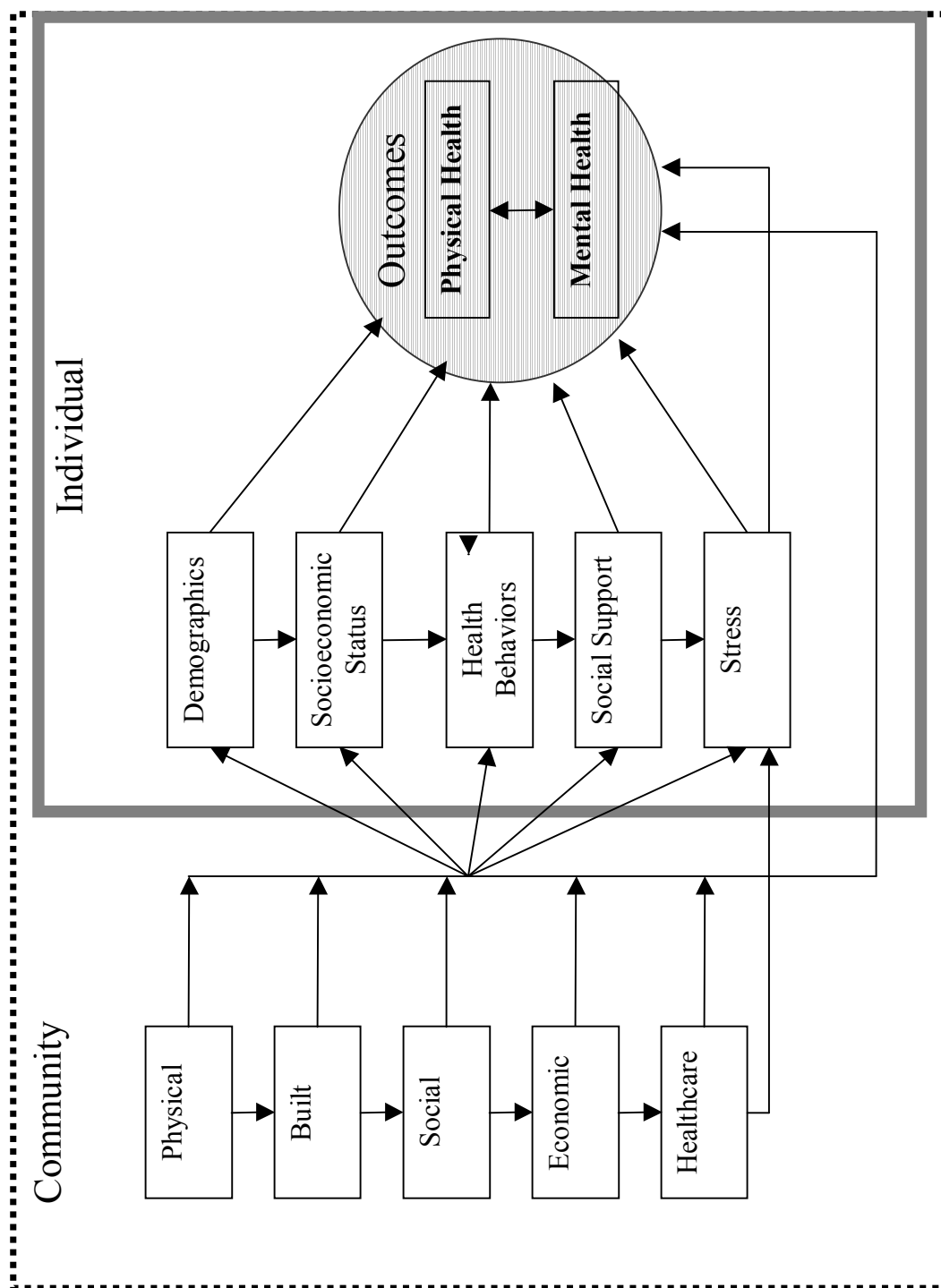


Figure 1. The Community Context and Health Disparities Model.

factors are proposed pathways between community context and physical and mental health outcomes.

Although theoretically the relationships between the individual and community factors are bi-directional, for the present purposes we will discuss the relationships in terms of a potential causal pathway. That pathway portrays the community context as a powerful, but often overlooked, predictor of racial or ethnic physical and mental health disparities. This is particularly important because the community context is mutable whereas race and ethnicity are not. Policymakers, engineers, educators, and healthcare professionals have the power to build or renew communities so all citizens live, work, and recreate in places that promote health and well-being. In addition, this model makes it possible to examine the interactions between individual and community characteristics. The individual is a key player but the burden for eliminating health disparities falls on the wider societal order as suggested by Schulz and colleagues (2002), rather than on the victim.

Measures of Community Context

Five community context factors are proposed to help explain physical and mental health disparities: physical, built, social, economic, and healthcare (Figure 1). These domains are listed in a loose hierarchy, with the expectation that the physical environment affects building design which affects the social community and economic conditions which affect access to the healthcare system. We suggest that shared variance between these conditions can be examined in terms of how a new factor reduces the effect of a previous factor when added to a statistical model. Community context factors are expected to have a direct effect on physical and mental health outcomes and to

indirectly impact these outcomes through their effect on individual behaviors and characteristics. These domains are described below.

Physical Environment

At the most basic level, health outcomes are influenced by the physical attributes of the environment, such as climate, toxins, and noise (Balfour & Kaplan, 2002; Evans & Kantrowitz, 2002). As in the *Social Determinants of Health and Environmental Health Promotion Model*, we also include aspects of topography and climate conditions such as extreme cold or heat, which are associated with increased morbidity and mortality (Klinenberg, 2002; McGeehin & Mirabelli, 2001). Expanding upon Schulz and Northridge (2004), we add pollutants such as toxic waste sites and water quality to this factor.

African Americans and Hispanics are more likely to live in areas where they are exposed to environmental pollutants and to live closer to toxic waste sites (Anderton, Anderson, Oakes, & Fraser, 1994; Moses et al., 1993; Pastor, Sadd, & Hipp, 2001). Segregated areas are also more likely to have high levels of air toxins associated with higher cancer risks and poor mental health (Evans, 2003; Morello-Frosch & Jesdale, 2006). Natural disasters caused by climate lead to increased rates of depression (Ginexi, Weihs, Simmons, & Hoyt, 2000). Lack of exposure to daylight, a feature of the physical environment, is thought to be the primary cause of seasonal affective disorder, which is characterized by depression and fatigue (Rosenthal et al., 1984).

Built Environment

Built structures are nested within the conditions of the physical environment. Unlike Schulz and Northridge (2004), our conceptualization of the built environment is

limited to the attributes of the buildings, transportation systems and roads, services and stores in the community, but not healthcare services or schools which are covered elsewhere.

The presence of boarded up housing is associated with higher mortality rates (Cohen et al., 2003). Poor housing conditions, such as exposure to lead, overcrowding, poor insulation, dampness, rodent infestation, and inadequate heating have been linked to asthma, heart diseases, injuries, neurological disorders, and mental health disorders (Burridge & Ormandy, 1993; Evans, 2003; Halpern, 1995; Krieger & Higgins, 2002; Shaw, 2004). Urban sprawl is associated with health outcomes such as hypertension (Ewing, Schmid, Killingsworth, Zlot, & Raudenbush, 2003). Neighborhood conditions such as land use and building deterioration may affect both depression and life satisfaction (Chapman & Beaudet, 1983; Galea, Ahern, Rudenstine, Wallace, & Vlahov, 2005). Features of local transportation systems, such as traffic and vehicular accidents, are associated with poorer self-rated health (Gee & Takeuchi, 2004). The presence and characteristics of stores, libraries and museums, recreation facilities, parks, and community centers can impact health (MacIntyre, Maciver, & Soomans, 1993; Morland et al., 2002). Among African Americans, the types of restaurants and grocery stores in residential areas have been linked to poor diet (Morland, et al., 2002).

Social Environment

Social interactions and conditions exist in the context of the physical and built environments. As with Schulz and Northridge (2004), we note the important impact of neighborhood social context on health outcomes. Three major domains of the social environment are included in the new model: organized social institutions, informal social

conditions, and the sociodemographic characteristics of other community residents. Organized civic, political, social, and religious institutions can empower a community and buffer individuals from more harmful aspects of the environment (LaVeist, 1993; Rich, Edelstein, Hallman, & Wandersman, 1995). Both supportive and harmful aspects of the informal social environment have been linked to physical health and well-being. Supportive environments are characterized by high levels of collective efficacy, or willingness of residents to intervene on behalf of other residents, and high levels of social capital, which are characterized by civic engagement, solidarity, and trust in the community. These concepts have been shown to mediate the effects of community characteristics on individual health outcomes (Cagney, Browning, & Wen, 2002; Franzini, Caughy, Spears, & Esquer, 2005; Sampson, Raudenbush, & Earls, 1997). Negative conditions such as crime and disorder have also been shown to affect health (Ross & Mirowsky, 2001; Sampson et al., 1997). And social demographics of the community such as racial and ethnic composition, female-headed households, and housing turnover rates are associated with depression and health (Franzini et al., 2005; Wen, Browning, & Cagney, 2003).

Economic Environment

Community economic conditions such as aggregate poverty, affluence, quality of educational systems, and employment opportunities are often included as social conditions, but are a separate domain in this model. Low community socioeconomic status, or “deprivation,” has been linked to stroke, cardiovascular and all-cause mortality, and self-rated health, controlling for individual attributes (Davey Smith, Hart, Watt, Hole, & Hawthorne, 1998; Jones & Duncan, 1995; Maheswaran, Elliott, & Strachan, 1997).

Living in a community with high poverty doubles the mortality rate among adults aged 25 to 54, even after individual socioeconomic conditions and health behaviors are statistically controlled (Waitzman & Smith, 1998). There are higher rates of depression and psychiatric disorders in poorer urban communities (Brown et al., 1977; Ostler et al., 2001) and higher levels of well-being in neighborhoods where more people have adequate personal resources (Schwirian & Schwirian, 1993). In some cases, these differences can be fully accounted for by the lower individual socioeconomic status of residents in these areas (Reijneveld & Schene, 1998). In other studies, however, community characteristics had significant effects on mental health after controlling for individual characteristics (Fone & Dunstan, 2006; Skapinakis, Lewis, Araya, Jones, & Williams, 2005).

Conversely, a social environment that includes affluent residents may help increase social organization and mobility leading to better self-rated health (Browning, Cagney, & Wen, 2003). People in more affluent communities are in significantly better health, even when compared to people with the same income in less affluent Census tracts. Poor individuals living in upper-middle income neighborhoods were 43 percent more likely to report better self-rated health than people with the same income living in poorer neighborhoods (Hou & Myles, 2005). Moving from a low-income to a middle-income community has positive effects on the mental health of both children and adults (Dalgard & Tambs, 1997).

In addition to the economic conditions of the people living in the community, the educational and employment opportunities are important facets of the economic environment. Education and employment are included under the macro level factor of

inequalities and social context of “educational quality” by Schulz and Northridge (2004). Here, drawing on Williams and Collins (2001), these aspects are considered components of the community economic context. Community racial segregation has been linked to disparities in education and income (Cutler, Glaeser & Vigdor, 1997), and these aspects of community socioeconomic status are associated with health (Adler, Boyce, Chesney, Folkman, & Syme, 1993). The concentration of minorities in communities with poor quality education systems and limited job opportunities represents a mechanism by which socioeconomic disparities are developed and reinforced (Orfield & Eaton, 1996; Williams & Collins, 2001).

Educational experiences are also shaped by residential community. Although school segregation was officially abolished by the Brown versus Board of Education decision (1954), it still exists. The use of private, magnet, and charter schools by white children leads to sustained conditions of segregation in many school districts (Saporito & Sohoni, 2006). A higher percentage of African American and Hispanic students attended primarily minority schools in 2000 than in 1970 (Frankenberg, Lee, & Orfield, 2003). The schools that minorities attend have more students from poor socioeconomic backgrounds (Orfield & Lee, 2005), which is associated with lower levels of student achievement, regardless of individual socioeconomic characteristics (Rumberger & Palardy, 2005).

Employment opportunities are an important part of the community economic context as well. Individuals search for jobs near where they live and African Americans and Hispanics who live in segregated areas generally live and search for jobs in areas of low job growth compared to whites (Stoll & Raphael, 2000). This *Spatial Mismatch*

Hypothesis has been used to explain lower wages and higher rates of unemployment among minorities, particularly following the movement of industrial jobs out of inner cities to more affluent suburbs in the 1980s (Kain, 1968; Zax & Kain, 1996). This, in turn, affects health. People living in areas with lower unemployment rates have a lower risk for depression (Zimmerman & Bell, 2006). Job market characteristics vary geographically (Kain, 1968). Jobs with low autonomy are more likely to be found in minority communities and these types of jobs are associated with depressive symptoms (Rugulies, Bultmann, Aust, & Burr, 2006).

Healthcare Environment

The local healthcare system is another facet of the community that influences health and is shaped by the aforementioned community characteristics. Although medical facilities are included by Schulz and Northridge (2004) in the built environment, a large number of studies document the independent relationship between characteristics of the healthcare system and health disparities, making it important to highlight the influence of the system itself (Smedley, Stith, & Nelson, 2003). Within this domain, healthcare system characteristics include availability, accessibility, and quality. Urban communities with high percentages of African Americans are more likely to have hospitals close down, thereby changing the number and type of healthcare options available to them (Whiteis, 1992). In rural areas, there are fewer mental health services, and thus more unmet need (Hauenstein et al., 2006). Regardless of individual and healthcare system characteristics, adults in poorer neighborhoods are less likely to have a usual source of care and more likely to report an unmet healthcare need in the past year (Kirby & Kaneda, 2005), reflecting accessibility and structural barriers (Smedley, et al., 2003). A

greater proportion of African Americans and Latinos than whites receive healthcare in hospital outpatient departments, clinics, or emergency rooms, even when individual traits such as insurance status and income are controlled (Lillie-Blanton, Martinez, & Salganicoff, 2001). Poorer quality healthcare in minority communities has been offered as an explanation for racial and ethnic health disparities. Rates of standard and effective treatments, which may be considered measures of healthcare quality, including the use of beta-blockers following a heart attack, preventive mammograms and colonoscopies, and pneumonia and flu vaccinations, vary geographically. In regions with the highest concentrations of African Americans, older diabetics of all ethnicities are less likely to receive annual eye exams than in other areas (Baicker, Chandra, & Skinner, 2005). Primary care physicians are also the first source of help for depression and anxiety problems (Gorn, Icaza, & Cantu, 2003) so the availability, accessibility, and quality of these physicians will impact mental health disorder diagnosis and treatment, as well.

Measures of Individual Context

In the *Community Context and Health Disparities Model*, individual demographics, socioeconomic status, health behaviors, social support, and stress, which are often employed as control measures in studies of racial differences in health, here are shaped by the community context described above and have both direct and indirect effects on physical and mental health. We describe the variables used to measure these conditions and then discuss how they may mediate the influence of community context on health.

Demographics

Age, race, ethnicity, and gender are considered in this model. Increased age is associated with poorer physical health (House et al., 1990) and, to a lesser degree, mental health (Jorm, 2000). As described earlier, race is predictive of poorer health outcomes (c.f., Sorlie et al., 1992). Here, we are interested in whether race has additional effects on health outcomes when community context is controlled. Ethnicity, particularly if the individual is of Hispanic origin, is measured separately. Research has shown an independent negative effect on physical and mental health associated with being Hispanic of any race (Hummer et al., 2004). Gender is also important. Women have longer life expectancies, but with higher incidences of chronic conditions such as arthritis and osteoporosis (Verbrugge, 1985). They are also more likely to suffer from depression (Roberts et al., 1997).

Socioeconomic Status

Individual economic conditions are hypothesized to mediate the effects of community social and economic contexts (Pickett & Pearl, 2001; Williams & Collins, 2001). Socioeconomic status includes income, level of education, assets, employment, and occupational class (Krieger, Williams, & Moss, 1997). Poor health outcomes and higher mortality rates are highly associated with lower individual socioeconomic status (Adler, Boyce, Chesney, Folkman, & Syme, 1993; Syme & Berkman, 1976). There is a negative correlation between income and morbidity and mortality (Adler et al., 1993; Ecob & Davey Smith, 1999), a relationship that persists throughout the life course (Smith & Kington, 1997; Starfield, Robertson, & Riley, 2002). Lower socioeconomic status also

increases the likelihood of having a psychiatric or common mental health disorder (Dohrenwend, et al., 1992; Roberts, et al., 1997).

Health Related Behaviors

This domain includes actions that individuals take to improve their health status which include: a regular source of healthcare, seeking preventive care, exercising, not smoking, and not drinking to excess. Differences in these behaviors are hypothesized to explain differences in health outcomes and also, in the aggregate, differences between communities. Others have found that these individual behaviors mediate the community context, that is, healthy behaviors are a stronger predictor of health outcomes than the physical, built, or economic environments (Ellaway & MacIntyre, 1996; Robert, 1999; Ross, 2000). We suggest the opposite; measures of community context will remain good predictors, when individual health behaviors are included. For example, better health outcomes are associated with having a usual source of healthcare, getting regular check-ups and seeking preventive care such as screenings (Corbie-Smith, Flagg, Doyle, & O'Brien, 2002; Newacheck, Hung, Park, Brindis, & Irwin, 2003; Politzer et al., 2001). We need to understand how the healthcare system has an impact on these behaviors. Exercise and increased physical activity are associated with positive physical and mental health outcomes (Cress et al., 1999; Stathopoulos, Powers, Berry, Smits, & Otto, 2006). Heavy drinking increased the likelihood of depression (Manninen, Poikolainen, Vartiainen, & Laatikainen, 2006) and the deleterious effects of smoking and heavy drinking on physical health have been documented (Shopland, Eyre, & Peachacek, 1991; Thorogood, Mann, & McPherson, 1993).

Social Support

This domain includes the size and characteristics of the individual's social networks, and whether they feel the social environment is supportive. Longer tenure in a neighborhood is associated with greater levels of support (Schulz et al., 2006). The social support that an individual receives from a network of family and friends is positively associated with physical and mental health outcomes including lower depression and mortality (Berkman & Glass, 2000; Kawachi & Berkman, 2000; Leskela et al., 2006). The extent to which an individual feels supported by other members of the community, or a sense of strong neighborhood social capital, may also indicate social supportive conditions (Davidson & Cotter, 1991).

Stressors

This domain includes individual stressful life events and the perception of stress due to neighborhood conditions. Experiencing a number of stressful life events, which include things like death of a spouse, change in financial status, or loss of a job lead to worse physical and mental health outcomes (Holmes & Masuda, 1974; Leskela et al., 2006). Individual perceptions of stress from community conditions have often been operationalized as exposure to neighborhood conditions such as noise and pollution, fear of crime, and neighborhood problems or disorder (Franzini, et al., 2005; Gee & Payne-Sturges, 2004; Ross & Mirowsky, 2001). In the new model, however, these attributes are measures of the physical, built, and social environments within the community context. Within the individual context, we focus on the individual's assessment of the community as stressful and examine whether or not this mediates the effects of community context on health outcomes. That is, an objective measure of crime (social environment) may be

mediated by an individual's self assessment of feeling safe and secure and lead to better mental health outcomes.

Measures of Individual Outcomes

As described above, individual physical health and mental health outcomes are associated with both community context and individual characteristics. Aspects of community context including rates of unemployment, overcrowding, public assistance, and median household income have been associated with individual measures of physical health including blood pressure (Hart, Ecob, & Davey Smith, 1997), myocardial infarction (Diez Roux et al., 2001), and cardiovascular mortality (Davey Smith, et al., 1998). Because this new model addresses the effects of community context on individual overall health, we examine self-reported measures of physical functioning, number of chronic conditions, or self-rated health (Browning, et al., 2003; Robert & Lee, 2002) rather than incidence of specific diseases or health indicators. The latter line of research is important especially when examining very specific community context (e.g. neighborhood pollution and rates of chronic obstructive pulmonary disease). Similarly, mental health is assessed with general measures of functioning (Reijneveld & Schene, 1998) such as depression, happiness, and life satisfaction.

Physical and mental health outcomes are closely related. Cognitive impairment and depressive symptoms are associated with physical functioning (Fultz, Ofstedal, Herzog, & Wallace, 2003). People with poor self-rated health are more likely to report that they are unhappy (Subramanian, Kim, & Kawachi, 2005). The increasing gap between levels of depression between people with high and low levels of education is primarily explained by differences in physical health (Meich & Shanahan, 2000). In fact,

it may be that it is the community context of the educational and healthcare systems that are implicated.

Potential Interactions

The large number of variables measured at both community and individual levels make it possible to include many cross-level interactions to examine the moderating effects of individual characteristics on community conditions when explaining health outcomes (Hox, 1995). Individual behaviors may or may not overcome the risks associated with features of the community context. Based on previous research, we expect interactions between individual socioeconomic status, social support, and stress with community factors in predicting health outcomes.

Poorer or unemployed individuals may be more affected by community conditions than those who have more economic resources (Fone & Dunstan, 2006; Weich, Twigg, Holt, Lewis, & Jones, 2003). We expect high levels of social support, particularly from neighbors, to buffer against the harmful effects of community conditions (Cassel, 1976), although Latkin and Curry (2003) did not find such an interaction. Individual appraisals of stress from the community may lower immune system function and therefore increase susceptibility to pollutants and toxins in the neighborhoods, leading to the development of disease and functional loss that would not occur if a person does not feel stressed (Cohen, Tyrrell, & Smith, 1991; Gee & Payne-Sturges, 2004). Or the more straight forward explanation may be true. Pollution and toxins may lead to higher levels of chronic diseases and the individual's perception of living in a stressful community is simply an accurate one with the expected outcome—poor health.

Discussion

Proposed factors such as socioeconomic inequality (Williams & Collins, 1999), innate biological differences (Boyle, 1970), health behaviors, and psychosocial stress (Dressler et al., 2005) fail to fully account for racial and ethnic health inequities. Instead, aspects of the environment have been posited as potential explanations for these disparities (Williams & Collins, 2001). Although the *Social Determinants of Health and Environmental Health Promotion Model* (Northridge, et al., 2003; Schulz & Northridge, 2004; Schulz et al., 2002) outlines a number of community conditions and the mechanisms through which they impact health, the full model has not been empirically tested, and many of the proposed causes are too complex to be translated into measurable variables. It would also be enhanced with additional, measurable, pathways between community context and individual health.

The *Community Context and Health Disparities Model* presented here is both a refinement and an expansion of the previous theory using community context to explain racial and ethnic health disparities. We improve upon this model by adding economic and healthcare domains (Williams & Collins, 2001) and proposing a direct association between community conditions and health. In addition, the model is designed to be applied in empirical research that tests the relationships between community context and health. This research can be readily translated into changes in policy and practice.

We hypothesize about the causal relationships between these factors, and although associations have been shown between some of the community domains and health outcomes, longitudinal data are needed to establish causality. With Geographic Information Systems it is now possible to link individual data from large-scale

community-based studies to exogenous community characteristics. For example, distance to the nearest Superfund or toxic waste site is now easily calculated. The U.S. Census provides measures of a number of community social, economic, and even built environment characteristics from the American Housing Survey so that researchers need not rely on measures of community created by aggregating study participant data. Multilevel statistical modeling can test the relative contribution of community and individual characteristics and the interactions between these factors without committing an ecological fallacy by drawing conclusions about individuals from aggregated data and without violating the assumption of independent observations. Instead, the net effects of community variables can be measured by holding individual variables constant and allowing error to vary randomly across communities. With these advancements, it is possible to employ this theoretical model for research examining the role of community context on health disparities.

Testing this model requires working across disciplines and taking into account concepts and measures from public health, psychology, sociology, and related fields and putting them into a geographical framework. The work of urban planners, environmentalists, and educators may be identified as essential to the elimination of health disparities. Using a more geographic perspective to examine conditions in all of these areas will not only identify the role of the community in shaping health outcomes, but also highlight the unique relationship between the individual and place. We are recommending that research shift in focus from the individual to both the individual and the community.

A recent report from the Brookings Institute (Fellowes, 2006) highlighted how poor people living in poverty areas pay more for everything from groceries to insurance premiums, supporting the importance of the social and economic pathways suggested here. Testing the *Community Context and Health Disparities Model* demonstrates the relative contribution of both community and individual characteristics and will perhaps eradicate the “blame the victim” mentality by showing the circumstances under which community conditions cannot be easily overcome. Community conditions may be as strong, if not stronger, predictors of health than individual characteristics. Both models described here are based on the societal and historical conditions, such as racism and segregation that create and perpetuate these community disparities, with the aim of demonstrating the resultant harm caused by such community contexts. The identification of key community factors can lead to policy interventions targeting these conditions, making it possible to reduce health disparities.

For example, northern urban areas where housing rarely includes air conditioning are learning the importance of extreme weather and the built environment on mortality of older people. Recent policy research has suggested that cities plan to identify vulnerable individuals and supply them with needed air conditioners (Klinenberg, 2006). School boards in regions of the country with chronically poorly performing schools and where graduates have poor access to well-paying jobs can work with businesses and community leaders to mitigate these pernicious conditions. Developers, architects, and builders can be required by municipalities to integrate healthy building concepts into housing and work environments. There has been much focus on rebuilding New Orleans, which faced many negative community conditions prior to Hurricane Katrina in 2005. Lessons learned

from this experience should serve as a blueprint for redevelopment planning. New Orleans has the potential to be a model for creating a healthy city.

Conclusion

The study of community context on health has been limited by the lack of a tested theoretical framework on which to base research. Drawing on other models (Schulz & Northridge, 2004; Williams & Collins, 2001) and related literature, we outline the *Community Context and Health Disparities Model* and delineate the elements and mechanisms by which neighborhood influences health. Societal characteristics shape the physical, built, social, economic, and healthcare environments of the community which directly and indirectly influence physical and mental health. Individual characteristics, such as demographic, socioeconomic status, health behaviors, social support, and stress mediate or moderate community conditions when explaining health outcomes. The use of multilevel modeling and geographical information systems data and analysis makes it easier to use such a model to test these relationships and suggest interventions in policy and practice.

CHAPTER 3: MEASURING HEALTHCARE AVAILABILITY AND ACCESSIBILITY

Introduction

The inability of factors such as socioeconomic inequality (Williams & Collins, 1995), innate biological differences (Boyle, 1970), health behaviors (Winkleby & Cubbin, 2004), or psychosocial stress (Dressler, Oths, & Gravlee, 2005) to fully account for racial and ethnic health disparities has led researchers to explore other potential causes. In recent years, differential conditions in the residential neighborhoods of whites, African Americans, and Hispanics have been offered as potential explanations for these differences (Browning, Cagney, & Wen, 2003; Cagney, Browning, & Wen, 2002; LeClere, Rogers, & Peters, 1997; Robert & Lee, 2002). For example, neighborhood poverty rate, unemployment rate, and median family income have been linked to health outcomes such as heart disease, chronic conditions, self-rated health, and mortality (LeClere, et al., 1997; Robert & Lee, 2002). Environmental conditions such as air pollution, water quality, and climate are associated with mortality and have been associated with residential segregation (Chinn, du, Florey, Baldwin, & Gorgol, 1981; Pocock et al., 1980; West & Lowe, 1976). Features of the local transportation systems, such as high levels of traffic and vehicular accidents, have been associated with poorer self-rated health (Gee & Takeuchi, 2004). However, the local healthcare system is also an important facet of the community that may explain health disparities (Smedley, Stith, & Nelson, 2003).

Healthcare System

The healthcare system has been described according to measures of availability (number of providers by population in a geographic area), accessibility (distance from population to providers), affordability (cost of care), acceptability (meeting patients' needs and desires), and accommodation (hours of operation, ease of getting an appointment) (Penchansky & Thomas, 1981), as well as the quality of care provided (Baicker et al., 2005). Research has shown that geographic variability exists in most of these attributes (Baicker, Chandra, & Skinner, 2005; Hauenstein et al., 2006; Whiteis, 1992). For example, urban communities with high percentages of African Americans are more likely to have hospitals close down, thereby changing the number and type of available healthcare options (Whiteis, 1992). In rural areas there are fewer healthcare services, particularly mental health services, and thus more unmet need (Hauenstein et al., 2006). Regardless of individual and healthcare system characteristics, adults in poorer neighborhoods are less likely to have a usual source of care and more likely to report an unmet healthcare need in the past year (Kirby & Kaneda, 2005), reflecting barriers to healthcare (Smedley, et al., 2003). Poorer quality healthcare in minority communities has been offered as an explanation for racial and ethnic health disparities. Rates of standard and effective treatments used to measure of healthcare quality (Chandra & Skinner, 2003), including the use of beta-blockers following a heart attack, preventive mammograms and colonoscopies, and pneumonia and flu vaccinations, vary geographically. In regions with the highest concentrations of African Americans, older diabetics of all ethnicities are less likely to receive annual eye exams than in other areas (Baicker et al., 2005). This growing body of literature suggests that features of the

healthcare system may play an important role in the creation and persistence of health disparities.

Previous research on the adequacy of the healthcare system has analyzed the geographic variability of provider availability and healthcare facility accessibility. We adopt the same focus here, rather than on aspects of affordability, insurance coverage, waiting times, utilization (“actual accessibility”), and quality. We do address the latter elsewhere (Zayac & Reader, 2007). In the next section we describe previous approaches for calculating spatial measures of healthcare availability and accessibility. Throughout the paper, we use the definition of availability as *the number of providers potentially available to the population* and accessibility as *the ease of reaching these providers as measured by distance*. As such, availability is operationalized as the ratio of providers to the population while accessibility is operationalized as distance to the nearest provider.

Provider Availability

Physicians and hospitals are not uniformly distributed throughout the United States (Rosenthal, Zaslavsky, & Newhouse, 2005), an issue which has been the focus of much research and concern, particularly because the adequate availability of physicians is associated with lower rates of avoidable hospitalization (Laditka, 2004). A simple ratio of providers, services, or hospital beds to the number of people living in a geographical area (e.g., county or city) is one of the most commonly employed measures of healthcare availability (Guagliardo, Ronzio, Cheung, & Joseph, 2004). This ratio does not take into account distance, thereby overweighting the availability of providers who are distant and not realistic options for the entire population within the area. Conversely, the use of geographic boundaries may underweight the availability of physicians in adjoining areas

who are as close as across the street (Guagliardo et al., 2004). For example, people living along the border of a rural county that is adjacent to an urban area may have ample healthcare options, but this would not be reflected in the provider ratios based on county boundaries typically used in previous research.

In recent years, researchers have developed two methodologies utilizing Geographic Information Systems (GIS) data that overcome these limitations. The first is the two-step floating catchment area (FCA) method (Luo, 2004; Wang & Luo, 2005), which involves first mapping physicians to point locations using geocoding. A popular choice of geocoding resolution has been the zip code, reflecting the widespread use of provider lists from the American Medical Association (AMA) in which many addresses are listed as “P.O. Boxes” with only zip code address information (Wang & Luo, 2005). In effect, physicians within a zip code are summed and assigned to the geographic centroid of that zip code. Then, using a “population catchment” area defined by travel time (or distance) away from each zip code centroid, the populations of any census divisions (typically census tracts) within the catchment area, as determined by their centroids, are summed. The number of physicians summed at the zip code centroid is then divided by the population in the catchment area to produce a physician-to-population ratio. The ratio is then assigned to the zip-code centroid. In step two of the FCA method, focus is shifted to the census division centroids and “physician catchment” areas, based again on travel time or distance, are determined for each census division centroid. Finally, for each census division, the physician-to-population ratios for any zip-code centroids falling within the physician-catchment area are summed and this becomes the

measure of physician availability for the census division. The approach is an elegant method that attempts to adjust for accessibility based upon population density.

The second method is based on kernel density estimation (KDE). In this approach, the units of analysis are square grid cells at a relatively fine spatial resolution, such as 100 meters, one-quarter mile, or one kilometer. A geographic area is first converted to a grid of equally-sized grid cells. For each grid cell, a weighted count, or *intensity*, of physicians within a certain radius of the cell centroid (known as bandwidth) is then determined, where the weight assigned to a physician declines with distance according to whatever kernel density function is assumed. A typical kernel density function is the quartic kernel which approximates a Gaussian distribution. The grid of kernel density values produces an easily-visualized surface and the individual cells can be divided by cell-estimated populations to produce cell-based population “densities.” The cells, being of fine spatial resolution, also can be approximately aggregated to such entities as census divisions and the average intensity across cells is used to produce census-division population “densities” or ratios (Guagliardo et al., 2004).

As implemented to date, these two approaches have a number of relative advantages and disadvantages. The use of a coarser spatial data resolution by the FCA method (zip codes and census tracts) has enabled computational efficiency and to use more realistic road network travel times in determining service catchments, whereas the KDE method uses a less realistic fixed Euclidean distance bandwidth to demarcate catchments for each grid cell. Conversely, the use of a finer spatial resolution in typical KDE implementation (geocoded physicians to points and high resolution grid cells) enables the weighting of physician counts by distance, and the estimation of physician

variability at very fine spatial scales not limited to standard census divisions, and therefore not affected so much by the arbitrary size and shape of census divisions that can significantly impact the centroid locations used in the FCA method. The FCA method has so far not implemented distance-based weighting of physician counts and so implicitly assumes that the physician-to-population ratio is uniform over the spatial unit being summarized; results which can also be sensitive to edge-effects when marginally-located centroids are included or excluded.

It is important to point out that this comparison of methods is “as implemented” rather than theoretical. In theory, the FCA method could be implemented with finer spatial scale data and could indeed implement distance-based physician counting. Similarly, the KDE method could be implemented as an “adaptive kernel” where the bandwidth in effect varied with road network distance. Here, with access to an address-based database of physicians, the emphasis is on illustrating spatial variability at relatively fine spatial scales and so the method chosen for implementation is the KDE method. It should be noted that Yang, Goerge and Mullner (2006) concluded that the two-step floating catchment area method is a better measure than kernel density estimation. However, their conclusion is largely based on the homogeneous estimates created by the former – exactly what we are trying to avoid.

Healthcare Accessibility

At the individual level, accessibility is typically considered to be actual accessibility, as measured by such aspects as service utilization, having a usual source of care, being insured, or the ability to obtain care (Joseph & Phillips, 1984). Research has less often focused on the *potential* accessibility of the healthcare system, or the spatial

and systemic factors which make it easy or difficult to obtain services (Joseph & Phillips, 1984). The most common measures of spatial accessibility are the distance to the nearest provider or the average distance to a specific number of providers (Yang, et al., 2006). Increased distance has been linked to lower rates of healthcare utilization (Gregory et al., 2000; Hadley & Cunningham, 2004; Monnet et al., 2006), which may impact health outcomes and explain health disparities.

Fortney, Rost, and Warren (2000) highlighted the error associated with using methods that calculate distances between physicians and populations assigned to zip code centers via geocoding, and concluded that actual road distance is a more accurate measure of accessibility than Euclidean (“crow flies”) distance. Using methodological advances in GIS, Brabyn and Skelly (2002) calculated travel time over the road network from each census enumeration district to the nearest public hospital throughout New Zealand, thus demonstrating that calculating travel time estimates based on road-network distances are relatively easily computed, even at a large scale. We implement a similar approach to that taken by Brabyn and Skelly except that we do not calculate travel time, which takes into account speed as well as road distance.

Objectives

There were three major objectives of this study. The first was to create measures of physician availability and emergency-room hospital accessibility. The second was to investigate the performance of these measures by comparing them to analogous measures created using the previously implemented methodologies described above. The third objective was to illustrate the spatial variation in physician availability and ER hospital

accessibility among different racial and ethnic populations. We calculated these measures for the entire state of Florida, but only analyze them for Central Florida.

For the first objective, we created a measure of physician availability that improved upon the previous methodologies described earlier, particularly by: 1) assigning physicians to specific addresses rather than zip code centroids and 2) using areal interpolation to assign physicians variable point locations within a zip code when only zip code level address information was available. For accessibility, we calculated the distance from each block group to the nearest hospital with an emergency department (ER hospital) based on the road network rather than straight-line (Euclidean) distance. For both availability and accessibility, we calculated our measures at finer geographic scales than has been typical for large area studies.

For the second objective, we first evaluated our measure of physician availability relative to the traditional method of area-based physician-to-population ratios. We then illustrated the spatial variability in our measure of physician intensity at fine geographic scales, so as to demonstrate that studies using coarse geographic resolutions may not be fully addressing the issues of healthcare availability, especially when the spatial activity spaces of individuals, or populations, are more constrained than the geographic scales being assumed for their behavior. Finally we compared the differences between distance estimates based on the road-network calculation and those based on Euclidean distance measurement.

To meet our third objective, we compared our measures across racial and ethnic groups by deriving average availability and accessibility values for the populations of non-Hispanic whites, non-Hispanic Blacks, and Hispanics in Central Florida. To

investigate the variability in these measures across areas where these populations are concentrated, we first identified a series of census block groups with high proportions of each population, and then mapped the variability of our measures by each of these series.

Method

Sample

There were three types of provider and population data employed: 1) physician point locations; 2) hospitals with emergency departments point locations; and 3) U.S. Census population data on block groups and Zip Code Tabulation Areas (ZCTA). These will be described next.

Physicians

Office addresses of all licensed physicians (N=51,639) in the state were obtained from the Florida Department of Health Licensee Data Center at the Florida Department of Health (Florida Agency for Health Care Administration [FL AHCA], 2006). Of these licensed physicians, 1,382 were inactive and 11,529, although licensed to practice in Florida, did not have addresses within the state so they were ineligible. An additional 72 were excluded because their addresses were confidential (N=57) or no address was listed (N=15). Of the eligible physicians with office addresses (N=38,658), 91% were successfully geocoded using standard GIS methods and mapped to block groups (N=35,291).

Of those physicians who could not be geocoded this way, another 2,183 (6%), were mapped using areal interpolation to assign these physicians to block group centroids within each zip code. To implement this, it was first necessary to perform a GIS spatial overlay between the zip code polygon layer and the block group polygon layer. This

allowed us to calculate the proportion of the total zip code area accounted for by each block group. A count of physicians with only the zip code was then summed and this quantity was then divided among the block group centroids within each zip code based upon their area proportion of the zip code. For example, if there were five physicians with only a zip code for an address in a particular zip code, and that zip code was composed of two block groups representing 20 percent and 80 percent of the total zip code area, respectively, then values of one and four would be assigned to the respective centers of these block groups. In practice, however, and given the complex geographic interplay between these two geographic layers, the calculations were more detailed than our simple example and the physician counts assigned to block group centroids would typically be fractional, and, in some cases, less than one. Finally, for physicians with zip codes that did not correspond to those from the 2000 U.S. Census, most likely because these were new postal areas, an internet zip code locator was used to find the x,y-coordinates of the center of these new zip codes (N=302; 0.8%). The remaining 882 physicians (2.3%) could not be geocoded. They were distributed throughout the 67 counties in the state and did not appear to introduce bias into the final sample. These quite exhaustive geocoding methods to retain providers with P.O. Boxes or addresses that could not be located and would normally be excluded represent an improvement on previous research where only physicians with street addresses were mapped to zip code centers (Wang & Luo, 2005).

Hospitals with Emergency Departments

The addresses of all licensed hospitals (N=209) in the state were obtained from the Florida Department of Health Licensee Data Center at the Florida Department of

Health (FL AHCA, 2006). Of these, we limited our analyses to hospitals with emergency departments (N=205) because patients are most likely to seek treatment at the nearest facility during acute health emergencies. In addition, a greater proportion of African Americans and Hispanics than whites receive healthcare in hospital outpatient departments, clinics, or emergency rooms, even when individual traits such as insurance status and income are controlled (Lillie-Blanton, Martinez, & Salganicoff, 2001). All 205 hospitals with emergency departments (ER hospitals) were successfully geocoded to their street address location.

U.S. Census population Data

Population data at the block group level were obtained from the Census 2000 Summary Tape File 1 (U.S. Census, 2000). Although 2005 estimates would be temporally more accurate, these estimates were not available at a spatial resolution finer than “cities and town,” so we used data from the 2000 Census which allowed us to calculate the healthcare measures at the desired resolutions (block group and zip code).

The total population in Florida in 2000 was 15,982,378, of which 65.4 percent were non-Hispanic white and 14.2 percent were non-Hispanic Black. Hispanics comprised 16.8 percent of the population (Table 1). In 2000, there was a total of 9,112 block groups in Florida with an average of 882 residents each. These were the smallest geographical units for which race and age data were available. We also used data from Census Zip Code Tabulation Areas (ZCTA), or zip codes, of which there were 917 in Florida in 2000 with an average of 17,429 residents. There were approximately 10 block groups in each zip code, although this varied tremendously.

For purposes of investigating these new measures, a study area of the Central Florida corridor was defined. This study area extends from the St. Petersburg-Clearwater-Tampa metropolitan area in the west, through the Orlando metropolitan area in the center, and east to Cape Canaveral. This region includes seven counties. The population in 2000 was 4,314,618 (33% of statewide population). There were 10,075 (27% of state total) physicians who had offices in this region, and 48 (23% of state total) hospitals with emergency departments in this region. The study area includes a wide range of urban and rural block groups, making this region a particularly interesting one in which to investigate the spatial variability in the measures of healthcare availability and accessibility. Although the racial and ethnic composition of this area is different from Florida as a whole, it is similar to that of the entire U.S. (Table 1, p. 51).

Measures

Physician Availability (Intensity)

First, we created a measure of physician availability that improves on the kernel density estimation techniques used in earlier studies. KDE is based upon a distance-weighted count of points that are assigned to a grid cell center, and whereby the bandwidth radius of the estimation is an order of magnitude greater than the grid cell resolution. It is therefore more accurate to interpret the KDE as a measure of intensity rather than density.

To create a measure of physician intensity for block groups, based upon the geocoded physician locations described above, we first calculated a quartic approximation of a true Gaussian kernel density estimate using kernel density tools available within ArcGIS 9.2 Spatial Analyst (Environmental Systems Research Institute

[ESRI], 2006) for the entire state of Florida at a grid cell resolution of 200 meters with a kernel bandwidth of two kilometers. We used a kernel density estimate because it provides a weighted count of the number of physicians within a two kilometer radius for each grid cell. Physician weights were inversely related to distance away from the center of the cell and followed the quartic approximation to a Gaussian kernel function. In other words, this estimate accounted for the fact that providers farther away were less available, and did not limit providers to only those within a defined area. One particular advantage of using the kernel density tool available in ArcGIS 9.2 Spatial Analyst is that it allowed us to specify additional weights to the point locations themselves, thereby allowing the use of point locations where the physician count was greater than one or, as in the case of physicians distributed to block group centroids based on ZIP Code, less than one (see above).

Following Bailey and Gatrell (1995), the quartic approximation to the Gaussian kernel density estimate takes the form:

$$\hat{\lambda}_{\tau}(\mathbf{s}) = k \sum_{h_i \leq \tau} \frac{3}{\pi \tau^2} \left(1 - \frac{h_i^2}{\tau^2} \right)^2$$

where $\hat{\lambda}_{\tau}(\mathbf{s})$ is the estimate of the kernel density at the center of grid cell \mathbf{s} , τ is the kernel bandwidth (2000 meters), h_i is the Euclidean distance (in meters) from physician i to the center of grid cell \mathbf{s} , and k is a scaling factor applied to adjust for the actual units and bandwidth used. This equation produces estimates based on a standard one-unit bandwidth radius. The scaling factor used in this analysis was 4,000,000 meters or the square of the actual bandwidth radius (2000 meters; Bailey & Gatrell, 1995).

Using this formulation for the kernel density estimation, one physician located at exactly the grid cell center would contribute 0.9549 to the kernel density estimate, one physician located one kilometer away would contribute 0.5371, and a physician located 1.75 kilometers away would contribute 0.0524. Therefore a grid cell with this particular set of three physicians within its two kilometer bandwidth would have a total kernel density estimate of 1.5444 (.9549+.5371+.0524).

Having derived such grid-cell based estimates of physician intensity across Florida, the Zonal Statistics function within ArcGIS 9.2 was then used to produce a physician intensity estimate for each census block group by averaging across all the grid cells making up a particular block group. Note that in GIS raster analysis, where spatial units are represented as grid cells, this average then becomes the value of every grid cell making up a block group (or raster zone). Finally, this physician intensity measure was expressed as physician intensity per 1000 population for each census block group.

Physician Availability Comparison Variables

For the first comparison, we sought to investigate the differences between our block-group level measures of physician intensity (per 1000) and what the measures would have been if zip code level estimates were used instead. Zip code level estimates of physician intensity were calculated by direct analogy to the method outlined for block groups but now averaging across all grid cells included all the grid cells making up a particular zip code using Zonal Statistics (ArcGIS 9.2). This zip code level intensity measure was then expressed as physicians per 1000 population, akin to the block group measure, but grouped by zip code rather than block group. However, as indicated previously, block group boundaries (or raster zones in this implementation) do not

correspond with zip code boundaries (zones). Therefore, to derive a block group level estimate of what its zip code level intensity measure would be, we needed to perform a further Zonal Statistics function that averaged across the zip code intensity grid cells making up each block group zone.

For the second comparison, we sought to investigate the difference between the kernel density based estimation of physician intensity per 1000 population and the traditional measure based on a simple count of physicians within an area, then expressed as a physician-population ratio for that area, i.e. physician density. Since the traditional measure is usually performed at the zip code level, we calculated physician densities for each zip code based upon our data. This was compared to the zip code level physician intensity measure derived from kernel density estimation that was produced in the first comparison. It should be noted that the 302 physician (0.8%) whose zip codes addresses did not correspond to the 2000 U.S. Census were excluded from these comparative analyses because there was no population data for these new zip codes.

We ranked each of the old physician density and new physician intensity measures by their ratios and then mapped the differences between the two rankings. A positive value difference indicates that the zip code ranked higher using the new intensity measure compared to the old density measure. A negative value indicates that the zip codes ranked higher using the old density measure compared to the new intensity measure. In cases where there was little to no difference in these indicators, the difference in rankings would be small (-19 to + 20).

Distance To Nearest ER Hospital

There were six steps taken to calculate the distance from each census block group to the closest emergency room (ER) hospital. First, the block group centroids were derived from the cartographic census block groups using standard GIS methods. Second, using the NEAR function within ArcGIS, the x,y-coordinates of the nearest location on the major road network from each centroid were determined. Third, based upon the x,y-coordinates of the centroids and the x,y-coordinates of their nearest locations on the major road network, line features were generated using the “Add XY Line Data from Table” tool from Hawth’s Spatial Analysis Tools for ArcGIS (Beyer, 2004). Fourth, these line features were merged with the major road network into a new GIS data layer in ESRI *shapefile* format. An identical method was then followed to incorporate the emergency room hospital point locations onto the network. In effect, to join the locations of block group centroids and ER hospitals to the original road network, a straight line segment was extended from the original road network to these points.

The fifth step involved using the NODEDISTANCE function within ARC/INFO to calculate the network distance between the block group centroids and the ER hospitals. Since this requires the GIS data layers to be in ARC/INFO *coverage* format, the extended road network *shapefile* was converted to this format. One advantageous aspect of this conversion was the ability to specify a “snap tolerance” and so clean up any minor topological errors in the extended road network, such as minor gaps between the centroid-network and hospital-network lines that arose due to lack of coordinate precision. The point attributes of the census block groups and ER hospitals were transferred to their corresponding nodes on the coverage-based network, to identify them

as “supply” and “demand” locations. This was achieved by first converting the block group centroids and ER hospital point *shapefiles* to point *coverages* and then making use of the POINTNODE function in ArcGIS. The sixth and final step involved using the ARC/INFO NODEDISTANCE function itself. This function calculated the network-based distances between each of a set of demand nodes (the census tract centroids) and each of a set of supply nodes (ER hospitals) up to a threshold distance. The threshold distance was set sufficiently high to ensure that every block group centroid supply node would have a distance calculated to at least one closest hospital. Determining the closest hospital and network distance for each block group then followed, by identifying these attributes from the resultant table of network distances.

Euclidean Distance To Nearest ER Hospital

A secondary measure of emergency room hospital accessibility was calculated for comparative purposes. This measure was the Euclidean distance between each block group centroid and the closest ER hospital. This is a simple task using ArcGIS that involves performing a spatial “Join” between the two point layers. That is, each block group was given two new attribute columns, one column containing the closest hospital based on Euclidean distance and one column containing that distance.

Evaluation

In order to evaluate our measures, we calculated the average physician availability and ER hospital accessibility for each of the populations of Non-Hispanic whites, Non-Hispanic Blacks, and Hispanics in the seven Central Florida counties using the new measure of physician intensity (block group based and geocoding of all addresses) and the old measure of physician density (zip code based and no geocoding of P.O. Box

addresses). To do this it was first necessary to calculate for each block group separate weights for each population group that reflected the share of that population group in Central Florida accounted for by the block group. These weights summed to 1.0 across all block groups for each population group. The availability and accessibility values in each block were then multiplied by their block group weight and these were summed across block groups to calculate the average for the entire population.

To investigate the spatial variation within race and ethnic groups in a parsimonious manner, we created four categories of block groups, reflecting concentrations of races/ethnicities that could then be mapped according to our measures. These four categories of block groups were defined as predominately Black (>50%), Hispanic (>50%), or white (>90%), or ethnically “diverse” (<10% white, <50% Black, and <50% Hispanic). The remainder of the block groups were relatively heterogeneous in race and ethnicity and not included in this particular analysis.

Results

One-third (33%) of the Florida population, 4.3 million people, lived in the Central Florida region in 2000 (Table 1). Compared to the entire state, the Central Florida population was slightly more white, and less Black or Hispanic. The racial composition was similar to that of the U.S. as a whole in 2000.

Table 1. Racial and Ethnic Composition of United States, Florida, and Central Florida, 2000

	<u>United States</u>	<u>Florida</u>	<u>Central Florida</u>
Population	281,421,906	15,982,378	4,314,618
Non-Hispanic White	69.1%	65.4%	70.7%
Non-Hispanic Black	12.1%	14.2%	12.3%
Hispanic	12.5%	16.8%	12.8%

Physician Availability

The results of the physician availability calculations are summarized in Table 2. We excluded block groups with populations of less than 100 from these analyses in order to prevent inflation of intensity and density estimates due to the small population in the denominator. The average physician intensity across block groups is 13.55 per 1000 people, with a maximum of physician intensity of 609.80. The physician intensity for block groups, which are simply spatial units, is not as meaningful as examining as describing the physician intensity for the population, which was an average 6.81 physicians per 1000 people in the study area.

Table 2. Physician Intensity and Network-based ER Hospital Distance in Central Florida

	<i>Physician Intensity (per 1000)</i>	<i>Network-based ER Hospital Distance</i>
Block groups		
N ¹	2381	2402
Min	0.00	0.05
Max	609.80	34.97
Mean	13.55	4.58
SD	34.94	3.17
Population		
Mean	6.81	5.07

¹Block group populations with less than 100 were excluded from these analyses.

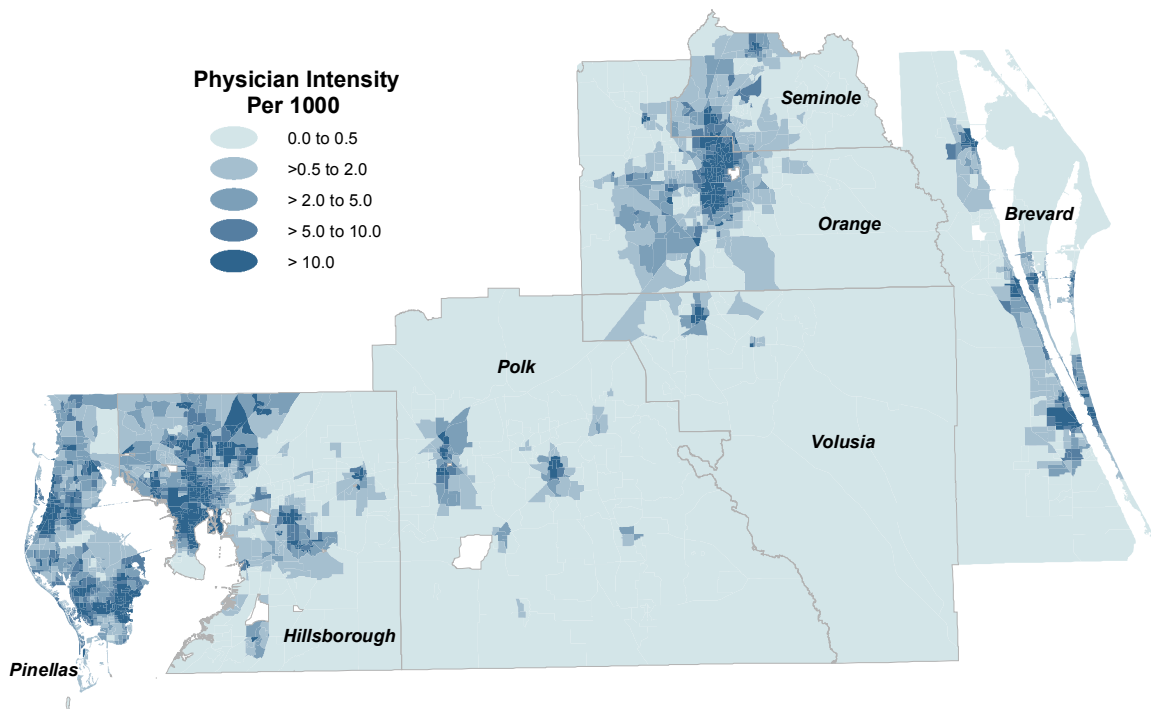


Figure 2. Physician intensity per 1000 population by census block group for Central Florida.

Physician intensity is mapped by census block group for Central Florida in Figure 2. At one level, the map clearly reflects a relationship between physician intensity and the level of urbanicity. However, it also illustrates a marked variability in physician intensity that can occur within urban areas. For example, Pinellas County, which has a relatively uniform spatial pattern of urban development, has a wide range of physician intensity values. Even in the two major metropolitan centers beyond Pinellas County, namely Tampa and Orlando, where there is a general intensity gradient with centrality such that availability increases as urbanicity increases, there are areas that contradict the trend.

Road Network-based ER Hospital Distance

The results of the network-based hospital distance calculations are displayed in Figure 3 and summarized in Table 2. The furthest block group is approximately 35 miles from the nearest ER hospital. The average distance to the nearest ER hospital across block groups is 4.58 miles. For the Central Florida population, the average ER hospital distance is 5.07 miles.

The expected pattern of higher levels of accessibility, based on road network distance, was found for block groups geographically closer to hospitals and a general pattern of declining accessibility for block groups that are at a further distance away (Figure 3). However, there are exceptions to this generally linear pattern which likely reflect the local structure of the road network.

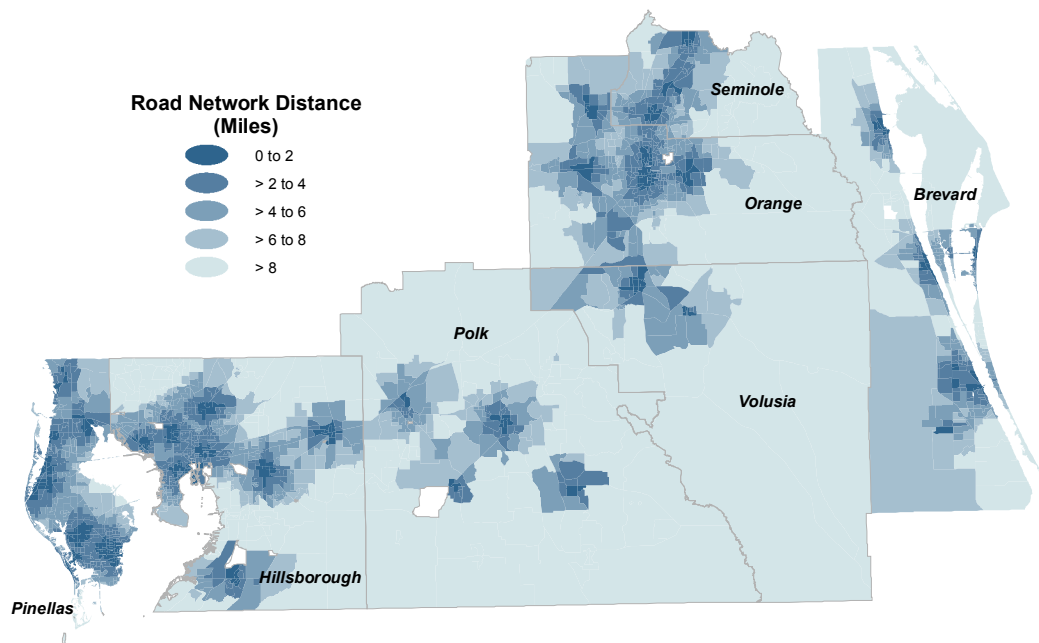


Figure 3. Road network distance to closest emergency room hospital by census block group for Central Florida.

Table 3. Comparison of physician availability as measured by physician-to-population ratio (density) and kernel-density estimated intensity for zip codes in Central Florida.

	Physician Density	Physician Intensity
Mean	2.18	0.45
SD	2.85	1.00
Max	16.22	9.71

N= 206; 13 zip codes with populations less than 100 excluded.

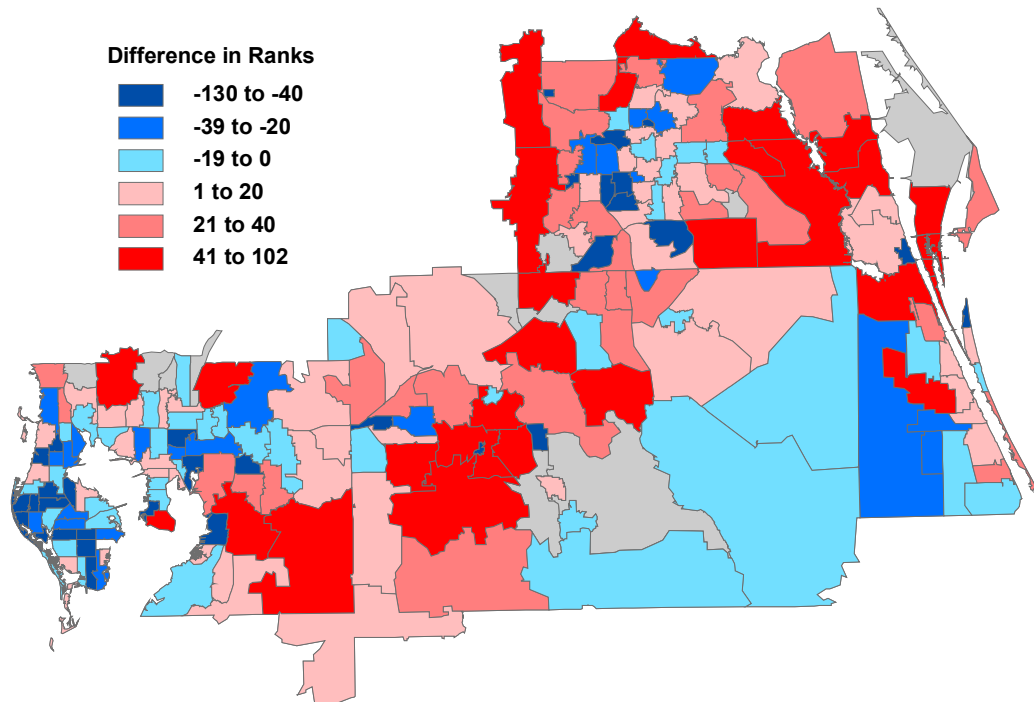


Figure 4. Difference in rank between physician density (negative) and physician intensity (positive) ratios.

Physician Intensity vs. Physician Density

The average zip code has a density of 2.18 physicians per 1000 people, but an intensity of 0.45 physicians per 1000 people (Table 3). As indicated earlier, however, since density and intensity measures are not synonymous, Figure 4 shows the differences in the relative rank orders of zip codes based upon the two measures of availability. Positive values indicate where the ranking of a zip code amongst all zip codes is higher based upon the intensity measure than it is based upon the density measure. The converse is true for negative values.

Most of the zip codes show low disagreement (-19 to +20 rankings) although there are pockets where there is a general pattern of higher density ranks, as indicated by negative differences, in some urban areas, and higher intensity ranks (positive differences) in some rural areas. This pattern may reflect the impact of border crossing such that the availability of physicians is understated by density measures for rural areas where there are available physicians outside the zip code boundaries. This is more likely to be the case for generally rural zip codes relatively close to urban areas. Conversely, in urban areas, zip codes that have high density rankings may experience a significant shift in rank when using the intensity measure when neighboring zip codes benefit as a result of the way in which intensity is calculated by kernel density estimation. That is, KDE does not limit by borders; physicians can serve people in more than one zip code or block group. There are some exceptions to this urban-rural trend, particularly among several large rural zip codes in the southeastern area of the study region that perhaps reflect a lack of nearby urban areas.

Table 4. Comparison of physician intensity for census block groups between unit of mean aggregation (zip code vs. block group) in Central Florida

	Zip Code	Block Group	Difference
Mean	6.78	13.55	1.46
SD	22.67	34.95	23.54
Max	392.87	609.8	347.39
N=2,381; Block groups with populations less than 100 excluded.			

Spatial Resolution Comparison

As hypothesized, the new physician intensity measure, across block groups, produces a higher mean and standard deviation compared to the physician intensity measure using zip codes (Table 4). The differences noted in the summary statistics of

these two measures obviously reflect differing levels of spatial averaging. Because intensity measures are population based these differences also reflect the fact that the zip code estimates assume population to be evenly distributed across all of the block groups within the zip code whereas using the disaggregated block group populations as denominators reflects the more specific location of populations.

For example, the variability in physician intensity measures between block groups within four zip codes in Pinellas County is displayed in Figure 5. The average physician intensity for these zip codes range from 4.35 to 19.95 and, as the map shows, there is significant variability between block group estimates within these zip codes. For example, the 33713 zip code is comprised of block groups in its southeastern corner with high physician intensity, but these are balanced by block groups in the northwestern corner with much lower physician intensities.

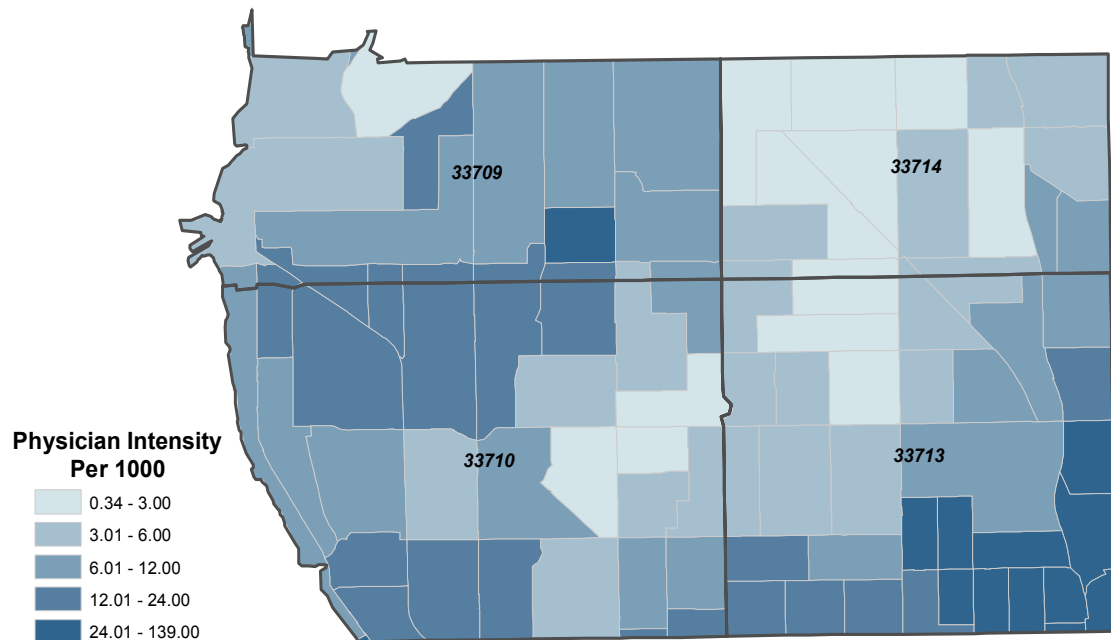


Figure 5. Variation of physician intensity by census block group within four illustrative urban zip codes of Pinellas County, Florida.

Table 5. Comparison of distance estimates (in miles) from census block group centroids to nearest ER hospital in Central Florida.

	Euclidean	Road Network	Difference
Mean	3.26	4.58	1.32
SD	2.4	3.17	1.13
Max	26.33	34.97	20.38
N= 2,402			

Euclidean vs. Road Network-based ER Hospital Accessibility

As hypothesized, the distances from the block group center to the nearest ER hospital based on the road network-based calculations show more variation than the Euclidean calculations (Table 5). Based on network calculations, the average block group is 40 percent further from the nearest ER hospital (4.58 miles) compared with the estimates from the Euclidean calculation (3.26 miles). The discrepancy between the two distance calculations ranges from 0.020 miles to 20.38 miles.

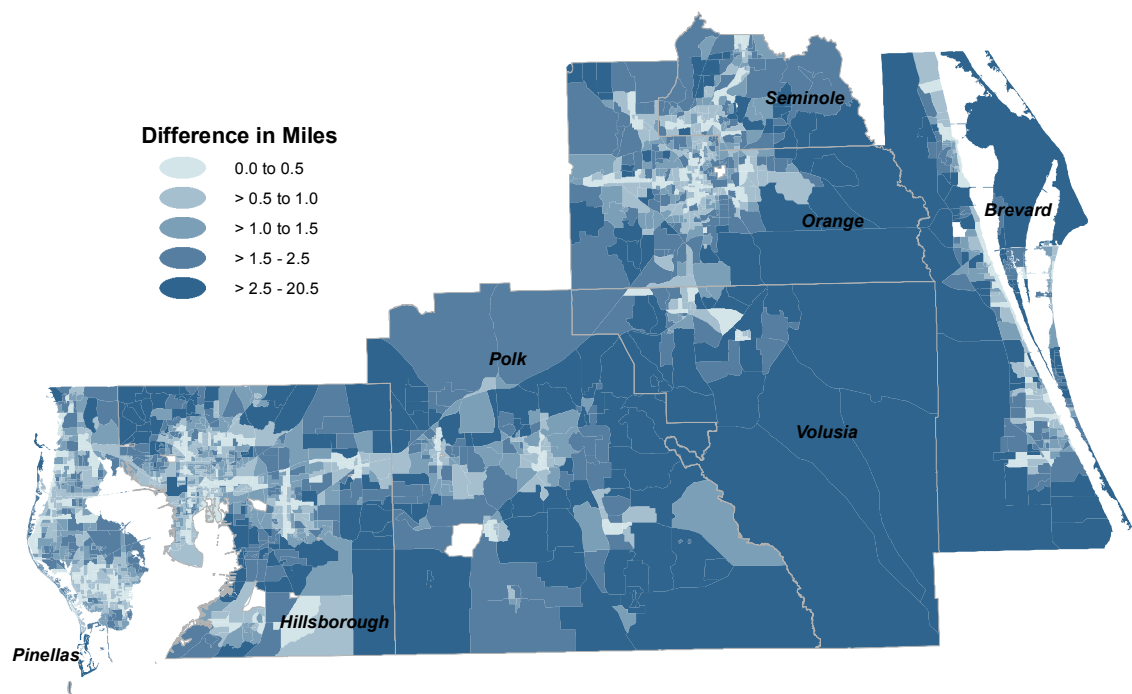


Figure 6. Difference between Euclidean and road network distance to the closest emergency room hospital by census block group for Central Florida.

The disparities between Euclidean and road network distance calculations are generally the greatest in rural areas, but this is not always the case (Figure 6). Euclidean-

based calculations also greatly underestimate the distance to the nearest hospital when the block group covers a large geographic area, and for barrier islands (e.g., Pinellas County coastline) where Euclidean distance calculations do not take into account the fact that intercoastal waterways must be crossed to reach the nearest hospital. However, even within the relatively urban area of Hillsborough County there is a centrally-located block group where the difference between the two distance measures is considerably larger than for neighboring block groups. The discrepancy is because this block group includes the Tampa International Airport and the centroid is far removed from the closest major road.

Racial and Ethnic Disparities in Healthcare

Physician Availability

There are pronounced differences in physician availability between racial and ethnic groups (Table 6). On average, Non-Hispanic Black residents live in areas with the highest physician intensities ($M = 8.18$), that are 22 percent higher than the average Non-Hispanic white resident ($M = 6.71$), and 32 percent higher than among Hispanics ($M=6.22$). These racial/ethnic availability patterns are not consistent in Hillsborough and Orange counties. In Hillsborough county, Hispanics have the highest physician availability ($M=11.64$) and non-Hispanic Blacks have the lowest availability ($M=8.22$). In Orange county it is non-Hispanic whites who have the highest availability ($M=8.91$), while Hispanics have the lowest availability ($M=3.19$).

Table 6. Differential physician availability (intensity) between racial and ethnic populations in Hillsborough and Orange Counties in Central Florida

	Total Population	Non-Hispanic White	Non-Hispanic Black	Hispanic
N	4,314,617	3,048,455	530,875	550,174
Hillsborough	10.47	10.65	8.22	11.64
Orange	7.19	8.91	6.72	3.19
Central Florida	6.81	6.71	8.18	6.22

The variability in physician availability across predominantly Black, predominantly Hispanic, predominantly white, and diverse block groups neighborhoods in Hillsborough and Orange counties, the locations of Tampa and Orlando, respectively, is displayed in Figure 7. There is a high degree of variability in physician intensity within these sets of block groups indicating variation in availability within racial and ethnic populations. For example, in central Hillsborough County, there are a number of contiguous, predominately Black block groups where the physician intensity ranges from less than 0.25 to more than 5 physicians per 1000 people. There are predominately white block groups concentrated at both ends of the accessibility range; some have very high availability in urban areas while others, particularly those in rural regions, have very low physician intensity. The gray areas are relatively heterogeneous and not included in these analyses.

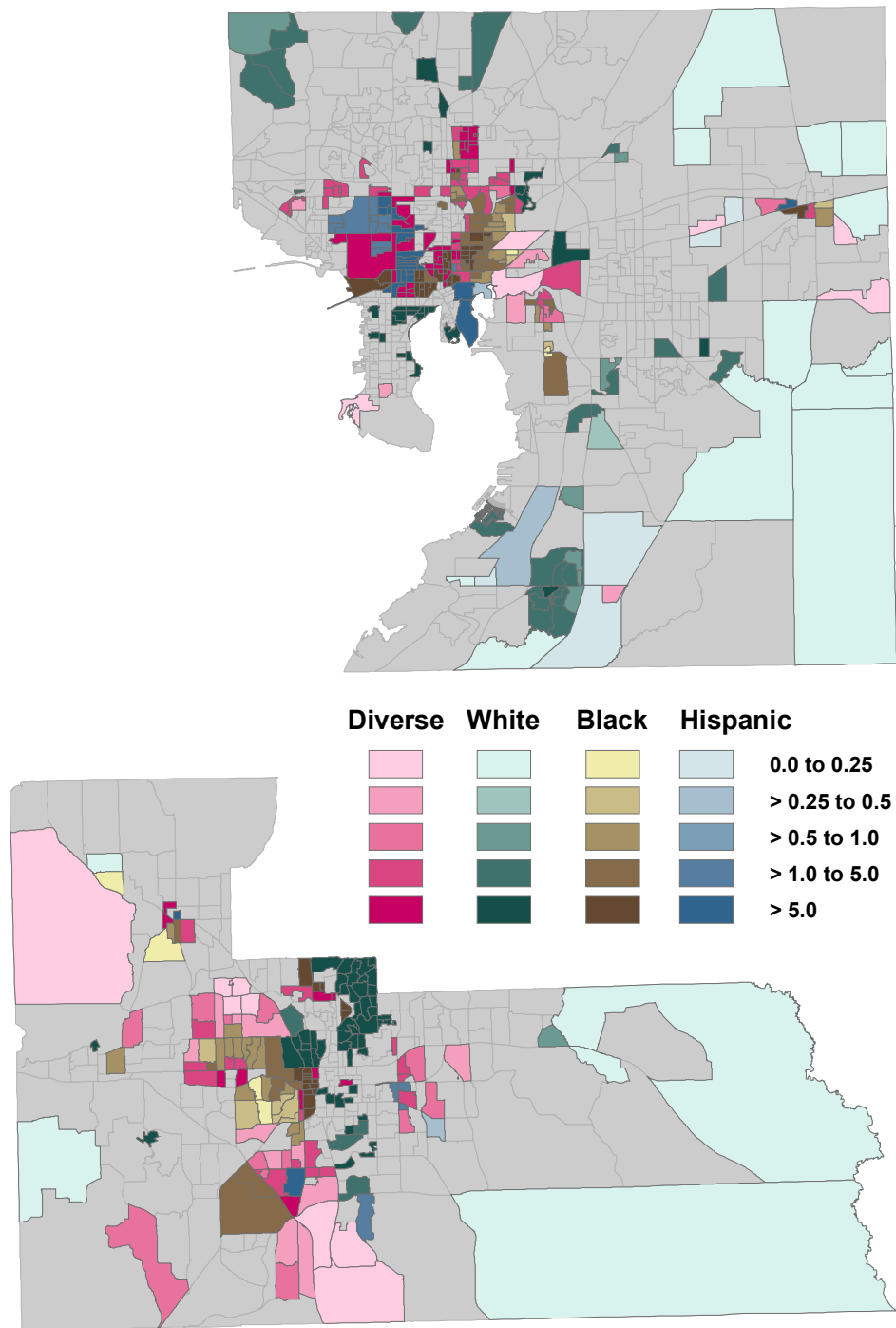


Figure 7. Variation in physician intensity among block groups with high concentrations of four racial/ethnic populations in Hillsborough and Orange Counties, Florida.

Table 7. Average miles to ER hospital between racial and ethnic populations in Hillsborough and Orange Counties in Central Florida

	Total Population	Non-Hispanic White	Non-Hispanic Black	Hispanic
N	4,314,617	3,048,455	530,875	550,174
Hillsborough	4.52	4.93	3.49	3.95
Orange	4.89	4.97	4.61	4.85
Central Florida	5.07	5.25	4.27	4.93

ER Hospital Accessibility

There are also differences in average road network distance to the nearest ER hospital by race and ethnicity (Table 7). The average distance for non-Hispanic whites is 5.25 miles, making them the furthest away from hospitals of all the ethnic groups. Non-Hispanic Blacks are the closest ($M = 4.27$ miles) and the average distance for Hispanics is between these two estimates ($M = 4.93$ miles). These patterns are consistent in Hillsborough and Orange counties.

These averages mask the variability in accessibility within areas with high populations of these ethnic groups, displayed in Figure 8. Similar to Figure 7, for the block groups with a high concentration of each racial group, there is a range of ER hospital accessibility values, even where block groups are contiguous. For example, there is lower accessibility among the highly Hispanic block groups in the southern part of Hillsborough County, but high accessibility for Hispanic block groups more centrally located in Tampa.

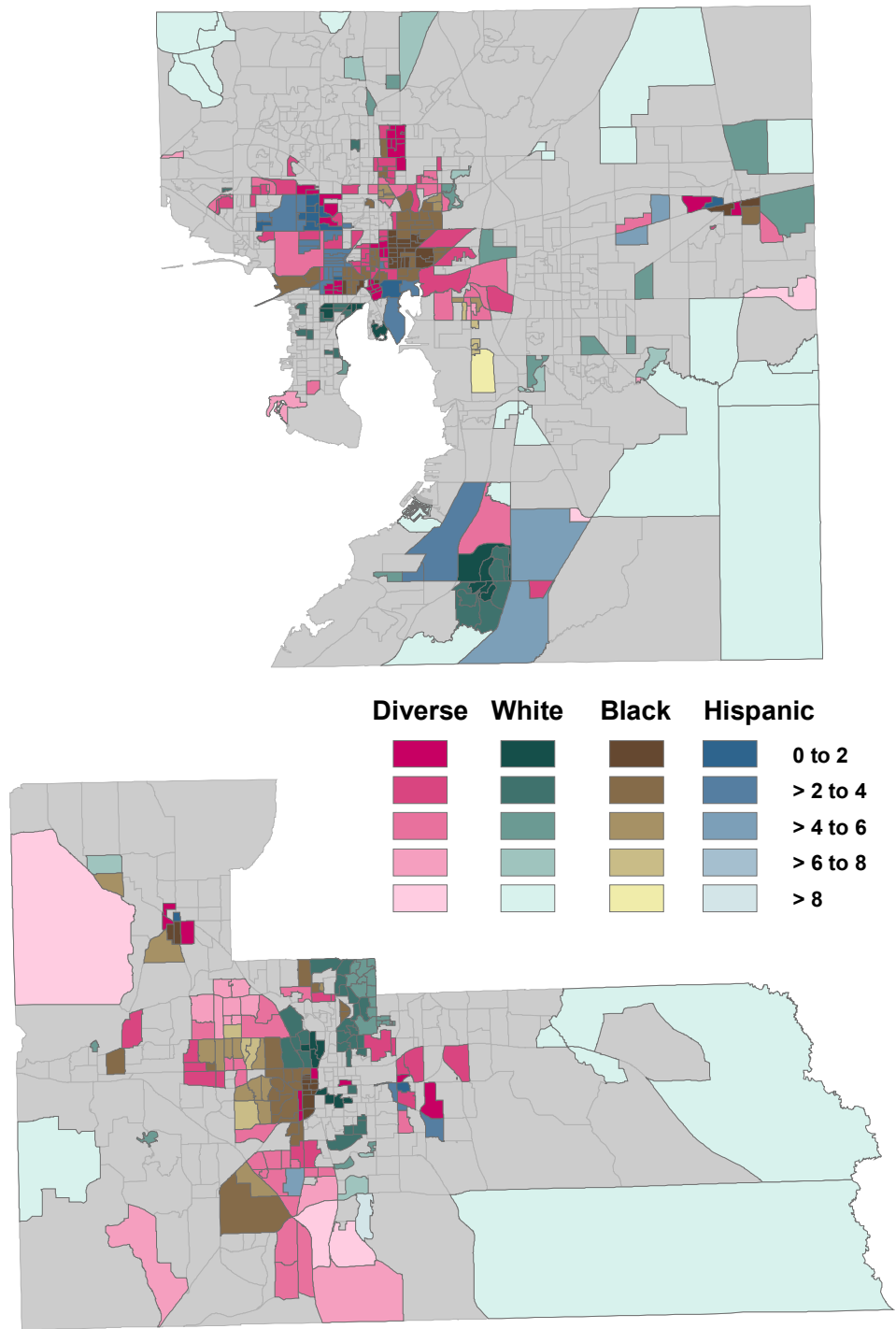


Figure 8. Variation in road network distance to nearest emergency room hospital among block groups with high concentrations of four racial/ethnic populations in Hillsborough and Orange Counties, Florida.

Discussion

Geographic variability in healthcare availability, accessibility, and quality, among other measures, have been proposed as pathways to the development and persistence of racial and ethnic health disparities (Williams & Collins, 2001). In order to determine the impact of the local healthcare system on health disparities, however, accurate geographic measures of these characteristics are needed. This study described the development of two measures, physician availability and ER hospital accessibility, which were calculated using methodological advances in GIS. Physician availability was calculated based on the geocoded office locations of physicians in Florida, with areal interpolation of the locations of physicians who could not be accurately geocoded in order to minimize data loss. We then used kernel density estimation with a bandwidth of two kilometers and calculated the average physician intensity per 1000 people for each block group. To measure hospital accessibility, we calculated the distance along the network of major roads to the nearest ER hospital. These data were analyzed for the Central Florida region, an area that has a racial composition similar to that of the U.S. as a whole, and with a number of urban and rural regions.

Evaluation of New Measures

We evaluated our new measures by comparing them to analogous measures created using previously-implemented methodologies and at varying spatial scales. We showed that calculating mean availability from zip code-level data and Euclidean distances to the nearest hospital mask the true variability in measures of availability and accessibility. Specifically, we showed that zip code physician density provides higher ratios of availability than physician intensity at the same spatial resolution, particularly

because the latter “spatially weights” physicians by distance. Next we highlighted how physician intensity summarized to the zip code masks the variation between block groups within these zip codes. Calculations of Euclidean distance to the nearest hospital are, on average, 1.32 miles shorter than those based on road network distances. Thus, we believe that physician intensity calculated with kernel density estimation for block groups and road network-based calculations of distance to the nearest ER hospital, represent significant advances in healthcare availability and accessibility measurement.

Racial and Ethnic Healthcare System Disparities

Other researchers have argued that differences in healthcare availability and accessibility explain health disparities. However, our results show that minorities, particularly Blacks and Hispanics, actually have higher average values of physician availability and ER hospital accessibility than whites in one county but not another. By examining these measures across block groups with predominantly white, Black, and Hispanic populations, however, we showed that intra-ethnicity variation in healthcare availability and accessibility may be masked by averages. The fact that Blacks live closer to ER hospitals or have higher physician to population ratios could be due to the clustering of minority population in inner cities near large medical centers (Kahn et al., 1994). As our analyses showed, physician offices often cluster near hospitals, putting both types of providers more often in poorer neighborhoods, but not necessarily ensuring better access to care.

It is important to note, however, that these results only take into account the potential availability and accessibility of healthcare options and fail to address non-spatial issues such as cost, appointment availability, and quality of care, which are

important facets of the healthcare system that impact realized access and outcomes. The measures of availability and accessibility created here should be validated by comparing them to utilization data to determine whether the features of the healthcare environment affect actual utilization and outcomes when non-spatial characteristics are statistically controlled.

Limitations

There are a few limitations to this study. The first is the temporal accuracy of the provider data compared to the population data. Data from the 2000 U.S. Census were used because population data were available at the block group level for the racial and ethnic populations of interest, but provider data were from 2005. This is of particular concern for physician intensity calculations, which may have failed to take into account growing populations.

Another problem is that, although block groups represent population data at a finer spatial resolution than zip codes, these units vary tremendously in size and, in rural areas, are rather large. We assumed that the population was geographically distributed evenly across the block group, but this is usually not the case.

Although using the road network to calculate the distance to the nearest hospital represents an improvement on Euclidean-based measures, there may be limitations associated with the GIS technology used to calculate these measures. For example, the road closest to the block group center may not, in fact, be the most direct or fastest route to the nearest hospital.

Validity

Although we evaluate our measures by comparing them to those created using former methodology, future research needs to establish the validity of these new measures. Construct validity is demonstrated when a measure correctly operationalizes the concept it is measuring. Data on actual utilization could be used to validate these measures. Of particular interest to practioners and policy-makers is identifying the level of physician intensity and ER hospital distance which is associated with higher utilization and better care. That is, how far is an individual willing to travel to a hospital to seek care and at what physician intensity does the population demand impact the ability of the supply of physicians to serve the population? Although difficult to measure with the data used here, actual patient address, characteristics, and utilization data could be used with GIS technology to answer these questions.

Conclusions

The increasing attention to the geographic variation in healthcare systems and widespread use of GIS, in conjunction with the availability of provider data and the ease at which these measures can be created, make it likely that this topic will continue to be explored by researchers, policy-makers, and practioners. The fine spatial resolution, which made it possible to show more marked variability, also makes it is possible to aggregate these measures to larger geographic units such as census tracts, cities, and counties and show how results vary at different spatial levels. Although we conducted relatively simple analyses of these measures, there are an unlimited number of ways to use them. For example, planners could identify areas with physician to population ratios of less than 1:3500, or 0.287 physicians per 1000 people, which is the general ratio used

by the US Department of Health and Human Services to designate Health Professional Shortage Areas (HPSA; U.S. Government Accountability Office [US GAO], 1995). The current ER hospital accessibility measures could be used in conjunction with population data to determine where to place new hospitals in order to minimize distance and maximize the number of potential patients that can be served.

More broadly, this research adds to the growing body of research examining the impact of environmental and community characteristics on individuals. The characteristics and behaviors of individuals are increasingly studied in relationship to the residential communities and life spaces that they occupy.

CHAPTER 4: COMMUNITY CONTEXT AND PHYSICAL HEALTH DISPARITIES

Introduction

Calls for interventions aimed at eliminating health disparities, such as the 1985 *Report of the Secretary's Task Force on Black and Minority Health* (US DHHS, 1985) and the Department of Health and Human Services' Healthy People 2010 campaign, have only begun to reduce differences in physical health between whites and racial/ethnic minority groups. Among older adults, African Americans and Hispanics remain significantly more likely than whites to report poor self-rated health, even when socioeconomic differences such as education and income are statistically controlled (Hayward, Miles, Crimmins, & Yang, 2000; Hummer, Benjamins, & Rogers, 2004).

The very slow progress towards the reduction of disparities results in part from the complex array of forces that lead to disparities in the first place. During the past ten years, features associated with the community context have emerged as possible sources of health disparities (Browning, Cagney, & Wen, 2003; Cagney, Browning, & Wen, 2005; LeClere, Rogers, & Peters, 1997; Oakes, 2004; Robert & Lee, 2002). These factors offer a particularly pertinent explanation for disparities in part because racial residential segregation still exists to a great extent in many areas throughout the United States (Glaeser & Vigdor, 2001). Moreover, African Americans in general are more likely to live in areas lacking in services, and there is some evidence that African Americans as well as whites living in these areas are more likely to have poorer health outcomes (Massey & Fischer, 2000; Subramanian, Acevedo-Garcia, & Osypuk 2005).

The literature, in other words, suggests that it is not segregation alone that leads to these health disparities. Rather, it may be the greater likelihood for racial and ethnic minorities to be exposed to poorer social and environmental conditions, and to have less access to services. While such problems are associated with residential segregation, community context becomes a relevant explanation for the development and persistence of health disparities. For example, high rates of poverty and unemployment and low median family income in the community are associated with heart disease, chronic conditions, self-rated health, and mortality (LeClere, Rogers, & Peters, 1998; Robert & Lee, 2002). Lack of access to services such as full-service grocery stores and healthcare facilities are associated with poorer diet and fewer opportunities for healthy behaviors (Ellaway & MacIntyre 1996; Morland, Wing, & Diez Roux 2002).

Community Context and Health Disparities Model

Despite the linkages that have been established between segregation, discrete community conditions, and health disparities, there is little research or few theoretical frameworks that focus on the multiple pathways and conditions by which community features affect health. The *Community Context and Health Disparities Model* (Figure 1; p. 16), was developed by the authors drawing from the existing literature and previous theoretical frameworks (Northridge, Sclar, & Biswas, 2003; Schulz & Northridge, 2004; Schulz, Williams, Israel, & Lempert, 2002; Williams & Collins, 2001). The model proposes that community conditions such as pollution, poor housing quality, unstable social conditions, limited educational and employment opportunities, and poor healthcare systems have an association with poor health, as well as indirectly shape health by limiting individual socioeconomic status and opportunities, affecting health behaviors,

heightening stress, and lessening social support (see Chapter 2). With longitudinal data, these pathways have the potential to demonstrate causality.

Community Context

The broadest unit of analysis in the model is the community context, which includes the physical, built, social, economic, and healthcare environments. Factors in each of these domains have been shown to affect health outcomes (such as exposure to toxins, poor housing conditions, and high rates of poverty; e.g., Krieger & Higgins, 2002; Morello-Frosch & Jesdale, 2006; Waitzman & Smith, 1998). The physical environment includes local climate and toxins in the air and water, which have been linked to health outcomes (Balfour & Kaplan, 2002; Evans & Kantrowitz, 2002). Housing stock, traffic, local shops, and services are measures of the built environment which have also been associated with health outcomes such as hypertension (Ewing, Schmid, Killingsworth, Zlot, & Raudenbush, 2003) and mortality (Cohen et al., 2003). Aspects of the social environment, such as civic and religious organizations and characteristics of neighborhood residents, are associated with health (Franzini, Caughy, Spears, & Esquer, 2005; Wen, Browning, & Cagney, 2003) and may buffer individuals from more harmful aspects of the environment (LaVeist, 1993; Rich, Edelstein, Hallman, & Wandersman, 1995). Low community socioeconomic status, one aspect of the economic environment, has been linked to stroke, cardiovascular and all-cause mortality, and self-rated health, net of individual attributes and risk factors (Davey Smith, Hart, Watt, Hole, & Hawthorne, 1998; Jones & Duncan, 1995; Maheswaran, Elliott, & Strachan, 1997). Finally, the availability, accessibility, and quality of healthcare have been suggested as possible causes for health disparities (Baicker, Chandra, & Skinner, 2005; see Chapter 3).

Individual Context

In the *Community Context and Health Disparities Model*, individual demographics, socioeconomic status, health behaviors, social support, and stress, which are often employed as control measures in studies of racial differences in health, here are shaped by the community context. For example, individual economic conditions are hypothesized to mediate the effects of community social and economic contexts (Pickett & Pearl, 2001; Williams & Collins, 2001). Poor health outcomes and higher mortality rates are highly associated with lower individual socioeconomic status (Adler, Boyce, Chesney, Folkman, & Syme, 1993; Syme & Berkman, 1976). Differences in health-related behaviors such as having a regular source of healthcare, seeking preventive care, exercising, not smoking, and not drinking to excess mediate the effect of community context on health (Ellaway & MacIntyre, 1996; Robert, 1999; Ross, 2000). Social support (e.g., the size and characteristics of the individual's social networks, and whether they feel the social environment is supportive) is positively associated with lower rates of mortality (Berkman & Glass, 2000; Kawachi & Berkman, 2000; Leskela et al., 2006). Stress, particularly from objective assessment of community conditions such as crime rate, noise, and pollution, have been linked to health (Franzini, et al., 2005; Gee & Payne-Sturges, 2004; Ross & Mirowsky, 2001). In the *Community Context in Health Disparities Model*, we focus on the individual's subjective assessment of the community as stressful and examine whether or not this mediates the effects of community context on health outcomes.

Older Adults

Implicit in the model is that there may be a greater impact of the community context on the health of older adults because they have lived in the community for a longer time, have a greater need for services, and spend less time at work and hence more time in the residential community than younger adults (e.g., Robert & Lee, 2002; Robert & Li, 2001). On the other hand, differential mortality effects may actually reduce the ability to detect the influence of these conditions (Robert & Li, 2001; Waitzman & Smith, 1998). Individuals most impacted by neighborhood conditions may be more likely to die earlier resulting in an older population of survivors who are resilient to these effects.

Research Questions

The goal of this research was to evaluate the impact of the community context on the self-rated health of older adults using the *Community Context and Health Disparities Model*. Specifically, we sought to determine:

1. Are there significant differences in self-rated health across communities?
2. What are the direct relationships between community context and individual self-rated health?
3. To what extent are differences in individual self-rated health across communities due to differences in the characteristics of the individuals within these communities?
4. What are the effects of community context net of individual context on self-rated health? That is, does individual context mediate community context?
5. How do community conditions interact with individual factors to explain self-rated health of older adults?

We conducted secondary data analysis using hierarchical linear modeling to examine the effect of community context, net of individual context, on self-rated health. Each question corresponds to one step in the HLM procedure.

Method

Sample

The Survey of Older Floridians (SOF) received approval from the Institutional Review Board of the University of South Florida on 3/19/2004 (IRB # 102334G).

Communities

Previous research has grouped individuals into communities based on county (Fiscella & Franks, 1997), U.S. Census tract (Franzini & Spears, 2003; LeClere, et al., 1997; Robert 1998), U.S. Census block group (Franzini & Spears, 2003), and defined communities (Davey Smith, et al., 1998; Feldman & Steptoe, 2004; Reijneveld & Schene, 1998; Ross, 2000). The smaller geographic units are generally more homogeneous, and both individual and community variability increases as the geographic unit increases in size, making it more difficult to accurately assess the effects of community context. This difficulty is the modifiable area unit problem (Waller & Gotway, 2004). As an example, Franzini and Spears (2003) found that four percent of the variance in heart disease mortality was accounted for by variation at the Census tract level, but county-level variation contributed less than one half of a percent.

In this study, we defined “communities” using a combination of U.S. Census “Places” in Miami-Dade County and Neighborhood Enhancement Team (NET) boundaries within the City of Miami. The U.S. Census “Places” include incorporated areas, consolidated cities, and Census-designated places (CDP). CDPs are the “statistical counterparts of incorporated places” created by the U.S. Census “for concentrations of

population, housing, and commercial structures that are identifiable by name but are not within an incorporated place” (U.S. Census, 2001).

The city of Miami, while defined by the U.S. Census as a single “place” is very diverse and contains a number of neighborhoods, as well as 141 of the 733 Miami-Dade participants in the SOF. The remainder lived in the other parts of Miami-Dade County and place names came from the U.S. Census. Within the city of Miami, we obtained the geographical boundaries of Neighborhood Enhancement Team (NET) areas within the city. These areas, designed to link community residents to the city government, were designated based on established neighborhoods in Miami (City of Miami, 2004). Because the NET area communities did not coincide with U.S. Census entities, we assigned Census block group identifiers to each community based on their centroid location. Community measures were calculated by aggregating the data for all of the block groups within that community. This process resulted in the creation of 38 communities that included both urban (including city of Miami) and suburban areas in Miami-Dade County. We were able to use 36 of these 38 communities in the current study.

Individuals

The Survey of Older Floridians (SOF) was a telephone survey designed to assess the health and healthcare needs of four populations of interest: older Floridians in general, and specifically older African Americans, Cubans, and other Hispanics. Participants in the state-representative sample were contacted by random-digit dialing. A stratified sampling procedure was applied to subsequent sampling frames. We sorted telephone exchanges by the proportions of older African Americans, Cubans, and other Hispanics to increase the productivity of random digit dialing and created a sample of all

the exchanges needed to get coverage of approximately 70 percent of these populations. Phone numbers in the exchanges were called in this order until each sample had reached the desired sample size. Adults over the age of 65 in these target groups were interviewed regardless of the sampling frame. A supplemental sample of 122 whites living in the same communities as the minority oversamples was also interviewed to examine the effects of the summer 2004 hurricanes that hit Florida approximately three months prior to the oversample data collection phase. The statewide participants are therefore a random sample of the entire state, whereas the oversample participants are a sample of adults drawn from telephone exchanges with high proportions of older minorities. Conducted in 2004-2005, the final sample included telephone interviews with 1,433 white, African American, Cuban, and other Hispanic older adults. Response rates ranged from 55 percent to 62 percent, with the lowest rates for the minority oversamples and the highest rates for the statewide survey (Zayac et al., 2005). Although the data were weighted for epidemiological reporting, the data were unweighted for these analyses.

For this study, we selected a subset of those SOF participants whose residences were geocoded using Geographical Information Systems (GIS) techniques. Of the 1,433 participants in the SOF, 1,412 (98.5%) were successfully geocoded. Participants who could not be geocoded did not significantly differ from the rest of the sample in terms of age, gender, race, ethnicity, or self-rated health. Consistent with the distribution of the actual population of older minorities in Florida, most (N=733; 51.9%) of the participants resided in communities in Miami-Dade County. The geographic distribution of participants elsewhere in the state limited our ability to designate community clusters

outside of Miami-Dade County. That is, 48 percent of the SOF participants were scattered through the remaining 66 counties.

Measures

Community Measures

Community measures were chosen based on availability, heterogeneity within Miami-Dade County, and relevance. For example, the climate is homogeneous throughout the county so it was not possible to test the effect of this community attribute with this sample. The *Community Context and Health Disparities Model* suggests multiple measures for each domain. In order to minimize multicollinearity, we followed the recommendation of Bryk and Raudenbush (1992), who suggested fitting separate sub-models with predictors from each of the neighborhood domains (e.g., physical, built, social, economic, and healthcare) and retaining the strongest predictor from each sub-model in the main model. Data sources and the measures employed for each of the five domains are described next. The correlations between the variables used to measure each domain are displayed in Table 8.

Physical environment. One measure of the physical environment was the presence of toxins, assessed using the Toxics Release Inventory (TRI), which includes the geographical locations of releases of over 300 toxins to air, water, and land by the manufacturing industry. These locations are released by the Environmental Protection Agency (EPA) per a mandate by the 1986 Section 313 of the Emergency Planning and Community Right-to-Know Act (EPCRA). Certain industries must report their waste emissions if they use more one or more of 650 specified toxic chemicals (U.S. EPA,

2004). Higher densities of TRI sites have been associated with asthma among children (Maantay, 2007) and could potentially affect the health of older adults.

Because the influence of toxins is likely to cross community boundaries, we used kernel density estimation to measure TRI exposures. First, the 2006 locations of these sites were geocoded to a point shapefile. There were 51 TRI locations in Miami-Dade County. We next converted Miami-Dade County into a grid of equally-sized cells 100 feet by 100 feet. We then created a kernel density estimation using the Spatial Analyst tool in ArcGis 9.2, which created a surface of toxin intensity. The kernel density estimation provided a distance-weighted count of toxins where the influence of each of the TRI sites was inversely weighted by the distance away from the center of the cell and followed the quartic approximation to a Gaussian kernel function (see Chapter 3). In other words, this estimate accounted for the fact that people will be less exposed to toxins sites that are further away. Values were scaled by a factor of 27,878,400 (or 5280^2) and then by a factor of 1000 to make values comparable to other variables in the model. The TRI value for each community was obtained by averaging the values in each cell in the community ($M = 2.04$; $SD=3.36$). These values represent an intensity of TRI sites within the community, with a large TRI score indicating a higher likelihood of exposure to toxins within a community

Built environment. Many aspects of the built environment, including attributes of the buildings, transportation systems and roads, services and stores in the community have been linked to health outcomes. We limited our measure of the built environment to the proportion of supermarkets that were major chain retailers because previous research has shown that the availability and type of food stores in one's residential neighborhood

influence diet, and these retailers are more likely to be sources of fresh fruit and vegetables (Morland et al., 2002). Data on the locations of these stores came from the GeoPlan Center at the University of Florida that provides geographic datasets and shapefiles for the state of Florida, available through the Florida Geographic Data Library (Florida Geographic Data Library [FGDL], 2003). The original shapefile, created from a 2003 online telephone directory search, included supermarkets, grocery stores, and shopping centers, which were geocoded based on address. We limited our analyses to stores categorized as “supermarkets” and identified major supermarket chain retailers (e.g., Publix, Winn Dixie). Of the 306 supermarkets in Miami-Dade County, 85 (27.7%) were major chain retailers. In the communities in this study, an average of 36.66 percent of the supermarkets were major chain retailers ($SD=36.08$).

Social environment. The U.S. Census (2000) provided data on the characteristics of the residents within each community as measures of the social composition, including racial, ethnic, and age composition, proportion of households headed by females and owner occupied, and housing tenure. These measures were highly correlated so the proportion of households that were owner-occupied was employed as the measure of social environment ($M=56.74\%$; $SD=18.34$).

Economic environment. The proportion of residents living below the federal poverty level in 2000 was calculated from U.S. Census (2000) data ($M=17.28\%$; $SD=10.06$). Other relevant data on employment and educational systems were available only at the county level and not used here.

Healthcare environment. The distance to the nearest hospital via the network of major roads was used to measure of healthcare accessibility (Chapter 3). Hospital

addresses were obtained from the Florida Agency for Health Care Administration's database of licensed hospitals (FL AHCA, 2006). Only facilities with an emergency department were included. A network analysis along major roads in Florida was used to calculate the distance from each block group center to the nearest hospital along these roads ($M=2.99\text{mi}$; $SD=1.36\text{mi}$). For a more thorough explanation of this methodology, see Chapter 3.

Table 8. Correlations between community (level 2) predictors

	1	2.	3.	4.
1. TRI Score				
2. Proportion Chain Supermarkets	-0.042			
3. Owner-occupied Housing Units	-0.047	0.456**		
4. Poverty Rate	-0.033	-0.558***	-.713***	
5. Hospital Distance	0.075	0.119	.320	-.374*

N=36

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

Individual Measures

Demographics, socioeconomic status, health behaviors, social support, and stress were used as independent and potential mediator variables in the analyses to answer the research questions. In order to minimize multicollinearity, we examined the correlation between variables in each domain at the community and individual level and removed variables which were highly ($r>0.50$) correlated within a domain (Table 9). The dependent variable was self-rated health.

Demographics. Age, gender, and race or ethnicity were used to measure demographic characteristics. Age was a continuous variable and gender was coded Male = 0 and Female = 1. Although participants in the SOF were enrolled as white, African-American, Cuban, or Non-Cuban Hispanic, we combined the two Hispanic groups and

created two dummy variables: Black vs. all others and Hispanic vs. all others, with whites as the reference group.

Socioeconomic status. Education was categorized as less than high school (1), high school degree (2), or more than high school (3). Yearly household income was recoded into six groups from less than \$10,000 (1) to more than \$50,000 (6).

Health behaviors. There were five independent variables for health behaviors: exercise, smoking patterns, alcohol consumption, having a personal doctor, and having sufficient food. Physical exercise was assessed by asking respondents whether they took part in at least one hour of aerobic exercise a week (No=0, Yes=1). Participants identified whether they were a current smoker (0), former smoker (1), or had never smoked (2). Alcohol consumption was a dichotomous variable, coded as drinker (1 or more drinks per day = 0) or non-drinker (fewer than 1 drink per day = 1). Participants identified if they have a personal doctor (No=0; Yes=1) and how frequently they had sufficient food (Always=2; Sometimes=1; Never=0).

Social support. Marital status was dichotomized (Not Married=0; Married=1). Participants indicated how often they could count on friends and family in times of need (Never=0; Most or some of the time=1; Always=2). Finally, we asked participants how long they had lived in their home, a continuous measure aimed at assessing the potential for social support from neighbors.

Stress. In the *Community Context and Health Disparities Model* we focus on the individual's subjective perception of the community as stressful. We asked participants to rate the safety of their neighborhood (0=Poor; 1=Fair; 2=Good; 3=Very Good; 4=Excellent).

Table 9. Correlation between individual (level 1) predictors and self-rated health.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. Self-rated health														
2. Age	-07													
3. Female	-06	08												
4. Black	-03	-02	08											
5. Hispanic	-06	-04	-06	-75***										
6. Income	22***	-17***	-28***	06	-22***									
7. Education	18***	-12**	-13**	-13**	-01	31***								
8. Exercise	12**	-10*	03	05	-09*	15**	04							
9. Enough food	16***	-07	-00	-04	01	14**	07	14**						
10. Regular doctor	-10*	01	06	-04	02	06	08	09*	04					
11. Drinker	05	-01	-17***	-04	-10*	12*	09	11*	04	01				
12. Smoker	02	02	24***	-05	10*	-01	-06	05	-04	08	-13**			
13. Married	05	-04	-41***	-14**	13**	30***	11*	-05	03	-00	05	-01		
14. Count on family	14**	05	-01	10*	-11*	14**	-01	09	17***	08	03	-05	11*	
15. Safety	21***	11*	-06	-05	-06	17***	11*	08	10*	09*	12**	01	08	17***

Notes: N=487; Pearson's r is a decimal. * $p < .05$, ** $p < .01$, *** $p < .001$.

Dependent Variable

The dependent variable was self-rated health, which had four categories (Poor=1; Fair=2; Good=3; Excellent=4). The continuous nature of the variable made it appropriate for these analyses. Increasing scores indicated better health.

Statistical Analyses

This study tests the *Community Context and Health Disparities Model*, in particular, the hypothesis that differential health outcomes are attributable to characteristics of the residential community rather than to race or ethnicity. There are two levels of data: individuals (level 1) nested in communities (level 2), with predictors at both levels which must be analyzed together in order to understand their independent, additive, and interactive effects.

One way the effects of community context have been examined is using ordinary least squares (OLS) regression with community-level predictors from exogenous data sources. But, including individuals nested within communities in ordinary least squares (OLS) regression violates the assumption of independent errors (Steenbergen & Jones, 2002) because these individuals will be more similar than individuals in other communities. Such an error would lead to an underestimation of standard errors and increased probability of Type I errors (Hox, 1995; Pedhazur, 1997). In addition, it is not possible to study the cross-level interaction of community and individual attributes with OLS regression (Hox, 1995; Stoker & Bowers, 2002). In OLS there is no way to account for the similarity in variance among individuals in the same community, differences between individuals within communities, and the effects of individual characteristics cannot vary across communities. The impact of individual-level variables is “fixed”

(Jones & Duncan, 1995), that is, there is one specified relationship between each predictor and the outcome for all individual in all communities. Residual differences between individuals are summarized by a single error term.

Hierarchical linear modeling (HLM; Stoker & Bowers, 2002), addresses these issues, taking into account the nested structure of the data which leads to similarities between individuals within communities. HLM models simultaneously include both individual- and community-predictors, can assess the interactions between predictors within and across levels, and partition the variance and covariance to individual and neighborhood levels (Bryk & Raudenbush, 1992; Hox, 1995; Stoker & Bowers, 2002). HLM allows us to model variance between individuals and between communities as random, representing only a sample of the possible relationships between the predictors and outcomes, drawn from all the possible combinations of individuals and communities. The outcome for each community is then an overall rate for all individuals in each plus a “random” difference that is allowed to vary between each community. It is then possible to specify individual characteristics and examine the extent to which similarities between individuals within a community are associated with the same outcome (Jones & Duncan, 1995).

Within HLM, there are a number of specifications for each model that must be made. First, differences between communities can be modeled as fixed or random effects. A fixed effects model is appropriate when highlighting the impact of a particular set of distinct communities on health outcomes, and when the number of communities is small. For example, this would be appropriate for comparing four distinctive areas such as Boston, the Southwestern U.S., North Carolina, and Iowa, as was the case for the

Established Populations for the Epidemiological Study of the Elderly (EPESE) studies (Cornoni-Huntley et al., 1993). Our analyses are based on a relatively large number of communities ($n=36$) and focus on the impact of community (level-2) predictors on health outcomes, rather than the impact of specific communities. That is, how do the physical, built, and other community attributes predict individual health outcomes across communities, rather than how the unique attributes of specific neighborhoods lead to these outcomes. The presence of a particular predictor in several communities is expected to impact the self-rated health across communities because the number of communities is large and generalizes to a larger population.

A random effects HLM model is appropriate when making generalizations about communities beyond those included in the study. In essence, the communities are considered as a random sample of the population of all possible communities. HLM essentially calculates a regression equation for each community (Pedhazur, 1997). Error variance is assumed to be constant between individuals within neighborhoods, but to vary randomly across communities (Ewart & Sunchday, 2002). This error variance may lead to differences in the mean values between groups (intercepts), as well as differing relationships between predictors and outcomes (slopes) across communities. As a result, the regression coefficients are expected to vary and are interpreted as random effects when sampled from the normally-distributed population of communities (Hox, 1995). In other words, the means (intercepts) and relationships between level 1 predictors and the outcome measure (slopes) are allowed to vary randomly across groups. These are thus random coefficients. Both level 1 and level 2 predictors can also be used as fixed

coefficients. The inclusion of both types of coefficients, random and fixed, is why these are also called “mixed” models.

HLM is commonly used for random slopes model, in which the relationship between individual-level predictors and self-rated health is allowed to vary across communities. Although we allowed the slopes to vary across communities for each individual-level predictor, there were no significant differences in the relationship between these predictors across communities. Instead, we report the independent and net effects of community conditions on mean self-rated health (the intercept or constant). All results are therefore from random intercept models with fixed community-level predictors and fixed individual-level predictors, with the latter having the same effect on self-rated health across communities (Yen & Kaplan, 1999).

Finally, although HLM can incorporate weighted data and SOF data were weighted for other analyses (Zayac et al. 2005), we are not using weights because the participants within the 36 selected communities were chosen solely because of their convenience within the dataset. Neither the communities nor the participants were selected with these analyses or HLM in mind, which would require randomly selecting individuals within randomly selected communities. Instead we selected communities and participants with the methods described earlier (see Sample).

All hierarchical linear models were run using the PROC MIXED procedure (Singer, 1998) in the SAS statistical software package (SAS, 9.1, 2004). Predictors of each of the five community domains and the individual-level domains suggested by the *Community Context and Health Disparities Model* were added in successive steps. Each model includes a constant (intercept), the random effects (variance) between individuals

within communities (level 1) and between communities (level 2), as well as the fixed effects of the level 1 and level 2 predictors. HLM does not produce an R^2 value indicating the proportion of the variance in the dependent measure that is explained by the predictors. Instead, we use reductions in variance, which indicates the proportion of the variance explained by the added predictors, an indicator which is analogous to R^2 values (Snijders & Bosker, 1994). We calculated the proportion of the variance estimates reduced from the initial, unspecified model (Model 1). Cases where unexplained variance increased from the initial model were indicated by a negative value. Improvement of model fit was assessed with the addition of each set of predictors by examining the change in the -2 REML Log Likelihood from the initial model, with negative values indicating a better fit from the previous model (Hox, 1995). The change in the -2 REML Log Likelihood was evaluated with a Wald statistic. This statistic compares the change in the -2 REML Log Likelihood to a chi-square distribution where the degrees of freedom are the number of predictors

To answer research question 1 (Model 1), a random-effects analysis of variance (RANOVA), an HLM model with no predictors, was used to determine whether there were differences in self-rated health across the communities without accounting for community or individual characteristics (Oakes, 2004; Raudenbush & Bryk, 2002). The constant (or intercept) produced by this analysis is the average self-rated health across communities. Statistical significance of between-community variance would show that there were differences in self-rated health between communities. The significance of between-individual variance indicates there are differences between individuals within communities. The relative size of these estimates would indicate what proportion of the

variance is due to individual and community characteristics. Non-significant differences would mean that the variance between communities or individuals has been accounted for by the predictors to be added in subsequent models. We also examine the intraclass correlation, or the correlation between self-rated health among participants in the same community.

To answer research question 2 (Model 2), community-level variables for each of the five domains (physical, built, social, economic, and healthcare environments, Figure 1; p. 16) were added to Model 1 sequentially, starting with the physical environment and ending with the healthcare environment, as predictors of health for individuals nested within each community. This step tests the hypothesized direct relationship between community contextual variables on self-rated health (Figure 1; p. 16). With the addition of each variable, the significance of the fixed effect indicates the strength of that characteristic as a predictor of self-rated health. The extent of decrease in between-community variance from Model 1 indicates the proportion of the variation between communities that can be accounted for by the addition of each domain.

Research question 3 (Model 3) adjusts for selection bias, or the possibility that individual characteristics of participants do not vary randomly within communities (Oakes, 2004). Self-rated health was regressed on individual demographic, socioeconomic status, health behavior, social support, and stress variables. These variables were entered sequentially in the order proposed by the theoretical framework, and non-significant measures were eliminated. Particular attention was paid to the between communities variance estimates. If this parameter were to become non-significant with the inclusion of individual-level predictors, it would indicate that

between-community differences in self-rated health were entirely attributable to differences in individual characteristics and not community differences.

To answer research question 4 (Model 4), significant community- and individual-level variables were used to predict self-rated health. The change in the significance of community-level predictors from the previous analyses indicated whether the community effect was mediated by individual-level variables. By comparing the decrease in the between-community variance estimate in this step to that in Model 3 we assess what additional proportion of the variation in self-rated health between communities is accounted for by community context rather than individual characteristics.

Finally, to answer Research Question 5 (Model 5), we tested the interaction between the remaining significant community-level and individual-level predictors. The significance of these interactions was used to indicate whether individuals are differentially impacted by community conditions.

All of the variables in Table 8 and Table 9 were entered into the model. Only those which were significant were retained in these results.

Results

Characteristics of Communities and Individuals

Community Characteristics

The average TRI score was 2.04 ($SD=3.36$; Table 10). On average, 36.66 percent of the supermarkets in each community were major retailers, but there was great variability ($SD=36.08$). The average owner-occupancy rate was 56.74% ($SD=18.34$) and the average poverty rate was just over 17 percent ($SD=10.06$). Finally, the nearest hospital was 2.99 miles, on average, from the community ($SD=1.36$ miles).

Table 10. Community (Level 2) Characteristics

	% or Mean	Std. Deviation
TRI Score	2.04	3.36
Proportion Chain Supermarkets	36.66	36.08
Owner-occupied Housing Units	56.74	18.34
Poverty Rate	17.28	10.06
Hospital Distance	2.99	1.36
N=36 Communities		

Individual Characteristics

The final sample included 487 participants living within one of the 36 communities. The average participant age was 72.7 years old (Table 11). The sample was primarily female (63.7%) and Hispanic (74.9%). Just over a quarter (26.3%) had a grade school education or less, 29.6 percent had completed high school, and 44.1 percent had more than a high school education. Almost one third (32.6%) of the participants had a yearly household income of less than \$10,000 and 7.8 percent earned more than \$50,000 per year. Most of the sample (72.1%) got at least an hour of aerobic exercise per week, always had enough of the food they wanted (89.3%) and had a regular doctor (83.0%). Few participants were drinkers (14.1%) or current smokers (8.3%). Less than half of the sample was married (44.2%), but over 78 percent of respondents said they could always count on family and friends in times of need. The majority of respondents felt their neighborhood safety was excellent (26.9%), very good (20.5%), or good (36.3). Finally, the average self-rated health was 2.6, between fair and good.

Table 11. Individual (Level 1) Characteristics

	% or Mean	Std. Deviation
Age	72.7	6.2
Females	63.7%	
<u>Race or ethnicity (ref=White)</u>		
Black	15.8%	
Hispanic	74.9%	
<u>Education</u>		
Grade School	26.3%	
High School	29.6%	
More than High School	44.1%	
<u>Income</u>		
Less than \$10,000	32.6%	
\$10,000-\$20,000	23.6%	
\$20,000-\$30,000	13.6%	
\$30,000-\$40,000	6.6%	
\$40,000-\$50,000	1.6%	
More than \$50,000	7.8%	
Exercise 1 hour per week	72.1%	
<u>Enough Food</u>		
Always	89.3%	
Sometimes	8.8%	
Never	1.8%	
Regular Doctor	83.0%	
Drinker	14.1%	
<u>Smoker</u>		
Never	56.2%	
Former	35.5%	
Current	8.3%	
Married	44.2%	
<u>Able to Count on Family</u>		
Always	78.0%	
Sometimes	12.7%	
Never	9.2%	
Neighborhood Safety		
Excellent	26.9%	
Very Good	20.5%	
Good	36.3%	
Fair	13.1%	
Poor	3.1%	
Self-rated health	2.6	0.9
N=487		

Research Question 1

The average self-rated health across communities was 2.592 (Table 12). There was a trend toward significant differences in self-rated health between communities ($\beta=0.040$, $p=0.064$) and intraclass correlation, ρ , was 0.050 (not displayed), indicating moderate correlation within communities. There was significant variance between individuals within these communities ($\beta =0.758$, $p<0.001$).

Table 12. Self-rated health between communities (Model 1)

Fixed Effects		
	β	
(Constant)	2.592	***
Random Effects		
	σ^2	
Between-individuals variance	0.758	***
Between-community variance	0.040	
-2 REML Log Likelihood	1267.5	
N=487 participants in 36 communities		
* $p<.05$, ** $p<.01$, *** $p<.001$		

Research Question 2

With the addition of each community context predictor (Table 13), we examined the fixed effects of that measure, the change in the between-community variance, and the change in model fit compared to Model 1. The TRI score was not a significant predictor of self-rated health ($\beta =-0.001$) and did not improve model fit (change -2 REML Log Likelihood increased 6.5 points rather than decreased). In addition, this measure did not explain any of the variance in self-rated health between communities; in fact, the inclusion of TRI score increased the between-communities variance by 7.5 percent.

The proportion of supermarkets that were chain retailers, a measure of the built environment, also did not significantly predict self-rated health ($\beta =-0.001$) and adding

this level-2 predictor worsened model fit significantly. This measure also did not explain any of the between-community variance on self-rated health.

The rate of owner-occupied housing units did not significantly predict individual self-rated health ($\beta = 0.006$) and explained only 5 percent of the variance between communities. Additionally, the inclusion of this predictor did not improve model fit.

Poverty rate significantly predicted self-rated health ($\beta = -0.028$, $p < 0.01$), with declining self-rated health scores as poverty rate increased. This variable explained 50 percent of the total change in variance between communities and, although fit was not improved from Model 1, there was a slight decrease in the -2 REML Log Likelihood from the previous model.

Finally, hospital distance did not significantly predict self-rated health ($\beta = 0.068$). Poverty rate remained a significant predictor ($\beta = -0.026$, $p < 0.01$) after hospital distance was added to the model and a total of 72.5 percent of the variance between communities was accounted for by all five community-level measures. There was a negligible decline in between-community variance and model fit worsened slightly with the inclusion of this variable.

Research Question 3

In Model 3, we examined the effects of individual- or level-1 predictors on self-rated health by adding groups of variables hierarchically as proposed by the model (demographics, socioeconomic status, health behaviors, social support, and stress). In the first step, being Black or Hispanic compared to white significantly predicted poorer self-rated health ($\beta = -0.384$, $p < 0.05$; $\beta = -0.370$, $p < 0.05$, respectively; Table 14). These differences in race or ethnicity accounted for 20 percent of the variance between

communities. In other words, 20 percent of the differences between communities on self-rated health are due to differences in the racial and ethnic characteristics of participants in these communities. These measures also improved model fit, although not significantly.

Education significantly predicted self-rated health ($\beta = 0.170$, $p < 0.001$). Black race was no longer a significant predictor when education was entered into the model, suggesting that the negative impact of being Black was explained by education differences. Differences in race or ethnicity and education accounted for 37.5 percent of the variance between communities. Including education also significantly improved model fit.

Health behaviors, including exercising, having enough food, and having a regular doctor, were significantly associated with self-rated health. Getting at least an hour of exercise a week significantly predicted a 0.100 point increase in self-rated health ($p < 0.05$). Similarly, self-rated health was positively related to having enough food ($\beta = 0.330$, $p < 0.01$). Counter to our expectation, having a regular doctor was associated with lower self-rated health scores ($\beta = -0.318$, $p < 0.01$). The inclusion of these measures significantly improved model fit, although they did not explain any additional variance between communities.

Being able to count on one's family and friends ($\beta = 0.159$, $p < 0.05$) significantly predicted self-rated health and mediated the negative effect of being Hispanic, which was no longer statistically significant after the inclusion of this social support variable. The addition of this variables improved model fit significantly and, with the measures added in previous steps, explained 45 percent of the between-community variance. The

inclusion of these variables added unexplained variance between communities, but improved model fit.

The subjective rating of neighborhood safety was a significant predictor, with increases in community safety associated with better self-rated health ($\beta = 0.122$, $p < 0.001$). This variable also improved model fit significantly. Together, all the individual-level predictors accounted for 72.5 percent of the between-community variance.

Research Question 4

In Model 4, the community predictor poverty rate (from Model 2) was added to the individual-level predictors of self-rated health from Model 3. Although it was significant in Model 2, poverty rate was no longer a significant predictor of self-rated health after individual characteristics are taken into account ($\beta = -0.008$), although an additional 12.5 percent of the variance between communities was explained by poverty rate. Overall, 85 percent of the between-community variability on self-rated health could be attributed to the individual characteristics and community differences in poverty rates.

Table 13. Community characteristics and self-rated health (Model 2)

	Model 1		Physical		Built		Social		Economic		Healthcare	
Fixed Effects	B		B		β		β		β		β	
(Constant)	2.592 ***		2.592 **	*	2.532 ***		2.261 **	*	3.298 **	*	3.155 ***	
<i>Community Predictors</i>												
TRI score			0.001		0.005		0.006		0.023		0.020	
Proportion chain supermarkets					-0.001		0.000		-0.002		-0.001	
Owner-occupied housing units							0.006		-0.003		-0.005	
Poverty rate									-0.028 **		-0.026 **	
Hospital distance											0.068	
Random Effects												
	σ^2		σ^2		σ^2		σ^2		σ^2		σ^2	
Between-individuals variance	0.758 ***		0.758 **	*	0.759 **		0.757 **	*	0.754 **	*	0.757 ***	
Between-community variance	0.040		0.043		0.043		0.038		0.020		0.011	
Percent change ¹			107.5%		107.5%		5.0%		50.0%		72.5%	
-2 REML Log Likelihood	1267.5		1274.0		1284.2		1290.5		1289.2		1291.3	
Change from Model 1			6.5		16.7		23.0		21.7		23.8	
					***		**	*	**	*	***	

¹Change in between-community variance from Model 1.

N=487 in 36 communities

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

Table 14. Individual characteristics and self-rated health (Model 3)

	Model 1		Demographics		Socioeconomic Status		Health Behaviors		Social Support		Stress	
	B	***	B	***	β	***	B	***	β	***	β	***
(Constant)	2.592	***			2.650	***	2.224	***	2.044	***	1.799	***
<i>Individual Predictors</i>												
<u>Race or ethnicity (ref=Whites)</u>												
Black			-0.384	*	-0.286		-0.285		-0.305		-0.247	
Hispanic			-0.370	*	-0.306	*	-0.282	*	-0.268		-0.215	
Education					0.170	***	0.166	***	0.170	***	0.160	***
Exercise							0.100	*	0.096	*	0.092	*
Enough Food							0.330	**	0.285	**	0.263	*
Regular Doctor							-0.318	**	-0.338	**	-0.359	***
Able to Count on Family									0.159	*	0.131	*
Neighborhood Safety											0.122	***
Random Effects												
	σ^2		σ^2		σ^2		σ^2		σ^2		σ^2	
Between-individuals variance	0.758	***	0.755	***	0.742	***	0.707	***	0.702	***	0.694	***
Between-community variance	0.040		0.032		0.025		0.027		0.022		0.011	
Percent change ¹			20.0%		37.5%		32.5%		45.0%		72.5%	
-2 REML Log Likelihood	1267.5		1265.1		1257.7		1242.7		1239.9		1233.5	
Change from Model 1			-2.4		-9.8	*	-24.8	***	-27.6	***	-34.0	***

¹Change in between-community variance from Model 1.

N=487 in 36 communities

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

Research Question 5

Although poverty was not a significant predictor of self-rated health in Model 4 when individual characteristics were statistically controlled, there was a significant cross-level interaction between poverty rate (level 2) and Hispanic ethnicity (level 1) as seen in Model 5 (Table 15). The significance of this interaction indicates that the relationship (slope) between poverty rate and self-rated health is moderated by being Hispanic. This interaction explains an additional 2.5 percent of the variance between communities. This is displayed in Figure 9. The relationship between community poverty rate and individual self-rated health is significant for Hispanics ($\beta=-0.016$, $p<0.05$) but not for non-Hispanics ($\beta=0.019$). Higher rates of community poverty have a negative impact on the health of older Hispanics, but not on non-Hispanic whites or African-Americans.

Table 15. Community characteristics net of individual characteristics on self-rated health and cross-level interactions (Models 4 and 5).

	Model 1		From Model 3		Model 4		Model 5	
Fixed Effects	β		β		β		β	
(Constant)	2.592	***	1.799	***	1.970	***	1.758	***
<i>Individual Predictors</i>								
<u>Race or ethnicity (ref=Whites)</u>								
Black			-0.247		-0.147		-0.429	*
Hispanic			-0.215		-0.187		0.142	
Education			0.160	***	0.149	**	0.146	**
Exercise			0.092	*	0.091	*	0.087	
Enough Food			0.263	*	0.255	*	0.272	**
Regular Doctor			-0.359	***	-0.365	***	-0.368	***
Able to Count on Family			0.131	*	0.131	*	0.124	*
Neighborhood Safety			0.122	***	0.110	**	0.108	**
<i>Community Predictor</i>								
Poverty Rate					-0.008		0.010	
<i>Interactions</i>								
Poverty Rate x Hispanic							-0.024	*
Random Effects	σ^2		σ^2		σ^2		σ^2	
Between-individuals variance	0.758	***	0.694	***	0.696	***	0.690	***
Between-community variance	0.040		0.011		0.006		0.005	
Percent change ¹			72.5%		85.0%		87.5%	
-2 REML Log Likelihood	1267.5		1233.5		1240.1		1242.1	
Change from Model 1			-34.0	***	-27.4	**	-25.4	**

¹Change in between-community variance from Model 1.

N=487 in 36 communities.

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

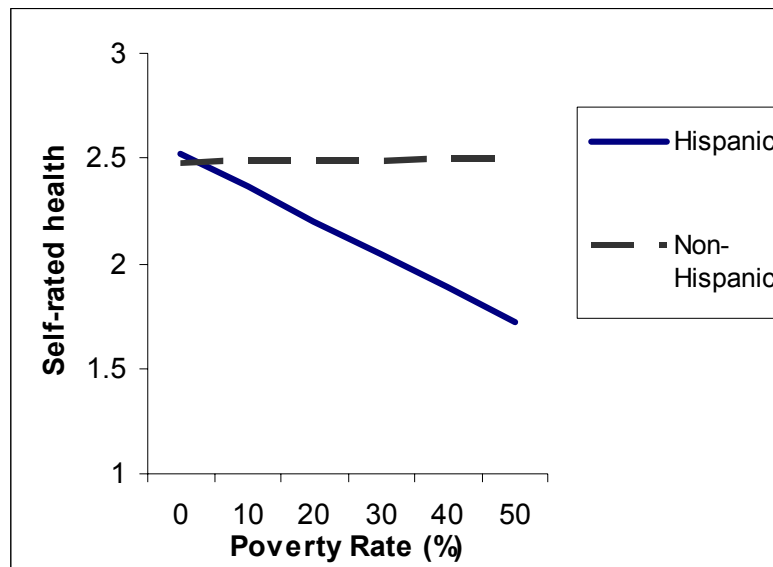


Figure 9. Relationship between community poverty rate and self-rated health: Hispanics vs. Non-Hispanics.

Discussion

In an effort to understand the causes of racial and ethnic health disparities among older adults, we tested the theoretical framework proposed by the *Community Context and Health Disparities Model* (Figure 1; p. 16). Using this model, we argue that characteristics of the community, including aspect of the physical, built, social, economic, and healthcare environments, directly influence health outcomes and are mediated by individual demographic characteristics, socioeconomic status, health behaviors, social support, and stress. The model was tested using a secondary data analysis of individual-level data from participants in the Survey of Older Floridians living in communities within Miami-Dade County, which were linked to contextual measures from outside sources through GIS. We discuss the findings in terms of the adequacy of the theoretical model, possible causes of health disparities among older racial and ethnic minorities, and recommendations for changes in public policy and healthcare practice.

Adequacy of the Community Context and Health Disparities Model

In general, our findings support the link between aspects of the community context and health outcomes and somewhat support the pathways proposed by the *Community Context and Health Disparities Model*. Differences in self-rated health across communities were low, particularly when compared to the variation between individuals within communities, but approached statistical significance. Community poverty rate was the only community predictor that remained statistically significant after the inclusion of all other community-level variables. Most of the variance between communities (72.5%) was explained by individual factors (race/ethnicity, education, exercise, having enough food, having a regular doctor, social support, ratings of neighborhood safety) and, when these individual characteristics were controlled statistically, community poverty rate was no longer a significant predictor of self-rated health. This level-2 predictor did, however, account for an additional 12.5% percent of the variation between communities on self-rated health. We examined cross-level interactions and found that community poverty rate interacted with Hispanic ethnicity so that participants who were Hispanic were significantly negatively impacted by community poverty, although there was no effect between non-Hispanics.

Our findings are similar to others that have linked poor community economic conditions to poor health outcomes (Davey Smith et al., 1998; Jones & Duncan, 1995; Maheswaran, et al., 1997; Waitzman & Smith, 1998). Like Reijneveld and Schene (1998), however, we found that the effect of community poverty was not significant net of individual characteristics and that most of the variability between communities on self-rated health was attributable to individual differences. Although we expected other

attributes of the community to predict a significant amount of the variation in self-rated health, the proportion of residents below the poverty level was the only persistent predictor. This suggests that other work that has linked community poverty to poor self-rated health both alone (Kobetz, Daniel, & Earp, 2003) and in combination with other economic measures (Davey Smith et al., 1998; Jones & Duncan, 1995; Robert, 1998) adequately assessed the aspect of community that influences health. Given the high correlation between community poverty and the other measures of the community context, it is necessary to further disentangle the pathways suggested by the *Community Context and Health Disparities Model*. This study provided preliminary examples of measures of each of the domains. Future studies using a more disparate array of communities are needed to examine the relationships between conditions across domains, relationships with self-rated health, and to better identify causal pathways for these relationships.

Possible Causes of Health Disparities Among Older Racial and Ethnic Minorities

At the individual level, being Black or Hispanic was associated with worse health, although the former was mediated by education and the latter was mediated by social support. This finding supports arguments that racial and ethnic disparities are mediated by differences in other characteristics, particularly socioeconomic status and social support. Increased health promotion behaviors, including getting at least an hour of exercise and having enough food were associated with better health. Although we expected having a personal doctor to be associated with better health, we found the opposite effect. This may be because people who are in worse health are more likely to see their physician on a regular basis. It was noteworthy that age and gender, which have previously been linked to self-rated health, were not significant in these analyses, perhaps

because they are mediated by other variables included in the model and it was a more age-homogenous sample. Finally, positive subjective ratings of neighborhood safety were associated with better health.

Recommendations

Although community conditions have long been the focus of public health researchers and practitioners, in more recent years researchers have tested interventions to focus on changing individual attributes and behaviors. We make recommendations in terms of all three areas: policy, practice, and future research.

Public Policy

Public policy alone cannot eradicate the biases and beliefs that cause segregation, which leads to disparities in residential communities between whites and ethnic minorities. Policy interventions can, however, focus on elements and pathways at the community and individual levels that impact health. For example, the Environmental Protection Agency (EPA) recently began an Aging Initiative, designed to better understand how aspects of the environment affect the health of older adults who may be more susceptible to things like toxins, pollution, and extreme climate events. The Healthy People 2010 program, which has set goals for health behaviors and conditions, includes information about creating healthy communities, recognizing that health and health behaviors are impacted by community.

Our research highlights the importance of creating more equitable economic conditions across communities. Individual level of education and community poverty rate are related to educational and employment opportunities, which are mutable characteristics of the local community. Interventions designed to alleviate economic

disparities should therefore focus on these systems, not individual conditions alone. As this study has shown, reducing community poverty benefits older adults as well as for its intended target--families and those still in the workforce.

One area that needs particular attention is the coexistence of multiple negative community conditions in areas where residents are already vulnerable because of low socioeconomic status. For example, although we did not find an effect for TRI, Browning and colleagues (2003) argued that not having affluent residents in a neighborhood increases susceptibility to adverse community conditions such as the placement of toxic waste sites. That is, these sites are more likely to be placed in communities with less affluence because of the effectiveness of more affluent communities to argue “Not in My Back Yard.”

In our study, there were fewer chain supermarkets in communities with high levels of poverty, indicating that it may be more difficult for residents, who are already at a disadvantage because of limited economic resources, to obtain adequate food. Indeed, having enough to eat was a factor in this study.

Practice

Because having a usual source of healthcare, getting regular check-ups and seeking preventive care such as screenings (Corbie-Smith, Flagg, Doyle, & O’Brien, 2002; Newacheck, Hung, Park, Brindis, & Irwin, 2003; Politzer et al., 2001) have been associated with better health outcomes, we expected to see a positive relationship between having a regular doctor and self-rated health, but we found the opposite: having a regular doctor significantly predicted poorer self-rated health. Although this may reflect that individuals who are sicker are more likely to have a regular doctor, it may also

reflect characteristics of the healthcare system. For example, the quality of care that these individuals are receiving may be worse. Baicker and colleagues (2005) showed that all patients received poorer quality healthcare in minority communities. So this affects care for all race and ethnic groups. In addition, it may be that the physician's personal characteristics (gender, race, ethnicity, language) are barriers to good physician-patient communication. Further studies are needed to better disentangle these relationships.

Limitations

Our study was limited by a very small sample size, particularly the small number of participants who were white or Black. This limited our power to detect differences between race and ethnic groups and communities. This was a secondary data analysis of a study where participants were not sampled from communities per se, so generalizations drawn about these communities are limited.

We limited our study to communities within the same county in order to be able to find community level data for all aspects of the theoretical model. But this may have limited the range of values for community-level predictors and minimized community differences. There were also some aspects of the community not measured, such as climate, vehicular accidents, and unemployment rate, because these measures are available at geographic resolutions not compatible with our study. In addition, high within-domain correlations made it necessary to include only one measure of each domain when it may, in fact, be other aspects of that domain that impact health. For example, we did not include poor transportation systems and lack of sidewalks in the built environment as predictors of health. There were moderate to high correlations between many of the community-level measures (Table 8) and poverty rate. The shared

variance between many of the community factors may explain why poverty rate was the only significant predictor.

Future Research

Further studies with large community and individual sample sizes are needed to more adequately parse the impact of conditions in each domain. Ideally, study participants should be sampled from distinct communities, in order to maximize variance on level-2 predictors. Finally, although we focused on older adults, research should focus on disparities individual conditions and health outcomes, as well as community conditions, throughout the life course.

Conclusion

This study has highlighted the importance of taking into account the community context when studying the individual. Contextual factors play an important role in the economic opportunities, social networks, and opportunities for exercise and healthy eating that an individual experiences. High rates of neighborhood poverty were associated with poorer self-rated health, with older Hispanics particularly vulnerable to poor neighborhood conditions. Public policies aimed at eliminating health disparities must take into account the characteristics of the communities where minorities are living. Although the pathways proposed by the *Community Context and Health Disparities Model* were not fully supported with this secondary data analysis, the role of community context has the potential to be an important mutable factor and should be included in future research studies of health disparities. Further studies are needed to determine additional attributes of the community that are related to poverty rate and to test the efficacy of community level data at various geographic levels.

CHAPTER 5: COMMUNITY CONTEXT AND MENTAL HEALTH DISPARITIES

Introduction

Interventions aimed at eliminating mental health disparities, such as a report to the Surgeon General in 1999 (US DHHS, 1999) and the 2000 creation of the National Center for Minority Health and Health Disparities in the National Institutes of Health (Oliver & Muntaner, 2005), highlight the increasing attention to disparities between whites and racial and ethnic minorities. African Americans and Hispanics are more likely to suffer from disorders such as depression (Roberts, Roberts & Chen, 1997), but are less likely to seek treatment and more often disabled by these disorders than whites (US DHHS, 1999).

The reasons for mental health disparities are complex, and not all are linked to factors such as bias in the quality of care provided, health beliefs, or even genetic differences. One promising new area of research focuses on the community context. Environmental psychology literature has long recognized the influence of the environment on well-being (e.g., Barker, 1968; Lawton, 1983), but the environment as an explanation for physical health disparities has only received attention within the past 10 years.

Environmental research has demonstrated the impact of a number of community attributes on mental health. High rates of poverty in an area are associated with higher rates of depression and schizophrenia (Silver, Mulvey, & Swanson, 2002; van Os, Driessen, Gunther, & Delespaul, 2000). Poorer housing stock and construction are

associated with a higher prevalence of depression in urban areas (Weich, Twigg, Holt, Lewis & Jones, 2003). On the other hand, an older adult population in the residential neighborhood has been linked to better mental health outcomes among the elderly (Kubzansky et al., 2005).

Multilevel statistical modeling of mental health disparities has been used to assess the impact of community conditions net of individual attributes. Although rates of depression, schizophrenia, and substance abuse vary across communities, the impact of community conditions declines significantly when individual characteristics are taken into account (e.g., Truong & Ma, 2006). Net of individual predictors, rates of residential mobility and material deprivation in the residential community persist as significant predictors of depression in the adult population (Matheson et al., 2006; Silver, et al., 2002). Community attributes such as poverty rate have been shown to explain variation in depressive symptoms among older Mexican Americans (Ostir, Eschbach, Markides, & Goodwin, 2003). Hybels and colleagues (2006) found no effect of neighborhood on depression among older adults when individual characteristics are controlled statistically. On the other hand, Kubzansky and colleagues (2005) found that, among the elderly, neighborhood poverty was positively associated with higher rates of depression, and the concentration of elderly with lower rates. Twenty-seven of the 29 studies that Truong and Ma (2006) reviewed found a significant association between neighborhood attributes and mental health outcomes net of individual attributes. There is, therefore, some evidence of a relationship between community context, depression, and well-being, although previous research has not provided an explanation of the pathways by which contextual factors impact mental health.

Community Context and Health Disparities Model

In studies of the relationship between community conditions and mental health disparities, researchers have used a variety of conditions including resident characteristics (Matheson et al., 2006; Silver, et al., 2002), resident ratings of the community social conditions (Cagney & Browning, 2004), and measures of the built structures (Weich et al., 2003 to measure community context. Although these studies suggest community attributes that may impact mental health, theoretically-based research is needed in order to help identify the specific pathways by which these conditions directly lead to mental health outcomes, explain higher rates of mental health problems among racial and ethnic minorities, and take into account for multiple co-existing community conditions (Kubzansky, et al., 2006). Building on previous theoretical frameworks (Northridge, Sclar, & Biswas, 2003; Schulz & Northridge, 2004; Schulz, Williams, Israel, & Lempert, 2002; Williams & Collins, 2001), a *Community Context and Health Disparities Model* was developed (Figure 1; p. 16).

The model proposes that characteristics of the residential community, which includes the physical, built, social, economic, and healthcare environments, have a direct effect on physical and mental health outcomes and indirectly impact these outcomes through their effect on individual behaviors and characteristics. The physical environment includes the role of the climate and air and water toxins. Physical environment attributes such as exposure to daylight, have been linked to mental health outcomes such as seasonal affective disorder, which is characterized by depression and fatigue (Rosenthal et al., 1984). The built environment includes the conditions of structures and transportation systems, as well as services and stores. Commercially zoned

areas and building deterioration are associated with depression and low life satisfaction (Chapman & Beaudet, 1983; Galea, Ahern, Rudenstine, Wallace, & Vlahov., 2005).

Aspects of the social environment, such as civic and religious organizations and characteristics of neighborhood residents, have been associated with depression and health (Franzini, Caughy, Spears, & Esquer, 2005; Wen, Browning, & Cagney, 2003) and may buffer individuals from more harmful aspects of the environment (LaVeist, 1993; Rich, Edelstein, Hallman, & Wandersman, 1995). Among older adults, high rates of residential mobility have been associated with increased depressive symptoms (Matheson et al., 2006). Studies have consistently shown that there are higher rates of depression and psychiatric disorders in poorer urban communities (Brown et al., 1977; Ostir et al., 2003; Ostler et al., 2001) and higher levels of well-being in neighborhoods where more people have adequate personal resources (Schwirian & Schwirian, 1993), two characteristics of the economic environment. In addition, residents of communities with lower unemployment rates have a lower risk for depression (Zimmerman & Bell, 2006). The availability, accessibility, and quality of healthcare, particularly from primary care physicians will impact mental health disorder diagnosis and treatment because they are usually the first source of help for depression and anxiety problems (Gorn, Icaza, & Cantu, 2003), although the availability of mental health services, which are inadequate in most communities (US DHHS, 1999), will affect treatment, prognosis, and outcomes.

In the *Community Context and Health Disparities Model*, individual demographics, socioeconomic status, health behaviors, social support, and stress, often employed as control measures in studies of community context, are influenced by the community context and have both direct and indirect effects on mental health. There is

empirical support for this proposition. For example, Matheson and colleagues (2006) showed that socioeconomic status is associated with aspects of mental health. Longer tenure in a neighborhood has been associated with greater levels of support (Schulz et al., 2006) and social support is positively associated with lower rates of depression and mortality (Berkman & Glass, 2000; Kawachi & Berkman, 2001; Leskela et al., 2006). Poorer or unemployed individuals may be more affected by community conditions than those who have more economic resources (Fone & Dunstan, 2006; Weich et al., 2003). High levels of social support, including that provided by neighbors, buffer against the harmful effects of community conditions (Cassel, 1976).

These conditions may affect older adults in particular because they usually have lived in the community for a longer time, have a greater need for services, and spend less time at work and hence more time in the residential community than younger adults (Robert & Lee, 2002; Robert & Li, 2001). They are also at increased risk of losing a spouse and face shrinking social networks (Krause, 1988; US DHHS, 1999). Experiencing a number of stressful life events, which include death of a spouse, change in financial status, or loss of a job is associated with worse physical and mental health outcomes (Holmes & Masuda, 1974; Leskela et al., 2006).

Research Questions

The goal of this research was to evaluate the impact of conditions of the community context on the mental health of older adults using the *Community Context and Health Disparities Model*. Specifically, we sought to determine:

1. Are there significant differences in depressive symptoms across communities?

2. What are the direct relationships between community conditions and depressive symptoms?
3. To what extent are differences in depressive symptoms across communities due to differences in the characteristics of the individuals within these communities?
4. What are the effects of community conditions net of individual factors on depressive symptoms?

We conducted secondary data analysis using hierarchical linear modeling (HLM) to examine the effect of community context, net of individual context, on depressive symptoms, measured by the 10-item version of the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977). Each question corresponds to one step in the HLM procedure.

Method

Sample

The Survey of Older Floridians (SOF) received approval from the Institutional Review Board of the University of South Florida on 3/19/2004 (IRB # 102334G).

Communities

Previous research has grouped individuals into communities based on county (Fiscella & Franks, 1997), U.S. Census tract (Franzini & Spears, 2003; LeClere, et al., 1997; Robert 1998), U.S. Census block group (Franzini & Spears, 2003), and defined communities (Davey Smith, et al., 1998; Feldman & Steptoe, 2004; Reijneveld & Schene, 1998; Ross, 2000). The smaller geographic units are generally more homogeneous, and both individual and community variability increases as the geographic

unit increases in size, making it more difficult to accurately assess the effects of community context. This difficulty is the modifiable area unit problem (Waller & Gotway, 2004). As an example, Franzini and Spears (2003) found that four percent of the variance in heart disease mortality was accounted for by variation at the Census tract level, but county-level variation contributed less than one half of a percent.

In this study, we defined “communities” using a combination of U.S. Census “Places” in Miami-Dade County and Neighborhood Enhancement Team (NET) boundaries within the City of Miami. The U.S. Census “Places” include incorporated areas, consolidated cities, and Census-designated places (CDP). CDPs are the “statistical counterparts of incorporated places” created by the U.S. Census “for concentrations of population, housing, and commercial structures that are identifiable by name but are not within an incorporated place” (U.S. Census, 2001).

The city of Miami, while defined by the U.S. Census as a single “place” is very diverse and contains a number of neighborhoods, as well as 141 of the 733 Miami-Dade participants in the SOF. The remainder lived in the other parts of Miami-Dade County and place names came from the U.S. Census. Within the city of Miami, we obtained the geographical boundaries of Neighborhood Enhancement Team (NET) areas within the city. These areas, designed to link community residents to the city government, were designated based on established neighborhoods in Miami (City of Miami, 2004). Because the NET area communities did not coincide with U.S. Census entities, we assigned Census block group identifiers to each community based on their centroid location. Community measures were calculated by aggregating the data for all of the block groups within that community. This process resulted in the creation of 38 communities that

included both urban (including city of Miami) and suburban areas in Miami-Dade County. We were able to use 36 of these 38 communities in the current study.

Individuals

The Survey of Older Floridians (SOF) was a telephone survey designed to assess the health and healthcare needs of four populations of interest: older Floridians in general, and specifically older African Americans, Cubans, and other Hispanics. Participants in the state-representative sample were contacted by random-digit dialing. A stratified sampling procedure was applied to subsequent sampling frames. We sorted telephone exchanges by the proportions of older African Americans, Cubans, and other Hispanics to increase the productivity of random digit dialing and created a sample of all the exchanges needed to get coverage of approximately 70 percent of these populations. Phone numbers in the exchanges were called in this order until each sample had reached the desired sample size. Adults over the age of 65 in these target groups were interviewed regardless of the sampling frame. A supplemental sample of 122 whites living in the same communities as the minority oversamples was also interviewed to examine the effects of the summer 2004 hurricanes that hit Florida approximately three months prior to the oversample data collection phase. The statewide participants are therefore a random sample of the entire state, whereas the oversample participants are a sample of adults drawn from telephone exchanges with high proportions of older minorities. Conducted in 2004-2005, the final sample included telephone interviews with 1,433 white, African American, Cuban, and other Hispanic older adults. Response rates ranged from 55 percent to 62 percent, with the lowest rates for the minority oversamples and the

highest rates for the statewide survey (Zayac et al., 2005). Although the data were weighted for epidemiological reporting, the data were unweighted for these analyses.

For this study, we selected a subset of those SOF participants whose residences were geocoded using Geographical Information Systems (GIS) techniques. Of the 1,433 participants in the SOF, 1,412 (98.5%) were successfully geocoded. Participants who could not be geocoded did not significantly differ from the rest of the sample in terms of age, gender, race, ethnicity, or self-rated health. Consistent with the distribution of the actual population of older minorities in Florida, most (N=733; 51.9%) of the participants resided in communities in Miami-Dade County. The geographic distribution of participants elsewhere in the state limited our ability to designate community clusters outside of Miami-Dade County. That is, 48 percent of the SOF participants were scattered through the remaining 66 counties.

Measures

Community Measures

Community measures were chosen based on availability, heterogeneity within Miami-Dade County, and relevance. For example, the climate is homogeneous throughout the county so it was not possible to test the effect of this community attribute with this sample. The *Community Context and Health Disparities Model* suggests multiple measures for each domain. In order to minimize multicollinearity, we followed the recommendation of Bryk and Raudenbush (1992), who suggested fitting separate sub-models with predictors from each of the neighborhood domains (e.g., physical, built, social, economic, and healthcare) and retaining the strongest predictor from each sub-model in the main model. Data sources and the measures employed for each of the five

domains are described next. The correlations between the variables used to measure each domain are displayed in Table 16.

Physical environment. One measure of the physical environment was the presence of toxins, assessed using the Toxics Release Inventory (TRI), which includes the geographical locations of releases of over 300 toxins to air, water, and land by the manufacturing industry. These locations are released by the Environmental Protection Agency (EPA) per a mandate by the 1986 Section 313 of the Emergency Planning and Community Right-to-Know Act (EPCRA). Certain industries must report their waste emissions if they use more one or more of 650 specified toxic chemicals (U.S. EPA, 2004). Higher densities of TRI sites have been associated with asthma among children (Maantay, 2007) and could potentially affect the health of older adults.

Because the influence of toxins is likely to cross community boundaries, we used kernel density estimation to measure TRI exposures. First, the 2006 locations of these sites were geocoded to a point shapefile. There were 51 TRI locations in Miami-Dade County. We next converted Miami-Dade County into a grid of equally-sized cells 100 feet by 100 feet. We then created a kernel density estimation using the Spatial Analyst tool in ArcGis 9.2, which created a surface of toxin intensity. The kernel density estimation provided a distance-weighted count of toxins where the influence of each of the TRI sites was inversely weighted by the distance away from the center of the cell and followed the quartic approximation to a Gaussian kernel function (see Chapter 3). In other words, this estimate accounted for the fact that people will be less exposed to toxins sites that are further away. Values were scaled by a factor of 27,878,400 (or 5280^2) and then by a factor of 1000 to make values comparable to other variables in the model. The

TRI value for each community was obtained by averaging the values in each cell in the community ($M = 2.04$; $SD=3.36$). These values represent an intensity of TRI sites within the community, with a large TRI score indicating a higher likelihood of exposure to toxins within a community

Built environment. Many aspects of the built environment, including attributes of the buildings, transportation systems and roads, services and stores in the community have been linked to health outcomes. We limited our measure of the built environment to the proportion of supermarkets that were major chain retailers because previous research has shown that the availability and type of food stores in one's residential neighborhood influence diet, and these retailers are more likely to be sources of fresh fruit and vegetables (Morland et al., 2002). Data on the locations of these stores came from the GeoPlan Center at the University of Florida that provides geographic datasets and shapefiles for the state of Florida, available through the Florida Geographic Data Library (Florida Geographic Data Library [FGDL], 2003). The original shapefile, created from a 2003 online telephone directory search, included supermarkets, grocery stores, and shopping centers, which were geocoded based on address. We limited our analyses to stores categorized as "supermarkets" and identified major supermarket chain retailers (e.g., Publix, Winn Dixie). Of the 306 supermarkets in Miami-Dade County, 85 (27.7%) were major chain retailers. In the communities in this study, an average of 36.66 percent of the supermarkets were major chain retailers ($SD=36.08$).

Social environment. The U.S. Census (2000) provided data on the characteristics of the residents within each community as measures of the social composition, including racial, ethnic, and age composition, proportion of households headed by females and

owner occupied, and housing tenure. These measures were highly correlated so the proportion of households that were owner-occupied was employed as the measure of social environment ($M=56.74\%$; $SD=18.34$).

Economic environment. The proportion of residents living below the federal poverty level in 2000 was calculated from U.S. Census (2000) data ($M=17.28\%$; $SD=10.06$). Other relevant data on employment and educational systems were available only at the county level and not used here.

Healthcare environment. The distance to the nearest hospital via the network of major roads was used to measure of healthcare accessibility (Chapter 3). Hospital addresses were obtained from the Florida Agency for Health Care Administration's database of licensed hospitals (FL AHCA, 2006). Only facilities with an emergency department were included. A network analysis along major roads in Florida was used to calculate the distance from each block group center to the nearest hospital along these roads ($M=2.99\text{mi}$; $SD=1.36\text{mi}$). For a more thorough explanation of this methodology, see Chapter 3.

Table 16. Correlations between community (level 2) predictors

	1	2.	3.	4.
1. TRI Score				
2. Proportion Chain Supermarkets	-0.042			
3. Owner-occupied Housing Units	-0.047	0.456**		
4. Poverty Rate	-0.033	-0.558***	-.713***	
5. Hospital Distance	0.075	0.119	.320	-.374*

N=36

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

Individual Measures

Demographics, socioeconomic status, health behaviors, social support, and stress were used as independent and potential mediator variables in the analyses to answer the

research questions. In order to minimize multicollinearity, we examined the correlation between variables in each domain at the community and individual level and removed variables which were highly ($r > 0.50$) correlated within a domain (Table 17). The dependent variable was CES-D score.

Demographics. Age, gender, and race or ethnicity were used to measure demographic characteristics. Age was a continuous variable and gender was coded Male = 0 and Female = 1. Although participants in the SOF were enrolled as white, African-American, Cuban, or Non-Cuban Hispanic, we combined the two Hispanic groups and created two dummy variables: Black vs. all others and Hispanic vs. all others, with whites as the reference group.

Socioeconomic status. Education was categorized as less than high school (1), high school degree (2), or more than high school (3). Yearly household income was recoded into six groups from less than \$10,000 (1) to more than \$50,000 (6).

Health behaviors. There were five independent variables for health behaviors: exercise, smoking patterns, alcohol consumption, having a personal doctor, and having sufficient food. Physical exercise was assessed by asking respondents whether they took part in at least one hour of aerobic exercise a week (No=0, Yes=1). Participants identified whether they were a current smoker (0), former smoker (1), or had never smoked (2). Alcohol consumption was a dichotomous variable, coded as drinker (1 or more drinks per day = 0) or non-drinker (fewer than 1 drink per day = 1). Participants identified if they have a personal doctor (No=0; Yes=1) and how frequently they had sufficient food (Always=2; Sometimes=1; Never=0).

Social support. Marital status was dichotomized (Not Married=0; Married=1). Participants indicated how often they could count on friends and family in times of need (Never=0; Most or some of the time=1; Always=2). Finally, we asked participants how long they had lived in their home, a continuous measure aimed at assessing the potential for social support from neighbors.

Stress. In the *Community Context and Health Disparities Model* we focus on the individual's subjective perception of the community as stressful. We asked participants to rate the safety of their neighborhood (0=Poor; 1=Fair; 2=Good; 3=Very Good; 4=Excellent).

Dependent Variable

The dependent variable was depressive symptoms, as measured with the 10-item version of the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977). The instrument asks how often 8 negatively stated symptoms and 2 positively stated symptoms were experienced during the past week. The items include loneliness, feelings of fearfulness, and restless sleep and responses were coded on a 4 point scale (0= Rarely or Never, 1= Some of the time, 2= Moderate amount of the time, 3=Most of the time) and summed. A score of 10 or higher on the short form of the CES-D is generally indicative of depression.

Table 17. Correlation between individual (level 1) predictors and CES-D score.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. CES-D score	-03													
2. Age	21 ***	07												
3. Female	-05	-04	06											
4. Black	09	-05	-05	-72 ***										
5. Hispanic	-32 ***	-17 **	-28 ***	05	-22 ***									
6. Income	-16 **	-16 **	-12 **	-16 **	-00	33 ***								
7. Education	-18 ***	-09	01	04	-09	14 *	02							
8. Exercise	-24 ***	-05	06	-06	00	13 *	07	18 ***						
9. Enough food	-03	-07	02	-04	01	08	09	09	10 *					
1 Regular doctor	-02	04	-14 **	-06	-09	12 *	11 *	10	06	05				
11. Drinker	03	02	19 ***	-06	12 *	-00	-08	05	00	03	-06			
12. Smoker	-15 **	-10 *	-41 ***	-11 *	12 *	31 ***	11 *	-02	02	03	03	01		
13. Married	-28 ***	05	-01	08	-09	18 **	-02	11 *	16 **	10	02	-02	10	
14. Count on family	-26 ***	05	-08	-10	-03	16 **	12 *	10 *	13 *	10 *	11 *	01	09	17 ***
15. Safety														

Notes: N=374; Pearson's r is a decimal. * $p < .05$, ** $p < .01$, *** $p < .001$

CES-D scores are calculated by summing responses to each question, with the positively stated symptoms reverse coded. In the original SOF dataset, 19.8 percent participants were missing at least one response to a CES-D item. In the subsample used in these analyses, 21.8 percent of participants were missing at least one CES-D response. There were no systematic differences in terms of age, race, ethnicity, gender, education, or income between participants who answered all CES-D items and those who did not. We therefore limited our analyses to participants with complete CES-D data (N=374). The average CES-D score was 7.45 (SD=6.70) and Cronbach's alpha for the ten CES-D items was 0.819.

Statistical Analyses

This study tests the *Community Context and Health Disparities Model*, in particular, the hypothesis that differential mental health outcomes, particularly depressive symptoms, are attributable to characteristics of the residential community rather than to race or ethnicity. There are two levels of data: individuals (level 1) nested in communities (level 2), with predictors at both levels which must be analyzed together in order to understand their independent, additive, and interactive effects.

One way the effects of community context have been examined is using ordinary least squares (OLS) regression with community-level predictors from exogenous data sources. But, including individuals nested within communities in ordinary least squares (OLS) regression violates the assumption of independent errors (Steenbergen & Jones, 2002) because these individuals will be more similar than individuals in other communities. Such an error would lead to an underestimation of standard errors and increased probability of Type I errors (Hox, 1995; Pedhazur, 1997). In addition, it is not

possible to study the cross-level interaction of community and individual attributes with OLS regression (Hox, 1995; Stoker & Bowers, 2002). In OLS there is no way to account for the similarity in variance among individuals in the same community, differences between individuals within communities, and the effects of individual characteristics cannot vary across communities. The impact of individual-level variables is “fixed” (Jones & Duncan, 1995), that is, there is one specified relationship between each predictor and the outcome for all individual in all communities. Residual differences between individuals are summarized by a single error term.

Hierarchical linear modeling (HLM; Stoker & Bowers, 2002), addresses these issues, taking into account the nested structure of the data which leads to similarities between individuals within communities. HLM models simultaneously include both individual- and community-predictors, can assess the interactions between predictors within and across levels, and partition the variance and covariance to individual and neighborhood levels (Bryk & Raudenbush, 1992; Diez-Roux, 2000; Hox, 1995; Stoker & Bowers, 2002). HLM allows us to model variance between individuals and between communities as random, representing only a sample of the possible relationships between the predictors and outcomes, drawn from all the possible combinations of individuals and communities. The outcome for each community is then an overall rate for all individuals in each plus a “random” difference that is allowed to vary between each community. It is then possible to specify individual characteristics and examine the extent to which similarities between individuals within a community are associated with the same outcome (Jones & Duncan, 1995).

Within HLM, there are a number of specifications for each model that must be made. First, differences between communities can be modeled as fixed or random effects. A fixed effects model is appropriate when highlighting the impact of a particular set of distinct communities on health outcomes, and when the number of communities is small. For example, this would be appropriate for comparing distinctive four distinctive areas such as Boston, the Southwestern U.S., North Carolina, and Iowa, as was the case for the Established Populations for the Epidemiological Study of the Elderly (EPESE) studies (Cornoni-Huntley et al., 1993). Our analyses are based on a relatively large number of communities (N=36) and focus on the impact of community (level-2) predictors on health outcomes, rather than the impact of specific communities. That is, how do the physical, built, and other community attributes predict individual health outcomes across communities, rather than how the unique attributes of specific neighborhoods lead to these outcomes. The presence of a particular predictor in several communities is expected to impact the individuals across communities in the same way to predict depressive symptoms. Therefore, we used random effects HLM models.

A random effects HLM model is appropriate when making generalizations about communities beyond those included in the study. In essence, the communities are considered as a random sample of the population of all possible communities. HLM essentially calculates a regression equation for each community (Pedhazur, 1997). Error variance is assumed to be constant between individuals within neighborhoods, but to vary randomly across communities (Ewart & Sunchday, 2002). This error variance may lead to differences in the mean values between groups (intercepts), as well as differing relationships between predictors and outcomes (slopes) across communities. As a result,

the regression coefficients are expected to vary and are interpreted as random effects when sampled from the normally-distributed population of communities (Hox, 1995). In other words, the means (intercepts) and relationships between level 1 predictors and the outcome measure (slopes) are allowed to vary randomly across groups. These are thus random coefficients. Both level 1 and level 2 predictors can also be used as fixed coefficients. The inclusion of both types of coefficients, random and fixed, is why these are also called “mixed” models.

HLM is commonly used for random slopes model, in which the relationship between individual-level predictors and depressive symptoms is allowed to vary across communities. Although we allowed the slopes to vary across communities for each individual-level predictor, there were no significant differences in the relationship between these predictors across communities. Instead, we report the independent and net effects of community conditions on mean depressive symptoms (the intercept or constant). All results are therefore from random intercept models with fixed community-level predictors and fixed individual-level predictors, with the latter having the same effect on depressive symptoms across communities (Yen & Kaplan, 1999).

Finally, although HLM can incorporate weighted data and SOF data were weighted for other analyses (Zayac et al. 2005), we are not using weights because the participants within the 36 selected communities were chosen solely because of their convenience within the dataset. Neither the communities nor the participants were selected with these analyses or HLM in mind, which would require randomly selecting individuals within randomly selected communities. Instead we selected communities and participants with the methods described earlier (see Sample).

All hierarchical linear models were run using the PROC MIXED procedure (Singer, 1998) in the SAS statistical software package (SAS, 9.1, 2004). Predictors of each of the five community domains and the individual-level domains suggested by the *Community Context and Health Disparities Model* were added in successive steps. Each model includes a constant (intercept), the random effects (variance) between individuals within communities (level 1) and between communities (level 2), as well as the fixed effects of the level 1 and level 2 predictors. HLM does not produce an R^2 value indicating the proportion of the variance in the dependent measure that is explained by the predictors. Instead, we use reductions in variance, which indicates the proportion of the variance explained by the added predictors, an indicator which is analogous to R^2 values (Snijders & Bosker, 1994). We calculated the proportion of the variance estimates reduced from the initial, unspecified model (Model 1). Cases where unexplained variance increased from the initial model were indicated by a negative value. Improvement of model fit was assessed with the addition of each set of predictors by examining the change in the -2 REML Log Likelihood from the initial model, with negative values indicating a better fit from the previous model (Hox, 1995). The change in the -2 REML Log Likelihood was evaluated with a Wald statistic. This statistic compares the change in the -2 REML Log Likelihood to a chi-square distribution where the degrees of freedom are the number of predictors

To answer research question 1 (Model 1), a random-effects analysis of variance (RANOVA), an HLM model with no predictors, was used to determine whether there were differences in depressive symptoms across the communities without accounting for community or individual characteristics (Oakes, 2004; Raudenbush & Bryk, 2002). The

constant (or intercept) produced by this analysis is the average CES-D score across communities. Statistical significance of between-community variance would show that there were differences in depressive symptoms between communities. The significance of between-individual variance indicates there are differences between individuals within communities. The relative size of these estimates would indicate what proportion of the variance is due to individual and community characteristics. Non-significant differences would mean that the variance between communities or individuals has been accounted for by the predictors to be added in subsequent models. We also examine the intraclass correlation, or the correlation between CES-D score among participants in the same community.

To answer research question 2 (Model 2), community-level variables for each of the five domains (physical, built, social, economic, and healthcare environments, Figure 1; p. 16) were added to Model 1 sequentially, starting with the physical environment and ending with the healthcare environment, as predictors of CES-D score for individuals nested within each community. This step tests the hypothesized direct relationship between community contextual variables on depressive symptoms (Figure 1; p. 16). With the addition of each variable, the significance of the fixed effect indicates the strength of that characteristic as a predictor of depressive symptoms. The extent of decrease in between-community variance from Model 1 indicates the proportion of the variation between communities that can be accounted for by the addition of each domain.

Research question 3 (Model 3) adjusts for selection bias, or the possibility that individual characteristics of participants do not vary randomly within communities (Oakes, 2004). CES-D score was regressed on individual demographic, socioeconomic

status, health behavior, social support, and stress variables. These variables were entered sequentially in the order proposed by the theoretical framework, and non-significant measures were eliminated. Particular attention was paid to the between communities variance estimates. If this parameter were to become non-significant with the inclusion of individual-level predictors, it would indicate that between-community differences in CES-D score were entirely attributable to differences in individual characteristics and not community differences.

To answer research question 4 (Model 4), significant community- and individual-level variables were used to predict depressive symptoms. The change in the significance of community-level predictors from the previous analyses indicated whether the community effect was mediated by individual-level variables. By comparing the decrease in the between-community variance estimate in this step to that in Model 3 we assess what additional proportion of the variation in CES-D score between communities is accounted for by community context rather than individual characteristics.

All of the variables in Table 16 and Table 17 were entered into the model. Only those which were significant were retained in these results.

Results

Characteristics of Communities and Individuals

Community Characteristics

The average TRI score was 2.04 ($SD=3.36$; Table 18). On average, 36.66 percent of the supermarkets in each community were major retailers, but there was great variability ($SD=36.08$). The average owner-occupancy rate was 56.74% ($SD=18.34$) and

the average poverty rate was just over 17 percent ($SD=10.06$). Finally, the nearest hospital was 2.99 miles, on average, from the community ($SD=1.36$ miles).

Table 18. Community (Level 2) Characteristics

	% or Mean	Std. Deviation
TRI Score	2.04	3.36
Proportion Chain Supermarkets	36.66	36.08
Owner-occupied Housing Units	56.74	18.34
Poverty Rate	17.28	10.06
Hospital Distance	2.99	1.36
N=36 communities		

Individual Characteristics

The final sample included 374 participants. The average participant age was 72.1 years old (Table 19). The sample was primarily female (62.0%) and Hispanic (72.5%). Just over a quarter (25.7%) had less than a grade school education, 28.9 percent had completed high school, and 45.4 percent had more than a high school education. More than 36 percent of the participants had a yearly household income of less than \$10,000, but 11.3 percent earned more than \$50,000 per year. Most of the sample (68.4%) got at least an hour of aerobic exercise per week, always had enough of the food they wanted (89.3%) and had a regular doctor (84.0%). Few participants were drinkers (14.4%) or current smokers (8.6%). Less than half of the sample was married (44.9%), but almost 80 percent of respondents said they could always count on family and friends in times of need. The majority of respondents felt their neighborhood safety was excellent (28.3%), very good (20.3%), or good (34.7). The mean score on the CES-D was 7.5 ($SD=6.7$).

Table 19. Individual (Level 1) Characteristics

	% or Mean	Std. Deviation
Age	72.1	7.3
Females	62.0%	
<u>Race or ethnicity (ref=White)</u>		
Black	16.3%	
Hispanic	72.5%	
<u>Education</u>		
Grade School	25.7%	
High School	28.9%	
More than High School	45.4%	
<u>Income</u>		
Less than \$10,000	36.8%	
\$10,000-\$20,000	26.1%	
\$20,000-\$30,000	16.7%	
\$30,000-\$40,000	7.0%	
\$40,000-\$50,000	2.1%	
More than \$50,000	11.3%	
Exercise 1 hour per week	68.4%	
<u>Enough Food</u>		
Always	89.3%	
Sometimes	8.8%	
Never	1.9%	
Regular Doctor	84.0%	
Drinker	14.4%	
<u>Smoker</u>		
Never	55.5%	
Former	35.8%	
Current	8.6%	
Married	44.9%	
<u>Able to Count on Family</u>		
Always	79.4%	
Sometimes	12.0%	
Never	8.6%	
Neighborhood Safety		
Excellent	28.3%	
Very Good	20.3%	
Good	34.7%	
Fair	13.9%	
Poor	2.7%	
CES-D score	7.5	6.7
N=374		

Research Question 1

The average CES-D score across the communities was 6.882 (Table 20). The variance between communities ($\beta=1.910$) was not statistically significant, and the variability between individuals within communities ($\beta=41.414$) was almost 22 times greater. The intra-class correlation, ρ , was 4.41 percent (not displayed).

Table 20. CES-D score between communities (Model 1)

Fixed Effects		
	β	
(Constant)	6.882	***
Random Effects		
	σ^2	
Between-individuals variance	41.414	***
Between-community variance	1.910	
-2 REML Log Likelihood	2469.0	
N=374 participants in 36 communities		
* $p<.05$, ** $p<.01$, *** $p<.001$		

Research Question 2

Table 21 displays Model 1 and the results of Model 2 with the addition of each level-2 predictor so that the change in between-community variance and model fit (-2 REML Log Likelihood) can be assessed. The TRI score was not a significant predictor of depressive symptoms ($\beta=0.109$), although this variable accounted for 8.22 percent of the variance between communities. The inclusion of this measure did not improve model fit, however.

The proportion of supermarkets that were chain retailers also did not significantly predict CES-D score ($\beta=0.012$). This measure both increased between-community variance by 8.22 percent and worsened model fit.

The proportion of housing units that are owner-occupied ($\beta=-0.058$, $p<0.05$) significantly predicted CES-D score, with a decrease in depressive symptoms as owner-occupancy rates increased. In addition to the measures of the physical and built environment, this measure predicted 12.04 percent of the variance in CES-D score between communities, but model fit was not improved from Model 1.

When poverty rate was added to the model, owner-occupancy rate was no longer a significant predictor ($\beta=-0.041$) perhaps because these two measures were so highly correlated ($r=-0.713$; Table 18). Poverty rate did not significantly predict depressive symptoms ($\beta=0.053$) and slightly worsened model fit. Even when aspects of the physical, built, social, and economic environments were included in the model, just under seven percent of the between community variance was explained.

Finally, when distance to the nearest hospital was added it was not a significant predictor ($\beta=-0.677$). However, the proportion of grocery stores that were major chain supermarkets became statistically significant ($\beta=0.034$, $p<0.05$) and 47.43 percent of the between-community unexplained variance was explained. Model fit was not improved.

Table 21. Community characteristics and CES-D score (Model 2)

	Model 1			Physical	Built	Social	Economic	Healthcare									
Fixed Effects																	
(Constant)	β	6.882	***	B	6.660	***	β	6.107	***	B	8.707	*	β	8.271	*		
<i>Community Predictors</i>																	
TRI score				0.109				0.145			0.143			0.105		0.136	
Proportion chain supermarkets								0.012			0.027			0.031		0.034	*
Owner-occupied housing units											-0.058	*		-0.041		-0.032	
Poverty rate														0.053		0.036	
Hospital distance																-0.677	
Random Effects																	
	σ^2			σ^2				σ^2			σ^2			σ^2		σ^2	
Between-individuals variance	41.414	***		41.526	***			41.374	**		41.451	*		41.157	***	41.326	*
Between-community variance	1.910			1.753				2.067			1.680			1.777		1.004	
Percent change ¹				8.22%				-8.22%			12.04%			6.96%		47.43%	
-2 REML Log Likelihood	2465.9			2467.5				2473.5			2474.1			2476.9		2473.7	
Change from Model 1				1.6				7.6			8.2			11.0		7.8	

¹Change in between-community variance from Model 1.

N=374 in 36 communities

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

Research Question 3

In Model 3 (Table 22), we examined the effect of individual, or level-1 predictors, on depressive symptoms by adding groups of variables hierarchically as proposed by the model (demographics, socioeconomic status, health behaviors, social support, stress) and comparing the changes in the variance estimates and model fit to Model 1. Being female was associated with an increase in depressive symptoms ($\beta=2.914$, $p<0.01$), while being Black or Hispanic was unrelated. These factors explained 13.51 percent of the between-community variance and the inclusion of these demographic characteristics significantly improved model fit.

Almost 40 percent of the between-community variance was accounted for by demographic characteristics and education, and the latter significantly predicted CES-D score ($\beta=-1.005$; $p<0.05$). Increased education was associated with fewer depressive symptoms. Model fit from Model 1 was also significantly improved when these factors were taken into account statistically.

Two health behaviors, getting at least one hour of exercise ($\beta=-1.216$, $p<0.01$) and having enough food ($\beta=-3.590$, $p<0.001$), significantly predicted CES-D score. A total of 60.26 percent of the between community variation in depressive symptoms was attributable to demographic, socioeconomic, and health behavior characteristics of the study participants.

Table 22. Individual characteristics and CES-D score (Model 3)

	Model 1	Demographics		Socioeconomic Status		Health Behaviors		Social Support		Stress
Fixed Effects	β	β	β	β	β	B	B	β	β	β
(Constant)	6.882	**	3.902	**	5.614	***	13.373	***	16.651	***
<i>Individual Predictors</i>										
Female		*	2.914	***	2.742	***	2.945	***	2.949	***
<u>Race or ethnicity (ref=Whites)</u>										
Black			0.329		-0.254		-0.747		-0.358	
Hispanic			1.659		1.312		0.835		0.748	
Education					-1.005	*	-0.905	*	-0.960	*
Exercise							-1.216	**	-1.061	**
Enough Food							-3.590	***	-2.939	***
Able to Count on Family									-2.641	***
Neighborhood Safety									-2.392	***
Random Effects	σ^2	σ^2	σ^2	σ^2	σ^2	σ^2	σ^2	σ^2	σ^2	σ^2
Between-individuals variance	41.414	**	39.550	***	39.344	***	36.597	***	34.327	***
Between-community variance	1.910	*	1.652		1.173		0.759		0.492	
Percent change ¹			13.51%		38.59%		60.26%		74.24%	
-2 REML Log Likelihood	2465.9		2439.9		2434.1		2401.6		2374.9	
Change from Model 1			-26.0	***	-31.8	***	-64.3	***	-91.0	***

¹Change in between-community variance from Model 1.

N=374 in 36 communities

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

Being able to count on one's family was also a statistically significant predictor ($\beta=-2.641$, $p<0.001$) and was associated with fewer depressive symptoms. Adding this variable statistically improved model fit and almost three-quarters of the between-community variance was explained by demographic, health behavior, and social support characteristics of the study participants.

Finally, participant assessment of neighborhood safety significantly predicted depression ($\beta=-0.882$, $p<0.001$), with fewer depressive symptoms as neighborhood safety increased. With all of the individual-level predictors entered in the model, 83.19 percent of the between-community variance was explained. In other words, the majority of the differences between communities on depressive symptoms was due to differences in individual characteristics; just over 17 percent of the between-community variance remained to be explained by community-level predictors or unexplained by individual characteristics.

Research Question 4

In Model 4 (Table 23, last two columns) both owner-occupancy rate and proportion chain supermarkets were added as community-level predictor because these variables had statistically significant associations with depressive symptoms in Model 2 (Table 21). Neither the proportion of chain supermarkets ($\beta=0.007$) nor owner occupancy rate ($\beta=-0.007$) significantly predicted CES-D score when individual characteristics were controlled statistically. The inclusion of these level-2 variables also did not explain any additional variance between communities on CES-D score and model fit was not as good with the inclusion of these measures.

Table 23. Community conditions net of individual factors on CES-D score (Model 4).

	Model 1		From Model 3		Model 4 Built		Social	
Fixed Effects	β		β		β		β	
(Constant)	6.882	***	18.510	***	18.139	***	18.812	***
<i>Individual Predictors</i>								
Female			2.806	***	2.805	***	2.800	***
<u>Race or ethnicity (ref=Whites)</u>								
Black			-0.929		-0.650		-0.988	
Hispanic			0.356		0.407		0.307	
Education			-0.890	*	-0.910	*	-0.876	*
Exercise			-0.992	*	-0.984	*	-0.985	*
Enough Food			-2.758	***	-2.743	***	-2.749	***
Able to Count on Family			-2.392	***	-2.408	***	-2.385	***
Neighborhood Safety			-0.882	***	-0.875	**	-0.864	**
<i>Community Predictors</i>								
Proportion chain supermarkets					0.007			
Owner-occupied housing units							-0.007	
Random Effects	σ^2		σ^2		σ^2		σ^2	
Between-individuals variance	41.414	***	33.658	***	33.595	***	33.688	
Between-community variance	1.910		0.321		0.476		0.385	
Percent change ¹			83.19%		75.08%		79.84%	
-2 REML Log Likelihood	2465.9		2366		2372.7		2372	
Change from Model 1			-99.9	***	-93.2	***	-93.9	***

¹Change in between-community variance from Model 1.

N=374 in 36 communities

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

Discussion

The goal of this research was to test the influence of community attributes on well-being as proposed by the *Community Context and Health Disparities Model* (Figure 1; p. 16). This theoretical framework posits that characteristics of the community, including the physical, built, social, economic, and healthcare environments directly influence mental health outcomes and are mediated by individual demographic

characteristics, socioeconomic status, health behaviors, social support, and stress. The model was tested using individual-level data from participants in the Survey of Older Floridians living in communities within Miami-Dade County, which were linked to contextual measures from outside sources through Geographic Information Systems.

Adequacy of the Community Context and Health Disparities Model

A better understanding of these results may be facilitated by reviewing the correlations within the community measures (Table 16) and the individual measures (Table 17). The community correlations were high ($r > .40$), while only one individual correlation reached this level (married and gender). The proportion of supermarkets, for example, was moderately and significantly correlated with the proportion of owner-occupied housing units, and with lower poverty rates. The proportion of owner-occupied units, in turn, was strongly correlated with lower rates of poverty. We excluded other measures that had high within domain correlations but kept these measures with high between domain correlations in order to test the theoretical model.

Given the level of correlation between community variables, it is not surprising that although owner-occupancy rate, a measure of community social environment, did predict CES-D score in Model 2, it was no longer a significant predictor when poverty rate was included (Model 2; Table 21). Similarly, our measure of the built environment, the proportion of supermarkets that were major chains, was only a significant predictor of depressive symptoms when all other community variables were controlled statistically. Neither owner-occupancy rate nor percent chain supermarkets significantly predict depressive symptoms after individual characteristics were controlled (Model 4; Table 23). In fact, including these measures led to a worse model fit and less between-

community variance explained than when individual-level predictors alone were included in the model. Individual-level measures were stronger predictors of depressive symptoms and accounted for most (83.19 percent) of the variance between communities. Increased education, getting at least an hour of exercise, having enough food, being able to count on one's family and friends, and living in what the participant felt to be a safe neighborhood significantly decreased depressive symptoms. On the other hand, being female was associated with a greater number of symptoms. These findings are similar to others who have found little to no impact of community on depression after individual factors were taken into account (Hybels et al., 2006; Troung & Ma, 2006)

Community Context as an Explanation for Mental Health Disparities

Although the theoretical framework was designed to facilitate examination of differences between whites and minorities in depressive symptoms, Black and Hispanic race/ethnicity were not significantly associated with CES-D score. This finding supports arguments that racial and ethnic disparities in mental health are likely due to other factors such as gender, socioeconomic status, social support, and stress.

Limitations

There are a number of reasons why the theoretical model may not have been validated by this study. First, the community-level variables that we used may have a minimal influence on mental health. The *Community Context and Health Disparities Model* suggests many variables to represent each domain and other attributes or measures of each domain may have been more appropriate for measuring context when explaining mental health. For example, we could have included the accessibility of mental health treatment centers to assess the healthcare environment.

We were also limited by our relatively small numbers of communities and participants within communities. The location of all the study communities within one county means that they were relatively homogenous on a number of measures, such as daylight, which have been associated with depression (Rosenthal et al., 1984) but could not be included in this analysis. The lack of ethnic diversity, particularly that over 70 percent of the sample was Hispanic, may have made it difficult to statistically detect differences between ethnic groups, although we were able to show this difference when explaining self-rated health (see Chapter 4). Future research should use communities with a range of values for each of the level-2 measures as well as a more diverse sample of individuals.

Participant rating of neighborhood safety was a significant predictor of depression scores. Although we included this as a measure of stress from the community, it is likely correlated with actual community conditions (e.g., crime). Further research is needed to identify what community attributes lead to a rating of “poor” safety since we did not find that any of our community measures were significant predictors. In particular, it may be interesting to highlight situations where there is a discrepancy between community attributes and individual assessments of safety in order to better understand whether this rating is indicative of specific community conditions or particularly vulnerable individuals.

Implications for Policy and Practice

This study highlights that it is possible to explore the impact of both individual and community-level factors on mental health outcomes. Although we did not find significant differences in depressive symptoms between communities, individual

demographic, socioeconomic, health behaviors, social support, and stress characteristics significantly predicted CES-D score and explained variability in these scores between communities. In other words, the individual characteristics that are associated with depression vary spatially. Community mental health interventions should identify areas where residents are at high risk based on these predictors. The clustering of people with these characteristics may make it easier to find the most effective locations for mental health services.

Conclusion

The *Community Context and Health Disparities* Model provides a theoretical framework for understanding how community and individual characteristics explain disparities in mental health. We tested the attributes and pathways suggested by this model as predictors of depressive symptoms and found that individual traits and behaviors are stronger predictors of depression, than community characteristics.

CHAPTER 6: CONCLUSION

Research on racial and ethnic health disparities has attempted to explore aspects of the community context as possible explanations for these gaps in health. The persistence of racial residential segregation (Glaeser & Vigdor, 2001), leading to discrepancies in the characteristics of the communities where whites and minorities live, make it plausible that there is a relationship between community factors and individual health status. Previous research on contextual factors has been limited, however, by the lack of a theoretical framework to direct the research. Although our work was guided by a new theoretical framework that proposed relationships between five community-level domains and five individual-level domains, we found limited utility of the model with our data. This may be why others (Northridge, Sclar & Biswas, 2003; Schulz & Northridge, 2004; Schulz, Williams, Israel, & Lempert, 2002) have not empirically tested similar models. In both cases, researchers have tried to aggregate a wide variety of research disciplines, disentangling community attributes that would explain differences in health by race and ethnicity.

We have argued that the older minority population may experience these disparities more since they spend more time in the community as most are no longer leaving the community during the day to work. We also acknowledge that these older minorities are survivors and therefore may not have been as impacted by community context as those who did not survive. Without studying contextual factors over time, it is

impossible to separate the impact of these conditions from individual characteristics. One example of this is in the Established Populations for the Epidemiological Study of the Elderly (EPESE) studies, which have been used to estimate the prevalence of health conditions between different racial and ethnic groups (Cornoni-Huntley et al., 1993). These studies are based on samples of urban whites living in Boston, urban and rural whites and Blacks living in North Carolina, and Mexican Americans living in five southwestern states. There are vast differences in the conditions of the environment, social systems, economic conditions, and healthcare systems between these geographic areas as well as cultural differences between Mexican-Americans and other Hispanic populations in the U.S. (e.g., Cubans in Miami, Florida; Puerto Ricans in New York City), as well as whites and Blacks. It is not valid to draw conclusions about race and ethnicity from these samples without accounting for the differences in both heritage and geographic location.

At the same time, our own analyses demonstrated the challenges of applying a theoretical model to examine health disparities among older minorities. In future research we need to design a study that includes an adequate number of discrete communities which each include diverse populations. Hierarchical linear modeling (HLM), the most appropriate statistical analysis for testing such a model, is most effective with at least 30 communities with at least 30 individuals in each community (Kreft, 1996). A larger data set such as the Medicare Current Beneficiaries Survey (U.S. DHHS, 2004) or the North Carolina EPESE study (Cornoni-Huntley et al., 1993) may be better suited for such an analysis. Although on one hand the fact that community conditions such as pollution, poor housing quality, a deteriorating social structure, few

job opportunities, and poor accessibility to healthcare reinforce the hypothesis that community affects health, the high correlations between these conditions in our study made it difficult to identify the particular factor that explains health disparities. Understanding community context may require many more disparate communities such as found in the EPESE or national MCBS studies.

Our research developed two important indicators of healthcare availability (physicians per population) and accessibility (distance to hospitals with emergency rooms). We were able to improve on previous indicators of availability which lost physician data due to not coding P.O. Box addresses and lost variability due to using zip codes rather than smaller census units like block groups or census tracts. And we improved on indicators of healthcare accessibility by calculating the actual road network distance to the nearest hospital rather than Euclidian distances. Our measure could be improved by accounting for travel time for a large number of locations, like commonly available programs such as Mapquest calculate for a single location. We identified challenges with matching community and population data which are collected at different time intervals. This would be particularly important for longitudinal research that attempts to show causality and not just associations as we have done here. Not only is temporality important but these community healthcare measures need to be validated in terms of whether or not they are accurately capturing what they are designed to measure. For example, although there may be what appears to be adequate potential physician availability and healthcare accessibility in a community, without a universal healthcare insurance or payment system in the United States for all age groups, actual healthcare availability and accessibility may not be adequate. Kahn and colleagues (1994) suggest

that African Americans may actually live closer to academic medical centers located in the inner city, but this does not mean that the populations living in these poorer areas have access to this care. Further explorations into the relationship between the quality of care received (Chandra & Skinner, 2003) may actually provide a more accurate assessment of the impact of the healthcare system on outcomes.

There are also a number of policy implications from this type of research. Given the persistence of community poverty levels in explaining self-rated health and Hispanics versus Blacks or whites in this study and elsewhere, we need to continue to wage a war on poverty. Although we did not find the built environment to be a consistent factor in explaining community differences on individual self-rated health or depression, probably because of the close proximity between communities, the built environment and land use planning does affect both these outcomes as others have found. The U.S. EPA recently began an Aging Initiative designed to create a national agenda for studying how negative environmental conditions affect older Americans. For example, older adults are more susceptible to extreme heat conditions, so heat watch/warning systems implemented in cities like Chicago and Seattle are one way to prevent heat fatalities (U.S. EPA, 2004). The Healthy People 2010 program includes a healthy communities component in recognition of the fact that exercise and other health behaviors are influenced by the community. There are a number of resources available to promote healthy communities by building coalitions, engaging community residents in physical activity, and measuring results (U.S. DHHS, 2001).

Over the past fifteen years, eliminating health disparities has been a goal of the U.S. government. Throughout the four articles written for this dissertation, there has been

evidence of a relationship between community conditions and health disparities, even in a single county in a single state. In the United States, these differences are more pronounced and since race and ethnic groups cluster differentially, these community differences need to be considered when designing policy. Although we find all race and ethnic groups in every urban and most rural areas of the country, African Americans are concentrated in the Southeast (Baicker, Chandra, & Skinner, 2005) while whites are concentrated in the Northeast and West. Since community conditions such as physical, built, and economic are different in these regions of the country, if health disparities between racial and ethnic groups are to be alleviated, policies must target the characteristics of the communities where minorities live that affect health. Although this aim is broad, it is more readily met through policy changes than other hypothesized causes of health disparities, particularly what some consider inherent biological differences. Improving educational and employment opportunities will help alleviate socioeconomic disparities. The improvement of community conditions will lead to better health and well-being among all populations, lowering healthcare costs and leading to a better quality of life. As described here, the disparities between communities are great and much work is needed to create equitable community conditions. These four studies in this dissertation provide important theoretical, methodological, and empirical evidence to support the ongoing investigation of health disparities and demonstrating the need to improve community conditions.

REFERENCES

- Achenbaum, W.A. & Bengtson, V.L. (1994). Re-engaging the disengagement theory of aging: On the history and assessment of theory development in gerontology. *The Gerontologist*, 24, 756-763.
- Adler, N.E., Boyce, T.W., Chesney, M.A., Folkman, S., & Syme, S.L. (1993). Socioeconomic inequalities in health: no easy solution. *Journal of the American Medical Association*, 269, 3140-3145.
- Anderton, D.L., Anderson, A.B., Oakes, J.M., & Fraser, M.R. (1994). Environmental equity: The demographics of dumping. *Demography*, 31, 229-248
- Baicker, K., Chandra, A., & Skinner, J.S. (2005). Geographic variation in health care and the problem of measuring racial disparities. *Perspectives in Biology & Medicine*, 48(1 supplement), S42-S53.
- Bailey, T. C. & Gatrell, A. C. (1995). *Interactive Spatial Data Analysis*. Longman Group Limited.
- Balfour, J.L. & Kaplan, G.A. (2002). Neighborhood environment and loss of physical function in older adults: evidence from the Alameda County study. *American Journal of Epidemiology*, 155, 507-515.
- Barker R G. (1968). *Ecological Psychology: Concepts and Methods for Studying the Environment of Human Behavior*. Stanford, CA: Stanford University Press.
- Berkman, L.F. & Glass, T. (2000). Social integration, social networks, social support, and health. In: L.F. Berkman & I. Kawachi (Eds.), *Social Epidemiology* (pp. 137-173). New York: Oxford University Press.
- Beyer, H. L. (2004). *Hawth's Analysis Tools for ArcGIS*. Retrieved September 21, 2006 from <http://www.spatialecology.com/htools>.
- Boyle, E. (1970). Biological patterns in hypertension by race, sex, body weight, and skin color, *Journal of the American Medical Association*, 213, 1637-1643.
- Brabyn, L. & Skelly, C. (2002). Modeling population access to New Zealand public hospitals. *International Journal of Health Geographics*, 1, 3.

- Brown, G.W., Davison, S., Harris, I., Maclean, U., Pollock, S., & Prudo, R. (1977). Psychiatric disorder in North Uist and London. *Social Science & Medicine*, 11, 367-377.
- Browning, C.R., Cagney, K.A., & Wen, M. (2003). Explaining variation in health status across space and time: implications for race and ethnic disparities in self-rated health. *Social Science & Medicine*, 57, 1221-1235.
- Bryk, A.S. & Raudenbush, S.W. (1992). *Hierarchical linear models: Applications and data analysis methods*, Newbury Park: Sage.
- Burridge, R. & Ormandy, D. (1993). *Unhealthy housing: Research, remedies, and reform*. New York : E. and F.N. Spon.
- Cagney, K.A. & Browning, C.R. (2004). Exploring neighborhood-level variation in asthma and other respiratory diseases. *Journal of General Internal Medicine*, 19, 229-236.
- Cagney, K.A., Browning, C.R., & Wen, M. (2002). Race and self-rated health at older ages: what difference does the neighborhood make? Unpublished manuscript.
- Cagney, K., Browning, C., & Wen, M. (2005). Racial disparities in self-rated health at older ages: What differences does the neighborhood make? *Journal of Gerontology*, 60B(4), S181-S190.
- Cassel, J. (1976). The contribution of the social environment to host resistance: the fourth Wade Hampton Frost lecture. *American Journal of Epidemiology*, 104, 107-123.
- Chandra, A. & Skinner, J. (2003). *Geography and racial health disparities* (NBER Working Paper No. 9513). New York, NY: National Bureau of Economic Research.
- Chapman, N.J. & Beaudet, M. (1983). Environmental predictors of well-being for at-risk older adults in a mid-sized city. *Journal of Gerontology*, 38, 237-244
- Chinn, S., du, C., Florey, V., Baldwin, I.G., & Gorgol, M. (1981). The relation of mortality in England and Wales 1969-73 to measurements of air pollution. *Journal of Epidemiology & Community Health*, 35, 174-179.
- City of Miami (2004). *Neighborhood Enhancement Team*. Retrieved September 13, 2006 from <http://www.ci.miami.fl.us/NETS/pages/AboutNET/Services.asp>
- Cohen, D.A., Mason, K., Bedimo, A., Scribner, R., Besolo, V., & Farley, T.A. (2003). Neighborhood physical conditions and health. *American Journal of Public Health*, 93, 467-471.

- Cohen, S., Tyrrell, D.A., & Smith, A.P. (1991). Psychological stress and susceptibility to the common cold. *New England Journal of Medicine*, 325, 606-612.
- Collins, C. & Williams, D.R. (1999). Segregation and mortality: the deadly effects of racism. *Sociological Forum*, 14, 495-523.
- Corbie-Smith, G., Flagg, E.W., Doyle, J.P., & O'Brien, M.A. (2002). Influence of usual source of care on differences by race/ethnicity in receipt of preventive services. *Journal of General Internal Medicine*, 17, 458-464.
- Cornoni-Huntley, J., Ostfeld, A.M., Taylor, J.O., Wallace, R.B., Blazer, D., Berkman, L.F., et al. (1993). Established populations for epidemiologic studies of the elderly: study design and methodology. *Aging*, 5(1), 27-37.
- Cress, M.E., Buchner, D.M., Questad, K.A., Esselman, P.C., deLateur, B.J., & Schwartz, R.S. (1999). Exercise: Effects on physical functional performance in independent older adults. *Journal of Gerontology*, 54A, M242-M248.
- Curtis, S.E. (1990). Use of survey data and small area statistics to assess the link between individual morbidity and neighborhood deprivation. *Journal of Epidemiology & Community Health*, 44, 62-68.
- Cutler, D.M., Glaeser, E.L., & Vigdor, J.L. (1997). Are ghettos good or bad? *Quarterly Journal of Economics*, 112, 827-872.
- Dalgard, O.S. & Tambs, K. (1997). Urban environment and mental health: a longitudinal study. *British Journal of Psychiatry*, 171, 530-536.
- Darden, J.T., & Kamel, S.M. (2000). Black residential segregation in the city and suburbs of Detroit: Does socioeconomic status matter? *Journal of Urban Affairs*, 22, 1-13.
- Davey Smith, G., Hart, C., Watt, G., Hole, D., & Hawthorne, V. (1998). Individual social class, area-based deprivation, cardiovascular disease risk factors, and mortality in Renfrew and Paisley study. *Journal of Epidemiology & Community Health*, 52, 399-405.
- Davidson, W. B. & Cotter, P.R. (1991). The relationship between sense of community and subjective well-being: A first look. *Journal of Community Psychology*, 19, 246-253.
- Diez Roux, A.V., Kiefe, C.I., Jacobs, D.R., Haan, M., Jackson, S.A., Nieto, F.J., et al. (2001). Area characteristics and individual-level socioeconomic position indicators in three population-based epidemiologic studies. *Annals of Epidemiology*, 11, 395-405.

- Dohrenwend, B.P., Levav, I., Shrout, P.E., Schwartz, S., Naveh, G., Link, B.G., Skodol, A.E., & Stueve, A. (1992). Socioeconomic status and psychiatric disorders: the causation-selection issue. *Science*, 255(5047), 946-952.
- Dressler, W.W., Oths, K.S., & Gravlee, C.C. (2005). Race and ethnicity in public health research: models to explain health disparities. *Annual Review of Anthropology*, 34, 231-252.
- Eberhardt, M.S., Ingram, D.D., & Makuc, D.M. (2001). *Urban and rural health chartbook, United States, 2001*, Hyattsville, MD: National Center for Health Statistics.
- Ecob, R. & Davey Smith, G. (1999). Income and health: what is the nature of the relationship? *Social Science & Medicine*, 48, 693-705.
- Ellaway, A. & MacIntyre, S. (1996). Does where you live predict health-related behaviors? A case study in Glasgow. *Health Bulletin*, 54, 443-446.
- Environmental Systems Research Institute (ESRI). (2006). *ArcGIS: Release 9.2* [software]. Redlands, California: Environmental Systems Research Institute, 1999-2006.
- Evans, G.W. & Kantrowitz, E. (2002). Socioeconomic status and health: The potential role of environmental risk exposure. *Annual Review of Public Health*, 23, 303-331.
- Evans, G.W. (2003). The built environment and mental health. *Journal of Urban Health*, 80, 536-555.
- Ewart, C.K. & Suchday, S. (2002). Discovering how urban poverty and violence affect health: Development and validation of a neighborhood stress index. *Health Psychology*, 21, 254-262.
- Ewing, R., Schmid, T., Killingsworth, R., Zlot, A., & Raudenbush, S. (2003). Relationship between urban sprawl and physical activity, obesity, and morbidity. *American Journal of Health Promotion*, 18, 47-57.
- Feldman, P.J. & Steptoe, A. (2004). How neighborhood and physical functioning are related: The roles of neighborhood socioeconomic status, perceived neighborhood strain, and individual health risk factors. *Annals of Behavioral Medicine*, 27, 91-99.
- Fellowes, M. (2006). *From poverty, opportunity: putting the market to work for lower income families*. Retrieved August 8, 2006 from http://www.brook.edu/metro/pubs/20060718_povop.htm

- Fiscella, K. & Franks, P. (1997). Poverty or income inequality as predictor of mortality: Longitudinal cohort study. *British Medical Journal*, 314, 1724-1727.
- Fiscella, K. & Williams, D.R. (2004). Health disparities based on socioeconomic inequities: implications for urban health care. *Academic Medicine*, 79, 1139-1147.
- Florida Agency for Health Care Administration (FL AHCA). (2006). Facility Locator. Retrieved August 7, 2006 from <http://www.floridahealthstat.com/>.
- Florida Geographic Data Library (2003). 2003 Shopping Center Facility Information. Retrieved August 29, 2006 from <http://www.fgdl.org/metadataexplorer/explorer.jsp>.
- Fone, D.L. & Dunstan, F. (2006). Mental health, places and people: A multilevel analysis of economic inactivity and social deprivation. *Health & Place*, 12, 332-344.
- Fortney, J., Rost, K., & Warren, M. (2000). Comparing alternative methods of measuring geographic access to health services. *Health Services and Outcomes Research Methodology*, 1, 173-184.
- Frankenberg, E., Lee, C., & Orfield, G. (2003). *A multiracial society with segregated schools: Are we losing the dream?* Cambridge, MA: Civil Rights Project, Harvard University.
- Franzini, L., Caughy, M., Spears, W., & Esquer, M.E.F. (2005). Neighborhood economic conditions, social processes, and self-rated health in low-income neighborhoods in Texas: A multilevel latent variables model. *Social Science & Medicine*, 61, 1135-1150.
- Franzini, L. & Spears, W. (2003). Contributions of social context to inequalities in years of life lost to heart disease in Texas, USA. *Social Science & Medicine*, 57, 1847-1861.
- Fultz, N.H., Ofstedal, M.B., Herzog, A.R., & Wallace, R.B., (2003). Additive and interactive effects of comorbid physical and mental conditions on functional health. *Journal of Aging and Health*, 15, 465-481.
- Galea, S., Ahern, J., Rudenstine, S., Wallace, Z., & Vlahov, D. (2005). Urban built environment and depression: a multilevel analysis. *Journal of Epidemiology & Community Health*, 59, 822-827.
- Gardner, M.J. (1973). Using the environment to explain and predict mortality. *Journal of Royal Statistical Society*, 136, 309-314.
- Gee, G.C. & Takeuchi, D.T. (2004). Traffic stress, vehicular burden, and well-being: A multilevel analysis. *Social Science & Medicine*, 59, 405-414.

- Gee, G.C., Payne-Sturges, D.C. (2004). Environmental health disparities: A framework integrating psychosocial and environmental concepts. *Environmental Health Perspectives*, 112, 1645-1653.
- Ginexi, E.M., Weihs, K., Simmons, S.J., & Hoyt, D.R. (2000). Natural disaster and depression: A prospective investigation of reactions to the 1993 Midwest floods. *American Journal of Community Psychology*, 28(4), 495-518.
- Glaeser, E.L. & Vigdor, J.L. (2001). *Racial segregation in the 2000 Census: promising news*. Brookings Institution Survey Series. Washington: Brookings Institution.
- Gorn, S.B., Icaza, M.E., & Cantu, M.A.L. (2003). Mental health services: Twenty-five years of research. *Salud Mental*, 26(5), 61-72.
- Gregory, P.M., Malka, E.S. Kostis, J.B., Wilson, A., Arora, J.K., & Rhoads, G.G. (2000). Impact of geographic proximity to cardiac revascularization services on service utilization. *Medical Care*, 38, 45-57.
- Guagliardo, M.F., Ronzio, C.R., Cheung, I., & Joseph, J.G.. (2004). Physician accessibility: an urban case study of pediatric providers. *Health & Place*, 10, 273-283.
- Hadley, J. & Cunningham, P. (2004). Availability of safety net providers and access to care of uninsured persons. *Health Services Research*, 39, 1527-1546.
- Halpern, D. (1995). *Mental health and built environment*. London: Taylor & Francis.
- Hart, M. (1998). How do you define a community? Retrieved July 26, 2006 from <http://www.sustainablemeasures.com/Training/Indicators/Cmmunity.html> .
- Hart, C., Ecob, R., & Davey Smith, G. (1997). People, places, and coronary heart disease risk factors: A multilevel analysis of the Scottish Heart Health Study archive. *Social Science & Medicine*, 45, 893-902.
- Hauenstein, E.J., Petterson, S., Merwin, E., Rovnyak, V., Heise, B., & Wagner, D. (2006). Rurality, gender, and mental health treatment. *Family & Community Health*, 29, 169-185.
- Hayward, M. D. & Heron, M. (1999) Racial inequalities in active life among adult Americans, *Demography*, 36, 77-91.
- Hayward, M.D., Miles, T.P., Crimmins, E.M. & Yang, Y. (2000). The significance of socioeconomic status in explaining the racial gap in chronic health conditions. *American Sociological Review*, 65, 910-930.

- Holmes, T.H. & Masuda, M. (1974). Life change and illness susceptibility. In B.S. Dohrenwend and B.P. Dohrenwen (Eds.), *Stressful life events: Their nature and effects*, pp. 45-72. New York: Wiley.
- Hou, F. & Myles, J. (2005). Neighborhood inequality, neighborhood affluence and population health. *Social Science & Medicine*, 60, 1557-1569.
- House, J.S., Kessler, R.C., Herzog, A.R., Mero, R.P., Kinney, A.M., & Breslow, M.J. (1990). Age, Socioeconomic status, and health. *Milbank Quarterly*, 68(3), 383-411.
- Hox, J.J. (1995). *Applied multilevel analysis*. Amsterdam: T.T. Publikaties.
- Hummer, R.A., Benjamins, M.R., & Rogers, R.G. (2004) Racial and ethnic disparities in health mortality among the U.S. elderly population. In N.B. Anderson, R.A., Bulatao, and B. Cohen (Eds.) *Critical perspectives on racial and ethnic differences in health in late life* (pp.53-94). Washington, DC: National Academies Press.
- Hybels, C.F., Blazer, D.G., Pieper, C.F., Burchett, B.M., Hays, J.C., Fillenbaum, G.G., et al. (2006). Sociodemographic characteristics of the neighborhood and depressive symptoms in older adults: using multilevel modeling in geriatric psychiatry. *American Journal of Geriatric Psychiatry*, 14, 498-506.
- Jargowsky, P.A. (1996). Take the money and run: economic segregation in US metropolitan areas. *American Sociological Review*, 61, 984-998.
- Jones, K. & Duncan, C. (1995). Individuals and their ecologies: analyzing the geography of chronic illness within a multilevel modeling framework. *Health & Place*, 1, 27-40.
- Jorm, A. F. (2000) Does old age reduce the risk of anxiety and depression? A review of epidemiological studies across the adult life span. *Psychological Medicine*, 30, 11-22.
- Joseph, A.E. & Phillips, D.R. (1984). *Accessibility and utilization: Geographical perspectives on health care delivery*. New York: Harper and Row.
- Kahn, K.L., Pearson, M.L., Harrison, E.R., Desmond, K., Rogers, W.H., Rubenstein, L.V., et al. (1994). Health care for Black and poor hospitalized Medicare patients. *Journal of the American Medical Association*, 271(15), 1169-1174.
- Kain, J. (1968). Housing segregation, Negro unemployment and metropolitan segregation. *Quarterly Journal of Economics*, 82, 175-197.
- Kawachi, I., & Berkman, L.F. (2000). Social cohesion, social capital, and health. In

- Berkman, L.F. & Kawachi, I. (Eds.), *Social epidemiology*, New York: Oxford University Press, pp. 174-190.
- Keppel, K.G., Percy, J.N. & Wagener, D.K. (2002). Trends in racial and ethnic-specific rates for the health status indicators: United States, 1990-98. *Healthy People 2000: Statistical Notes*, 23, Washington: National Center for Health Statistics.
- Kirby, J.B. & Kaneda, T. (2005). Neighborhood socioeconomic disadvantage and access to health care. *Journal of Health & Social Behavior*, 46, 15-31.
- Klinenberg, E. (2002). *Heat wave: A social autopsy of disaster in Chicago*. Chicago: University of Chicago Press.
- Klinenberg, E. (2006). *High temps prompt call for federal funds*. Retrieved August 23, 2006 from National Public Radio
<http://www.npr.org/templates/story/story.php?storyId=5598877> .
- Kobetz, E., Daniel, M., & Earp, J.A. (2003). Neighborhood poverty and self-reported health among low-income, rural women, 50 years and older. *Health & Place*, 9, 263-271.
- Krause, N. (1988). Stressful Life Events and Physician Utilization. *Journals of Gerontology*, 43(2), S53-S61.
- Kreft, I.G.G. (1996). Are multilevel techniques necessary? An overview, including simulation studies. Retrieved October 22, 2005 from
<http://www.calstatela.edu/faculty/ikreft/quarterly/quarterly.html>.
- Krieger, J. & Higgins, D.L. (2002). Housing and health: time again for public health action. *American Journal of Public Health*, 92, 230-236.
- Krieger, N. (1994). Epidemiology and the web of causation: Has anyone seen the spider? *Social Science & Medicine*, 39, 887-903
- Krieger, N. (2001). Theories for social epidemiology in the 21st century: an ecosocial perspective. *International Journal of Epidemiology*, 30, 668-677.
- Krieger, N., Chen, J.T., Waterman, P.D., Rehkopf, D.H., & Subramanian, S.V. (2003). Race/ethnicity, gender, and monitoring socioeconomic gradients of health: A comparison of area-based socioeconomic measures—The Public Health Disparities Geocoding Project. *American Journal of Public Health*, 93, 1655-1671.
- Krieger, N., Williams, D.R., & Moss, N.E. (1997). Measuring social class in U.S. public health research: Concepts, methodologies, and guidelines. *Annual Review of Public Health*, 18, 341-378.

- Kubzansky, L.D., Subramanian, S.V., Kawachi, I., Fay, M.E., Soobader, M., & Berkman, L.F. (2005). Neighborhood contextual influences on depressive symptoms in the elderly. *American Journal of Epidemiology*, 162, 253-260.
- Laditka, J.N. (2004). Physician supply, physician diversity, and outcomes of primary health care for older persons in the United States. *Health & Place*, 10, 231-244.
- Latkin, C.A. & Curry, A.D. (2003). Stressful neighborhoods and depression: A prospective study of the impact of neighborhood disorder. *Journal of Health and Social Behavior*, 44, 34-44.
- LaVeist, T.A. (1993). Segregation, poverty, and empowerment: health consequences for African Americans. *Milbank Quarterly*, 71, 41-64.
- LaVeist, T.A. (2000). On the study of race, racism, and health: a shift from description to explanation. *International Journal of Health Services*, 30, 217-219.
- LaVeist, T.A. (2005). Disentangling race and socioeconomic status: A key to understanding health inequalities. *Journal of Urban Health*, 82(2), 26-34.
- Lawton, M.P. (1983). Environment and other determinants of well-being in older people. *Gerontologist*, 23, 349-357.
- LeClere, F.B., Rogers, R.G. & Peters, K.D. (1997). Ethnicity and mortality in the United States: Individual and community correlates. *Social Forces*, 76, 169-198.
- LeClere, F.B., Rogers, R.G., & Peters, K. (1998). Neighborhood social context and racial differences in women's heart disease mortality. *Journal of Health and Social Behavior*, 39, 91-107.
- Leskela, U., Rytsala, H., Komulainen, E., Melartin, T., Sokero, P., Lestela-Mielonen, P., et al. (2006). The influences of adversity and perceived social support on the outcomes of major depressive disorder in subjects with different levels of depressive symptoms. *Psychosocial Medicine*, 36, 779-788.
- Lillie-Blanton, J., Martinez, R.M., & Salganicoff, A. (2001). Site of medical care: Do racial and ethnic differences persist? *Yale Journal of Public Health Policy, Law, & Ethics* 1, 15-32.
- Luo, W. (2004). Using a GIS-based floating catchment method to assess areas with shortage of physicians. *Health & Place*, 10, 1-11.
- Maantay, J. (2007). Asthma and air pollution in the Bronx: Methodological and data considerations for using GIS for environmental justice and health research. *Health & Place*, 13, 32-56.

- MacIntyre, S., Ellaway, A., & Cummins, S. (2002). Place effects on health: how can we conceptualise, operationalise and measure them? *Social Science & Medicine*, 55, 125-139.
- MacIntyre, S., MacIver, S., & Sooman, A. (1993). Area, class, and health: Should we be focusing on places or people? *Journal of Social Policy*, 22, 213-234.
- Maheswaran, R., Elliott, P. & Strachan, D.P. (1997). Socioeconomic deprivation, ethnicity, and stroke mortality in greater London and south east England. *Journal of Epidemiology and Community Health*, 51, 127-131.
- Manninen, L., Poikolainen, K., Vartiainen, E., & Laatikainen, T. (2006). Heavy drinking occasions and depression. *Alcohol and Alcoholism*, 41, 293-299.
- Massey, D.S. & Fischer, M.J. (2000). How segregation concentrates poverty. *Ethnic & Racial Studies*, 23, 670-691.
- Matheson, F.I., Moineddin, R., Dunn, J.R., Creatore, M.I., Gozdyra, P., & Glazier, R.H. (2006). Urban neighborhoods, chronic stress, gender, and depression. *Social Science & Medicine*, 63, 2604-2616.
- Mayberry, R.M., Mili, F., & Ofili, E. (2000). Racial and ethnic differences in access to medical care. *Medical Care Research and Review*, 57, 108-145.
- McGeehin, M.A. & Mirabelli, M. (2001). The potential impacts of climate variability and change on temperature-related morbidity and mortality in the United States. *Environmental Health Perspectives*, 109, 185-189.
- Meich, R.A. & Shanahan, M.J. (2000). Socioeconomic status and depression over the life course. *Journal of Health and Social Behavior*, 41(6), 162-176.
- Mitchell, R., Gleave, S., Bartley, M., Wiggins, D., & Joshi, H. (2000). Do attitude and area influence health? A multilevel approach to health inequalities. *Health & Place*, 6, 67-79.
- Monnet, E., Collin-Naudet, E., Bresson-Hadni, S., Minello, A., DiMartino, V., Carel, D., et al. (2006). Place of residence and distance to medical care influence the diagnosis of hepatitis C: A population-based study. *Journal of Hepatology*, 44, 499-506.
- Morello-Frosch, R. & Jesdale, B.M. (2006). Separate and unequal: residential segregation and estimated cancer risks associated with ambient air toxics in U.S. metropolitan areas. *Environmental Health Perspectives*, 114, 386-393.

- Morland, K., Wing, S., & Diez Roux, A. (2002). The contextual effect of the local food environment on residents' diets: the Atherosclerosis Risk in Communities Study. *American Journal of Public Health, 92*, 1761-1767.
- Moses, M., Johnson, E.S., Anger, W.K., Burse, V.W., Horstman, S.W., & Jackson, R.J. (1993). Environmental equity and pesticide exposure. *Toxicology & Individual Health, 9*, 913-959.
- Mutchler, J.E. & Burr, J.A. (1991). Racial differences in health and health care service utilization in later life: the effect of socioeconomic status. *Journal of Health and Social Behavior, 32*(4), 342-356.
- Newacheck, P.W. Hung, Y.Y., Park, M.J., Brindis, C.D., & Irwin, C.E. (2003). Disparities in adolescent health and health care: Does socioeconomic status matter? *Health Services Research, 38*(5), 1235-1252.
- Northridge, M.E., Sclar, E.D., & Biswas, P. (2003). Sorting out the connections between the built environment and health: A conceptual framework for navigating pathways and planning healthy cities. *Journal of Urban Health, 80*, 556-568.
- Oakes, J.M. (2004). The (mis)estimation of neighborhood effects: causal inference for a practicable social epidemiology. *Social Science & Medicine, 58*, 1929-1952.
- O'Campo, J.L. (2003). Invited commentary: Advancing theory and methods for multilevel models of residential. *American Journal of Epidemiology, 157*, 9-13.
- Oliver, M.N. and C. Muntaner. 2005. Researching health inequities among African Americans: the imperative to understand social class. *International Journal of Health Services, 35*, 485-498.
- Orfield, G. & Eaton, S.E. (1996). *Dismantling desegregation: the quiet reversal of Brown v. Board of Education*. New York: New Press.
- Orfield, G. & Lee, C. (2005). *Why segregation matters: Poverty and educational inequality*. Cambridge, MA: The Civil Rights Project, Harvard University.
- Ostir, G.V., Eschbach, K., Markides, K.S., & Goodwin, J.S. (2003). Neighborhood composition and depressive symptoms among older Mexican Americans. *Journal of Epidemiology and Community Health, 57*, 987-992.
- Ostler, K., Thompson, C., Kinmonth, A.L.K., Peveler, R.C., Stevens, L., & Stevens, A. (2001). Influence of socio-economic deprivation on the prevalence and outcomes of depression in primary care. *British Journal of Psychiatry, 178*, 12-17.

- Otten, M.W., Teutsch, S.M., Williamson, D.F., & Marks, J.S. (1990). The effect of known risk factors on the excess mortality of Black adults in the United States. *Journal of the American Medical Association*, 263, 845-850.
- Pastor, M., Sadd, J. & Hipp, J. (2001). Which came first? Toxic facilities, minority move-in, and environmental justice. *Journal of Urban Affairs*, 23, 1-21.
- Pedhazur, E.J. (1997). *Multiple regression in behavioral research*. Orlando: Hartcourt Brace & Company.
- Penchansky, R. & Thomas, J.W. (1981). The concept of access: definition and relationship to consumer satisfaction. *Medical Care*, 19, 127-140.
- Pickett, K.E & Pearl, M. (2001). Multilevel analyses of neighborhood socioeconomic context and health outcomes: a critical review. *Journal of Epidemiology & Community Health*, 55, 111-122.
- Pocock, S.J., Shaper, A.G., Cook, D.G., Packham, R.F., Lacey, R.F., Powell, P., et al. (1980). British regional heart study: geographic variations in cardiovascular mortality and the role of water quality. *British Medical Journal*, 280, 1243-1249.
- Politzer, R.M., Yoon, J., Shi, L., Hughes, R.G., Regan, J., & Gaston, M.H. (2001). Inequality in America: The contribution of health centers in reducing and eliminating disparities in access to care. *Medical Care Research & Review*, 58, 234-248.
- Potvin, L., Gendron, S., Bilodeau, A., & Chabot, P. (2005) Integrating social theory into public health practice. *American Journal of Public Health*, 95, 591-595.
- Radloff, L.S.(1977). The CES-D scale: a self-report depression scale for research in the general population. *Applied Psychological Measurement*, 1, 385-388
- Raudenbush, S.W. & Bryk, A.S. (2002). *Hierarchical linear models*. Thousand Oaks, CA: Sage Publications.
- Reijneveld, S.A. & Schene, A.H. (1998). Higher prevalence of mental disorders in socioeconomically deprived urban areas in the Netherlands: Community or personal disadvantage? *Journal of Epidemiology & Community Health*, 52, 2-7.
- Rich, R.C., Edelstein, M., Hallman, W.K., & Wandersman, A.H. (1995). Citizen participation and empowerment: the case of local environmental hazards. *American Journal of Community Psychology*, 23, 657-677.
- Robert, S.A. (1998). Community-level socioeconomic status effects on adult health. *Journal of Health and Social Behavior*, 39, 18-37.

- Robert, S. (1999). Neighborhood socioeconomic context and adult health: the mediating role of individual health behaviors and psychosocial factors. *Annals of the New York Academy of Sciences*, 896, 465-468.
- Robert, S.A. & Lee, K.Y. (2002). Explaining race differences in health among older adults. *Research on Aging*, 24, 654-683.
- Robert, S.A. & Li, L. (2001). Age variation in the relationship between neighborhood socioeconomic context and adult health. *Research on Aging*, 23, 234-258.
- Roberts, R.E., Roberts, C.R., & Chen, Y.R. (1997). Ethnocultural differences in prevalence of adolescent depression. *American Journal of Community Psychology*, 25, 95-110.
- Rogerson, P.A. (1998). The geography of elderly minority population in the United States. *International Journal of Geographical Information Science*, 12(7), 687-698.
- Rosenthal, N.E., Sack, D.A., Gillen, J.C., Lewy, A.J., Goodwin, F.K., Davenport, Y., et al. (1984). Seasonal affective disorder. *Archives of General Psychiatry*, 41, 72-80.
- Rosenthal, M.B., Zaslavsky, A. & Newhouse, J.P. (2005). The geographic distribution of physicians revisited. *Health Services Research*, 40, 1931-1952.
- Ross, C.E. (2000). Walking, exercising, and smoking: Does neighborhood matter? *Social Science & Medicine*, 51, 265-274.
- Ross, C.E. & Mirowsky, J. (2001). Neighborhood disadvantage, disorder, and health. *Journal of Health & Social Behavior*, 42, 258-276.
- Rugulies, R., Bultmann, U., Aust, B., & Burr, H. (2006). Psychosocial work environment and incidence of severe depressive symptoms: Prospective findings from a 5-year follow-up of the Danish work environment cohort study. *American Journal of Epidemiology*, 163(10), 877-887.
- Rumberger, R.W. & Palardy, G.J. (2005). Does segregation still matter/ The impact of student composition on academic achievement in high school. *Teachers College Record*, 107, 1999-2045.
- Sampson, R.J., Morenoff, J.D., & Gannon-Rowley, T. (2002). Assessing "neighborhood effects": Social processes and new directions in research. *Annual Review of Sociology*, 28, 443-478.
- Sampson, R.J., Raudenbush, S.W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, 227, 918-923.

- Sampson, R.J. & Wilson, W.J. (1995). Toward a theory of race, crime, and urban inequality. In J. Hagan & R.D. Peterson (Eds.), *Crime and inequality* (pp. 37-54). Stanford, CA: Stanford University Press.
- Saporito, S. & Sohoni, D. (2006). Coloring outside the lines: Racial segregation in public schools and their attendance boundaries. *Sociology of Education*, 79, 81-105.
- SAS Institute, Inc. (SAS). (2004). *SAS: Release 4.19.2* [software]. Cary, North Carolina: SAS Institute, Inc., 1999-2006.
- Schwirian, K.P. & Schwirian, P.M. (1993). Neighboring, residential satisfaction, and psychological well-being in urban elders. *Journal of Community Psychology*, 21, 285-299.
- Schulz, A.J., Israel, B.A., Zenk, S.N., Parker, E.A., Lichtenstein, R., Shellman-Weir, S., et al. (2006). Psychosocial stress and social support as mediators of relationships between income, length of residence and depressive symptoms among African American women on Detroit's eastside. *Social Science & Medicine*, 62, 510-522.
- Schulz, A. & Northridge, M.E. (2004). Social determinants of health: implications for environmental health promotion. *Health Education & Behavior*, 31, 455-471.
- Schulz, A.J., Williams, D.R., Israel, B.A., & Lempert, L.B. (2002). Racial and spatial relations as fundamental determinants of health in Detroit. *Milbank Quarterly*, 80, 677-707.
- Shaw, M. (2004). Housing and public health. *Annual Review of Public Health*, 25, 397-418.
- Shopland, D.R., Eyre, H.J., & Pachacek, T.F. (1991). Smoking-attributable cancer mortality in 1991: Is lung cancer now the leading cause of death among smokers in the United States? *Journal of the National Cancer Institute*, 83, 1142-1148.
- Silver, E., Mulvey, E.P. & Swanson, J.W. (2002). Neighborhood structural characteristics and mental disorder: Faris & Dunahm revisited. *Social Science & Medicine*, 55, 1257-1470.
- Singer, J.D. (1998). Using SAS PROC MIXED to fit multilevel models, hierarchical models, and individual growth models. *Journal of Educational and Behavioral Statistics*, 24, 323-355.
- Skapinakis, P., Lewis, G., Araya, R., Jones, K., & Williams, G. (2005). Mental health inequalities in Wales, UK: multi-level investigation of the effect of area deprivation. *British Journal of Psychiatry*, 186, 417-422.
- Sloggett, A. & Joshi, H. (1994). Higher mortality in deprived areas: Community or

- personal disadvantage? *British Medical Journal*, 309(6967), 1470-1474.
- Smedley, B.D., Stith, A.Y., & Nelson, A.R. (2002). *Unequal treatment: Confronting racial and ethnic disparities: Measurement and data needs*. Washington: National Academies Press.
- Smith, J.P. & Kington, R. (1997). Demographic and economic correlates of health in old age. *Demography*, 34, 159-170.
- Snijders, T. & Bosker, R. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. Thousand Oaks, CA: Sage.
- Snowden, L. R. (2005). Racial, cultural and ethnic disparities in health and mental health: Toward theory and research at community levels. *American Journal of Community Psychology*, 35, 1-8.
- Sorlie, P., Rogot, E., Anderson, R., Johnson, N.J., & Backlund, E. (1992). Black-white mortality differences by family income. *Lancet*, 340, 346-350.
- Starfield, B., Robertson, J., & Riley, A.W. (2002). Social class gradients and health in childhood. *Ambulatory Pediatrics*, 2, 238-246.
- Stathopoulous, G., Powers, M.B., Berry, A.C., Smits, J.A.J., & Otto, M.W. (2006). Exercise interventions for mental health: A quantitative and qualitative review. *Clinical Psychology- Science & Practice*, 13, 179-193.
- Steenbergen, M.R. & Jones, B.S. (2002). Modeling multilevel data structures. *American Journal of Political Science*, 46, 218-237.
- Steptoe, A. & Feldman, P.J. (2001). Neighborhood problems as sources of chronic stress: Development of a measure of neighborhood problems, and associations with socioeconomic status and health. *Annals of Behavioral Medicine*, 23, 177-185.
- Stoker, L. & Bowers, J. (2002). Designing multi-level studies: Sampling voters and electoral contexts. *Electoral Studies*, 21, 235-267.
- Stoll, M.A. & Raphael, S. (2000). Racial differences in spatial job search patterns: exploring the causes and consequences, *Economic Geography*, 76, 201-223.
- Subramanian, S.V., Acevedo-Garcia, D., & Osypuk, T.L. (2005). Racial residential segregation and geographic heterogeneity in black/white disparity in poor self-rated health in the US: a multilevel statistical analysis. *Social Science & Medicine*, 60, 1667-1679.
- Subramanian, S.V., Kim, D., & Kawachi, I. (2005). Covariation in the socioeconomic determinants of self rated health and happiness: a multivariate multilevel analysis

- of individuals and communities in the USA. *Journal of Epidemiology and Community Health*, 59, 664-669.
- Syme, S.L. & Berkman, L.F. (1976). Social class, susceptibility, and sickness. *American Journal of Epidemiology*, 104, 1-8.
- Thorogood, M., Mann, J. & McPherson, K. (1993). Alcohol intake and the U-shaped curve: do non-drinkers have a higher prevalence of cardiovascular-related disease? *Journal of Public Health*, 15, 61-68.
- Truong, K.D., & Ma, S. (2006). A systematic review of relations between neighborhoods and mental health. *Journal of Mental Health Policy and Economics*, 9(3), 137-154.
- U.S. Department of Commerce, Bureau of the Census (U.S. Census), 2000. *Summary Tape File 1*, Washington, DC.
- U.S. Department of Commerce, Bureau of the Census (U.S. Census), 2001. *Cartographic boundary files*. Retrieved September 13, 2006 from http://www.census.gov/geo/www/cob/pl_metadata.html.
- U.S. Department of Health & Human Services (U.S. DHHS). 1985. *Report of the Secretary's task force on Black & minority Health*. Volume I: Executive summary. Washington, DC.
- US Department of Health & Human Services (1999). *Mental health: a report of the Surgeon General*. Rockville, MD: Author.
- U.S. Department of Health and Human Services, Centers for Medicare and Medicaid Services *Medicare Current Beneficiary Survey*, Retrieved November 2, 2005, from <http://www.cms.hhs.gov/MCBS/>
- U.S. Department of Health and Human Services (US DHHS) (2001). *Healthy People in Healthy Communities*. Washington, DC: U.S. Government Printing Office.
- U.S. Environmental Protection Agency (US EPA) (2004). It's too darn hot—Planning for excessive heat events. Retrieved April 4, 2007 from http://epa.gov/aging/resources/factsheets/itdhpfehe_english_2004_09.pdf
- U. S. Environmental Protection Agency (U.S. EPA), Office of Environmental Information (2001). *The Emergency Planning and Community Right to Know Act Section 313 Release and Other Waste Management Reporting Requirements*. Author. Retrieved October 9, 2005, from <http://www.epa.gov/tri/>.

- US General Accounting Office (GAO). (1995). *Health Care Shortage Areas: Designations Not a Useful Tool for Directing Resources to Underserved*, (GAO/HEHS-95-200). Washington, DC: Author.
- van Os, J., Driessen, G., Gunther, N. & Delespaul, P. (2000). Neighborhood variation in incidence of schizophrenia: Evidence for person-environment interaction. *British Journal of Psychiatry*, 176, 243-248.
- Verbrugge, L.M.(1985). Gender and health: an update on hypotheses and evidence. *Journal of Health and Social Behavior*, 26, 156-182.
- Waitzman, N.J., & Smith, K.R. (1998). Phantom of the area: Poverty-area residence and mortality in the United States. *American Journal of Public Health*, 88, 973-976.
- Wallace, R. & Wallace, D. (1990). Origins of public health collapse in New York City: The dynamics of planned shrinkage, contagious urban decay and social disintegration. *Bulletin of the New York Academy of Medicine*, 66, 391-434.
- Waller, L.A. & Gotway, C.A. (2004). *Applied spatial statistics for public health data*. Hoboken, NJ: John Wiley & Sons.
- Wang, F. & Luo, W. (2005). Assessing spatial and nonspatial factors for healthcare access: towards an integrated approach to defining health professional shortage areas. *Health & Place*, 11, 131-146.
- Ware, J.E. & Sherbourne, C.D. (1992). The MOS 36-item short-form health survey (SF-36): Conceptual framework and item selection. *Medical Care*, 30, 473-483.
- Weich, S., Twigg, L., Holt, G., Lewis, G., & Jones, K. (2003). Contextual risk factors for the common mental disorders in Britain: a multilevel investigation of the effects of place. *Journal of Epidemiology & Community Health*, 57, 616-621.
- Wen, M., Browning, C.R., & Cagney, K.A. (2003). Poverty, affluence, and income inequality: neighborhood economic structure and its implications for health. *Social Science & Medicine*, 57, 843-860.
- West, R.R. & Lowe, C.R. (1976). Mortality from ischaemic heart disease: inter-town variation and its association with climate in England and Wales. *International Journal of Epidemiology*, 5, 195-203.
- Whiteis, D.G. (1992). Hospital and community characteristics in closures of urban hospitals, 1980-1987. *Public Health Reports*, 107, 409-416.
- Williams, D.R. (1999). Race, socioeconomic status, and health: the added effects of racism and discrimination. *Annals of the New York Academy of Sciences*, 896, 173-188.

- Williams, D.R. & Collins, C. (1995). U.S. socioeconomic and racial differences in health: patterns and explanations. *Annual Review of Sociology*, 21, 349-386.
- Williams, D.R. & Collins, C. (2001). Racial residential segregation: a fundamental cause of racial disparities in health. *Public Health Reports*, 116, 404-416.
- Winkleby, M.A. & Cubbin, C. (2004). Changing patterns in health behaviors and risk factors related to chronic diseases, 1990-2000. *American Journal of Health Promotion*, 19, 19-27.
- Yang, D., Goerge, R., & Mullner R. (2006). Comparing GIS-based methods of measuring spatial accessibility to health services. *Journal of Medical Systems*, 30(1), 23-32.
- Yen, I. & Kaplan, G. (1999). Neighborhood social environment and risk of death: multilevel evidence from the Alameda County study. *American Journal of Epidemiology*, 149, 898-907.
- Zax, J.S. & Kain, J.F. (1996). Moving to the suburbs: Do relocating companies leave their black employees behind? *Journal of Labor Economics*, 14, 472-504.
- Zayac, H. & Reader, S. (2007, February). *Racial and ethnic disparities in the availability, accessibility, and quality of healthcare in Florida*. Poster presented at the University of South Florida Health Research Day, Tampa, FL.
- Zayac, H., Salmon, J.R., Chiriboga, D., Dunlop, B., Guo, K.L., Casao, B.L., et al. (2005). *An assessment of physical, mental health, and long-term care service needs of Florida's elder population: Statewide sample*. Tampa, FL: Florida Policy Exchange Center on Aging.
- Zimmerman, F.J. & Bell, J.F. (2006). Income inequality and physical and mental health: testing associations consistent with proposed causal pathways. *Journal of Epidemiology & Community Health*, 60, 513-521.

ABOUT THE AUTHOR

Helen M. Zayac was born in Pearl River, NY and graduated from Pearl River High School in 1998. She attended Duke University and received a Bachelor of Science Degree in Psychology with a Minor in Biological Anthropology and Anatomy and a Certificate in Human Development in 2002. The title of her undergraduate thesis was “Old Age Club Memberships and Phone Use: Evidence of a Gender Crossover.” Helen was awarded a Presidential Doctoral Fellowship and began the Ph.D. in Aging Studies program at the University of South Florida in 2002. From 2003 until 2007, she served as the Project Manager for the Survey of Older Floridians, an Administration on Aging-funded longitudinal study of minorities in Florida.