Title
Network Quality over Quantity: Exploring the Influence of Network Structure and Function on U.S. Older Adult Physical and Mental Health

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Network Quality over Quantity: Exploring the Influence of Network Structure and Function on U.S. Older Adult Physical and Mental Health

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Sociology

by

Bonnie Bui

Dissertation Committee:
Professor Katherine Faust, Chair
Associate Professor Kristin Turney
Associate Professor Cynthia M. Lakon

2017

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I would like to acknowledge all the alters in my personal network who have provided me many types of support, from instrumental to emotional, through the dissertation process.

First, I wish to express my gratitude to my mentor and dissertation chair, Dr. Katherine Faust. I am so appreciative for the countless hours in Katie's office, all the e-mail communications, and all the time spent patiently reading draft after draft. Katie sparked my interest in social networks, and once that flame was lit, there was just no going back. Katie has supported me in more ways than she may realize. There was a moment when I had much doubt as to my abilities, and she compassionately saw me through that moment, successfully shepherding me through to the completion of my dissertation.

I also want to express my thanks to my committee members, Dr. Kristin Turney and Dr. Cynthia Lakon, for reading multiple drafts and providing me feedback for my dissertation, but also for valuable advice on how to move my research agenda forward by pushing me to think more deeply about the subject of my dissertation. Kristin has been my mentor almost from the very beginning, and I have benefited from her feedback since my Master's paper in this program. I am grateful for her incisive comments coupled with encouragement. I am thankful for Cynthia and her patience and gentle kindness.

Thanks to Dr. Ann Hironaka. Ann helped me develop a sense of belonging in this department, and has checked in on me at critical moments throughout the program.

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I am tremendously grateful to my colleague and friend Danielle Vesia. Her friendship and patience has been invaluable in keeping my nerves steady in the last few years. Danielle always has just the right quirky comment to snap me out of any bad mood and get me going again. Thanks also to Dr. Jessica Kizer, colleague, friend, and cheerleader.

Thanks to my cohort. We were such a cohesive and supportive bunch.

Thanks to the Sociology Department and the School of Social Sciences for financial support. Thanks to John Sommerhauser for logistics advice; thanks to Ekua Arhin for logistics advice as well, and also for the numerous pep talks in her office.

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CURRICULUM VITAE

Bonnie Bui

Education

Ph.D. in Sociology. December, 2017.
University of California, Irvine. Department of Sociology, School of Social Sciences.
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Master of Arts in Social Sciences (concentration in Demographic and Social Analysis). June, 2014.
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Master's Paper: *Examining the Association between Acculturation and Perceived Mental Health among Foreign-Born Asians in the U.S.*

Master of Arts in Sociology. January, 2010.
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Advisor: Eileen T. Walsh, Ph.D.
Master's Project: *A Health Needs Assessment of the Vietnamese Community in Orange County*

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Fellowships & Awards

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- UC Irvine Sociology Department Summer Fellowship Award, 2014

Continued from page vi

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Academic Work Experience

University of California, Irvine. Irvine, CA. September 2011 – December 2016.
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- Sociology 10B/Anthropology 10B, Winter 2012. Probability and Statistics II. Professor Katherine Faust.
- Anthropology 2A, Spring 2012. Introduction to Sociocultural Anthropology. Professor Victoria Bernal.
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- Sociology 120, Winter 2014. Sociological Theory. Professor Samuel Gilmore.
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Chapman University. Orange, CA. February 2016 – May 2017.
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Graduate Student Researcher.

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Continued from page vii

Pomona College, member of the Claremont Colleges. Claremont, CA.
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Lecturer.
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California State University, Fullerton. Fullerton, CA. February 2006 – December 2008.
Graduate Assistant.
- Teaching Assistant for Sociology classes, Spring 2006 to Fall 2008.
- Research Assistant for Eduardo Sanchez, Ed.D. Assisted with interviewing elementary-school children for Professor Sanchez's work on cognitive development. September 2006 – December 2006.
- Research Assistant in the Dean's Office (College of Humanities and Social Sciences). Summer 2006.

Research and Work Experience

United States Census Bureau. Washington, DC. June 2016 – August 2016.
Statistician Student Trainee.
- Foreign-Born Population Branch (FBPB), Population Division, Demographic Directorate.

Migration Policy Institute. Washington, DC. June 2014 – September 2014.
Research Intern.
- Program: U.S. Immigration Policy.
- Interned under Doris Meissner, former Commissioner of the U.S. Immigration and Naturalization Service (INS).

Public Policy Institute of California. San Francisco, CA. June 2013 – August 2013.
Richard J. Riordan Summer Research Intern.
- Project: California Poverty Measure.

United States Census Bureau. Washington, DC. June 2012 – September 2012.
Survey Statistician.
- Industry and Occupation Statistics Branch (IOSB), Social, Economic, and Housing Statistics Division (SEHSD), Demographic Directorate.

Orange County Health Needs Assessment (OCHNA). Garden Grove, CA.
September 2009 – June 2011.
Research Coordinator.
- Produced 4 publicly-released reports with the OCHNA research team (look below in "Research Reports").
- 2010 Community Benefits Reports for Orange County member hospitals.
- City of Irvine Health Needs Assessment.
- Pilot Study for the Oak View Mobile Health and Children's Wellness Program Initiative.

Continued from page viii

OCHNA. Garden Grove, CA. May 2007 – April 2008.
Data Analyst.

- Primary contact while the 2007 OCHNA health needs assessment was in the field. The 2007 OCHNA survey was a random digit-dial survey administered by Macro Int. (which also administers the Behavioral Risk Factor Surveillance Survey for the CDC).
- Produced a research proposal in October 2007 for the Children's Community Health Assessment and Planning Survey for Cook Children's Health Care System in Texas.
- Produced the Orange County Methamphetamine Needs Assessment 2007 for the Orange County Methamphetamine Task Force, funded by the Orange County Health Care Agency's Alcohol and Drug Education and Prevention Team.
- Produced a linguistic needs assessment and report in May 2007 for CalOptima, titled "CalOptima Healthy Families Cultural and Linguistic Needs Assessment."

Presentations

Society for the Study of Social Problems 2017 Annual Meeting. August 11-13, 2017.

- "The Costs of Isolation: An Examination of the Association between Social Integration and Physical and Mental Health."

Research Workshop: "Institutions in Context: Healthcare Institutions and Policy." Hosted by the North American Studies Program at the University of Tampere in Finland. June 5-11, 2017.

- Presented work titled "The Costs of Isolation: An Examination of the Association between Social Integration and Physical and Mental Health."
- Participated in dialogue sessions concerning Finland's changing health care system.

American Sociological Association 2016 Annual Meeting. August 20-23, 2016.

- Section on Social Psychology Roundtable: "Examining the Association between Acculturation and Perceived Mental Health among Foreign-Born Asians in the U.S."

Society for the Study of Social Problems 2016 Annual Meeting. August 19-21, 2016.

- "'Environmental Sacrifice Zones' in Los Angeles County: The Uneven Geospatial Distribution of Toxics Release Inventory (TRI) Facilities in 2010"

Population Association of America 2016 Annual Meeting. March 31, 2016.

- Poster Presentation Title: "Vietnamese Segregation within a Suburban Ethnic Enclave."

Methods Reading Group (housed in the Department of Sociology, UC Irvine). November 5, 2014.

- Workshop Title: "Essential First Steps for Data Analysis"
- Co-presented with Mikaela Smith, UC Irvine Sociology doctoral student.

Stats Reading Group (housed in the Department of Sociology, UC Irvine). November 5, 2013.

- Workshop on weighting sample survey data for a complex sample survey.

Continued from page ix

By Invitation
Vietnamese Forum Meeting. July 8, 2010.

- Presented findings of OCHNA's 2010 Vietnamese health report to meeting of direct service providers and community members.

Data Training Workshop
"Making Data Work for You, Your Organization and Your Funding Requests." February 4, 2008.

- Facilitated a workshop at Hoag Hospital to teach attendees how to understand data.
- Created a Powerpoint presentation and produced a data training information packet for the workshop.

Research Reports (publicly-released)

2014. Migration Policy Institute. Policy Beat in *The Source*: "The Stalemate Over Unaccompanied Minors Holds Far-Reaching Implications for Broader U.S. Immigration Debates."
<http://www.migrationpolicy.org/article/stalemate-over-unaccompanied-minors-holds-far-reaching-implications-broader-us-immigration>

- Policy brief with Muz Chishti and Faye Hipsman.

2013. Public Policy Institute of California. "The California Poverty Measure: A New Look at the Social Safety Net."
<http://www.ppic.org/content/pubs/report/R_1013SBR.pdf>

- Provided research support.

2010. Orange County Health Needs Assessment. "A Look at Health in Orange County's Hispanic/Latino Community."

2010. Orange County Health Needs Assessment. "A Look at Health in Orange County's Vietnamese Community."

2010. Orange County Health Needs Assessment. "Growing Older in Orange County: A Report on Older Adults."

2009. Orange County Health Needs Assessment. "From Prosperity to Poverty: The Changing Conditions in Orange County."

Professional Memberships

American Sociological Association (ASA) • Population Association of America (PAA) • International Network for Social Network Analysis (INSNA) • Society for the Study of Social Problems (SSSP) • Pacific Sociological Association (PSA) • Phi Kappa Phi National Honor Society

Certificates

Data Science Certificate, June 19, 2016
Awarded by: UC Irvine Graduate Division

Software Skills
Statistics: Stata, R, SPSS, SAS.
Social Network Analysis Software: R, UCINET, Pajek, NetDraw.
Mapping: ArcGIS, iXPRESS for MapInfo Professional.
Data Visualization: Tableau.
Publishing: R Markdown, Microsoft Publisher, Adobe Acrobat.

University and Department Service and Activities

Co-organizer. Methods Reading Group (housed in Dept. of Sociology, UC Irvine). 2014-2017.

- Served three terms.
- Invited UC Irvine faculty and graduate students from various departments to present the methods and findings of their current work.

Co-organizer. Stats Reading Group (housed in Dept. of Sociology, UC Irvine). 2013-2014.

- Invited UC Irvine faculty and graduate students, and one Stanford sociology graduate student, to present methods and findings of current work.

Elected member. Verano Residents Council (VRC). 2013-2016.

- Served three terms.
- One of five representatives for residents of Verano Place, UC Irvine Graduate Housing.

Invited speakers for a session of the Population, Society, and Inequality colloquium series (sponsored by the Center for Demographic and Social Analysis, UC Irvine). November 19, 2013.

- Speakers: Sarah Bohn, Ph.D. and Matt Levin, M.P.P. of the Public Policy Institute of California (PPIC).
- Title of talk: *The California Poverty Measure: A New Look at Hardship in the Golden State.*

UC Irvine Sociology Graduate Student Association (SGSA) officer positions:

- Alumni Relations Coordinator, 2 terms (2015-2017).
- Cohort Representative, 3 terms (2012-2015).
- Undergraduate Committee, 4 terms (2011-2015).
- Welcoming Committee, one term (2011-2012).

ABSTRACT OF THE DISSERTATION

Network Quality over Quantity: Exploring the Influence of Network Structure and Function on U.S. Older Adult Physical and Mental Health

By

Bonnie Bui

Doctor of Philosophy in Sociology

University of California, Irvine, 2017

Professor Katherine Faust, Chair

Does the structure of an individual's personal network effect their physical and mental health? Or does the structure of the network influence individual health by influencing the functions of the network or the individual's health behaviors? In my dissertation, I examine these questions using two waves of nationally representative data from the National Social Life, Health, and Aging Project and employing conditional change models.

In study 1, I examine the associations between network structure, network function, and health. I find no direct associations between baseline network structure and later health. However, I do find that baseline network structure is associated with later network function, which, in turn, is associated with health. I also find limited support for a feedback loop in which baseline health has effects on later network structure. Perceived social support may be more important for the health of older adults than network structure characteristics, but network structure is meaningful in that it provides the source from which support can be derived.

In study 2, I examined the effects of spousal loss on depression across different levels of spousal support, including baseline network structure and network function to observe whether they served as a buffer to spousal bereavement. The findings revealed that losing a spouse was positively associated with the number of depressive symptoms, but only for those with highly supportive spouses. None of the network structure and function measures at baseline were associated with later depression. The findings imply that spousal bereavement in late life depends on how supportive the spouse was.

In study 3, I examine the social network factors that influence health risk behaviors—specifically, cigarette use and alcohol consumption. Findings show that personal networks can have protective effects on smoking or drinking; however, for current smokers and drinkers, personal networks are enabling. Having more support and having health discussion partners reduced the adoption of health-compromising behaviors. In conclusion, health-compromising behaviors may not necessarily be adopted as a coping mechanism, but may be a pro-social activity that is increased when there are others in the network who also engage in similar activities.

INTRODUCTION

Social Networks in the Context of an Aging Population

An aging population faces both important health challenges and a potentially changing social context. Studies on the impact of social ties on health have shown that fewer ties result in higher mortality risk. This is because resources in a network often diminish with smaller networks compared to larger networks. In the context of an aging population, networks may diminish in size because of the passing of friends and family. However, research has also shown growth of networks among older adults because of increased leisure time to socialize and participate in community activities post retirement.

Other difficulties unrelated to health, such as financial difficulties, may also have impacts on change in network structure, particularly in family structure, as one strategy of dealing with financial difficulties may be through co-residences. Larger families or households via co-residences can provide resources to the group and serve as a buffer to negative shocks such as poor or declining health, loss of a job, divorce, or unexpected periods of dependency. I will be looking at the loss of a partner specifically in this dissertation, and whether impacts from that loss are buffered by the older adult's network.

Social Connections and Health: Distinguishing Network Function from Network Structure

Over the past two decades, there has been a growing body of literature that theoretically and empirically links the impact of social relationships on health (Berkman et al. 2000), with evidence of increased risk of mortality for persons with low quantity, and sometimes low quality, of social relationships (i.e., socially isolated individuals) (House, Landis, and Umberson 1988). Earlier work on the relationship between social networks and health have even found immunological benefits from networks (Pilisuk and Forland 1978). Some of the primary ways that social ties may affect health status are through the following:

- Social support, including emotional, instrumental, and informational (Thoits 1995);
- Social influence (via values and norms that influence health behaviors) (Friedkin 2001);
- Social engagement (via participation in group and community activities) (Glass et al. 2006);
- Person-to-person contact that impacts exposure rates to infectious disease (Laumann et al. 1989); and
- Access to material resources (Granovetter 1973).

Much of the literature relating social networks and health examine how the presence or absence of social support beneficially or adversely affects physical health, mortality, and mental health. As such, social support is a key determinant of health. However, we ought to be cautious before conflating social networks and social support, as one's social network may include supportive ties, but may also include others who are critical or who make demands on the individual. Indeed, social support is related to social networks (Berkman et al. 2000), with social support linking the composition of an individual's social network to their physical and mental health. Having more social ties has been associated with better health because there is more opportunity to receive social support and health information (Brummett et al. 2001). As such, social support acts as a function of a personal social network.

Furthermore, a distinction needs to be made between "core" and "extended" social networks (Hammer 1983). Family and close friends comprise the core network, whereas the extended network includes more distant friends and acquaintances. Instrumental and emotional support is primarily obtained from the core network moreso than the extended network. This is why focusing on the existence of social ties alone is inadequate, because sheer quantity of ties does not necessarily translate into the ability to derive social support.

The quantity and quality of social relationships affect many different kinds of health outcomes, both short- and long-term—mental health, health behavior, physical health, and mortality risk (Umberson and Montez 2010). Specifically, social support has been shown to facilitate employment and ability to meet basic needs, reduce stress, improve physical and mental health, reduce loneliness and despair, and enhance mental health. The difficulty with studying how social support links social networks to health status is in having to account for the fact that not all ties in a network are supportive, and some ties are more specialized in their support while other ties provide several types of support (multiplexity). Social ties can even be sources of social stress that manifest itself in worsening health (Walen and Lachman 2000). Because the maintenance of social ties requires energy and work, individuals with poor health or other physical or functional limitations may be unable to maintain the social ties from which they can derive social support. If social support can act as a buffer to declining mental health, then poor physical health compromises the ability to maintain that buffer so critical for health maintenance.

Social Integration and Health

The sociological interest in social integration is rooted in Durkheim's (1897) seminal work on suicide, where he emphasized the protective effects of stable social structure and norms, arguing that higher social integration is associated with lower rates of suicide. However, besides suicide, Durkheim did not link social integration explicitly to health and well-being, like Thoits (1983) did. In her "identity accumulation" hypothesis, Thoits argued that role-identities in society gave individuals meaning and purpose, and this in turn is an important part of psychological well-being. In addition to role expectations, integrated individuals are subject to social control that may promote the adoption of health behaviors or at least deter risky behaviors (Umberson 1987).

Studies have shown positive associations between social integration and health. Persons with more types of social relationships fare better on many objective health indicators (Berkman 1995). They have longer lives and lower risks of mortality. On the other hand, in reviewing the literature, Seeman (1996) finds that the evidence on physical health outcomes is less conclusive than the evidence supporting social integration's positive association with better mental health. This implies that beyond merely being socially integrated, having supportive ties may be more important for health. Those with more restricted or truncated networks show worse health outcomes, particularly with anxiety and depression (Cattell 2001).

Background to the Problem

The study of health and social networks focuses on how the composition of individuals' social networks impact physical and mental health. Social networks consist of who an individual knows, how many people an individual knows, and how supportive or stressful those connections are. Physical and mental health outcomes themselves are also linked, and investigators have shown that the existence of social support from people's connections can buffer the impacts of poor health on depression. However, poor physical health may incapacitate individuals from being able to maintain a large network, with dire consequences for mental health. I aim to examine the mechanisms through which lack of social integration affects health outcome, both self-reported and analyzing objective measures of health outcomes, namely disability and depression. I seek to understand whether social network structure matters for health independent of network functions like social support and strain, or whether network structure affects health through its impact on network functions. I also examine whether there are any feedback loops by assessing the impact of health on network structure.

Currently, we know that social relationships affect health. We also know that health can impact social network maintenance. We could better understand what specific measures matter and how they matter. In my research, my primary contribution is using a variety of social network measures over time to see which specific network characteristics have longer-term impacts on health. I aim to discover which dimensions of social connectedness matter, and also whether their impacts on health operate independently of social support, or if social support buffers the relationship between social connectedness and health outcomes.

Contributions

This dissertation builds on existing literature in important ways. This study uses data on respondent reports of their personal networks to measure structure and function of networks, building on research in social network analysis and research detailing how social relationships are important for health outcomes. In this study, I examine how social network structure and functions are associated with health and well-being of older adults. I differentiate between these two concepts carefully to find what specific aspects of social networks impact health and how these factors predict health at a later point in time.

This dissertation will contribute to understanding the relationship between health and social networks among an older population. In my dissertation, I seek to unpack the relationship between health and social networks in the first chapter. In the subsequent chapter, I aim to test the resilience factors that older adults have when experiencing the loss of a spouse or a partner, with a focus on how networks or support matter. In the third study, I will examine the association between social integration and smoking/drinking behavior as health risk behaviors. Using panel data allows me to look at network change over time.

Overview of Dissertation Chapters

In my dissertation, I look more closely at the pathways through which network structure can impact health. The first study examines the physiological and psychosocial pathways by first examining how social network characteristics can impact physical and mental health, both directly or through social support. The first study also seeks to examine whether baseline health conditions can impact social network characteristics and/or social support. The second study examines whether personal social networks can help buffer any adverse health impacts from spousal loss. The third study examines the behavioral pathway through which networks can impact health, looking at both the prevalence and the level of the health-compromising behaviors of smoking and drinking.

STUDY 1: THE RELATIONSHIP BETWEEN HEALTH AND NETWORK STRUCTURE AND FUNCTION AMONG OLDER ADULTS

Overview of the Study

This study explores the associations that social networks and social support have with the health of older adults, examining whether networks significantly impact future health, and also whether health matters for impacting future network characteristics. Data come from the National Social Life, Health, and Aging Project (NSHAP), a longitudinal, population-based study of health and social factors of adults aged 57 to 85 at baseline in 2005-2006. The second wave was conducted in 2010-2011. Using panel data permits stronger causal inferences than cross-sectional studies.

I find no associations between network characteristics and future health outcomes. However, health does influence network structure. While depression reduces contact with one's personal network, poor physical health has the opposite direction, possibly because the need for support from one's network becomes greater. I do find that network characteristics are associated with future levels of perceived social support, and that social support is associated with future health. Perceived social support may be relatively more important for the health of older adults than network structure characteristics, but network structure is meaningful in that it provides the source from which support can be derived. Efforts to enhance older adults' social relationships should be focused on ways to cultivate and strengthen supportive ties more specifically, versus simply expanding networks more generally.

Introduction

Social relationships are influential to the achievement and maintenance of good health (House, Umberson, and Landis 1988). The study of how social networks influence health is not new. The link between social relationships and indicators of health and well-being has been widely documented in the literature, such as links between social relationships and mortality (Berkman and Syme 1979), mental illness and psychological well-being (Kawachi and Berkman 2001, Umberson and Montez 2010), and disability and morbidity (House, Landis, and Umberson 1988; Mendes de Leon, Glass, and Berkman 2003). Given these benefits, the maintenance of social relationships is an important component of older adult health.

Past research has firmly established the importance of social relationships to health. The current research trend is to better understand how the structure of the network itself (e.g., network size, social contact) impacts health and the benefits that can be derived from an individual's network, such as social support. For instance, having large networks may be beneficial in and of themselves, or perhaps levels of support derived from a personal network matter more, regardless of the size of an individual's personal network.

An important limitation of studies that examine the relationship between social relationships and health is the focus on how social relationships impact health, taking the existence of the network itself as given and static rather than something that can be impacted by health. Few studies have explicitly examined how health can impact the structure of one's personal network. In addition, many studies are cross-sectional. In this study, I seek to unpack the differences in the impact that network structure and network functions have on health, focusing on older adult health. I also assess the impact that prior health status can have on network structure. My research contributes to the current literature by examining the bidirectional relationship of network structure, network function, and physical/mental health using two waves of data from a nationally representative longitudinal survey of older adults. In doing so, I contribute to better understanding networks and health while treating networks as an inherently dynamic phenomena.

Social Networks: Structure vs. Function

In this study, I differentiate between the structure versus the function of personal social networks, both as predictors of later physical and mental health, as well as outcomes affected by physical and mental health. I use social network structure to refer to the characteristics of the ties or set of ties between individuals and other members in their personal network. I use the concept of social network function to refer to the benefit that network ties can offer the individual as well as the demands that can be placed on an individual by other ties in their personal network (e.g., social support and social strain).

Individuals live within webs of social connections, often referred to as social networks. Common structural characteristics of social networks include network size, network density (capturing the extent to which network members know each other), and frequency of contact with other members of the network.

The functional characteristics of a social network include levels of social engagement, social support, social influence, and others (Berkman and Glass 2000). Social networks provide the contexts for which social interactions and social engagement can occur. Social support is a function of social networks that occurs when network members provide aid, either instrumental or emotional, to others in the network. Social strain is also a function of a network, whereby others who are in the individual's network do damage to the emotional and/or physical health of that individual.

By making a distinction between the functions of social relationships in a network and the structural characteristics of the network, I can investigate how structural characteristics of the network may be related to the functions of social ties, such as social support, and how the functions of a network may serve as a mediator between structural network characteristics and health and well-being. It is important to study network structure and network function as distinct concepts because there could be independent effects on health outcomes.

Social Support and Social Strain

In this study, the functions of a network are conceptualized as social support and social strain. One of the most important functions of social networks is the provision of social support (Thoits 2011). The relationship between social support and better health is well established in the literature. Less studied is social strain, but a few studies do document the negative impact that social strain has on health, particularly on mental health (Chen and Feeley 2014).

Social support theory, or the support buffer theory, asserts that social support is critical in buffering individuals from the stresses of their social environment and thereby diminishing the adverse impacts on their health from those stresses (Cohen and Wills 1985). Social support is commonly defined as the perception, if not the actuality, that one can rely on others in their network for support when needed. Support can be emotional, instrumental, informational, or provide companionship and a sense of belonging; sources of support can come from family, friends, neighbors, coworkers, etc. In this study I will focus on emotional and instrumental support from family and friends.

Social strain can also be conceptualized as a function of a network, albeit one that has adverse consequences. Network members may provide support to an individual, but also can be sources of strain. If other alters in an individual's network are demanding or critical rather than supportive, then the health impacts to the individual may very well be more negative than positive. In this case, having more social contacts is not necessarily beneficial to the individual.

Benefits of Social Relationships for Well-Being

Social ties in and of themselves may have an influence on health outcomes, regardless of whether an individual actually receives any social support from others in their personal network (Rook 1990, Unger et al. 1999). Being socially connected can have health benefits independent of any support received. Studies have shown the benefits of social ties, independent of social support (e.g., Rook 1987), suggesting the importance of considering structural and functional characteristics of a social network as independent and distinct constructs, as social support is oftentimes conflated to mean social connectedness (Smith and Christakis 2008). In this dissertation, I consider the structure and the function of the network separately. This will allow me to see whether, controlling for levels of social support, social connectedness alone matters for health, or if social ties are linked to health because of the potential resources that can be derived from those ties.

In the first study, I will be examining how both structural and functional characteristics of a network influence future health at a point five years from the baseline year. I make a distinction between social connectedness and social support or strain as functions of a social network, focusing on characteristics of an individual's local network as potential predictors of health in and of themselves, regardless of the level of perceived support reported by respondents. Because of the conceptual distinction, I can explore how the structural characteristics of a network can influence social support.

Associations Among Structural Network Characteristics, Social Support, and Health

Studies have shown that certain structural network characteristics are associated with social support. For instance, social support is higher among older adults with larger networks and denser networks, as well as among older adults who interact with other members of their network more frequently (Seeman and Berkman 1988).

Much of the recent research seeks to explain how social ties affect well-being. The question remains whether there are direct effects, or are the effects through some other mechanism, like social support. The literature establishing the link between social support and health is very extensive. However, the relationship does depend on the outcome of study. For some outcomes, like onset of activities of daily living (ADL) disability, protective effects are not found when looking at social network characteristics and measures of social support (Seeman, Bruce, and McAvay 1996). Other studies find that the association between social ties and health hold for mental health, but are less conclusive for physical health (Seeman 1996), even though depression increases the future risk of disability (Penninx et al. 1999)

Social support can reduce health-related uncertainty and therefore have health benefits. However, the extent to which support improves quality of life and well-being over time remains relatively unknown. Much of the literature on the positive impacts of social support on health are cross-sectional in nature, due to the availability of such kinds of data. These studies do clearly establish that social support, even if perceived, have beneficial effects on health, even if much of this research is correlational in nature (Cohen and Janicki-

Figure 1. Conceptual Model of Network Structure and Function impacting Health.

Social network structure and network functions influence health.

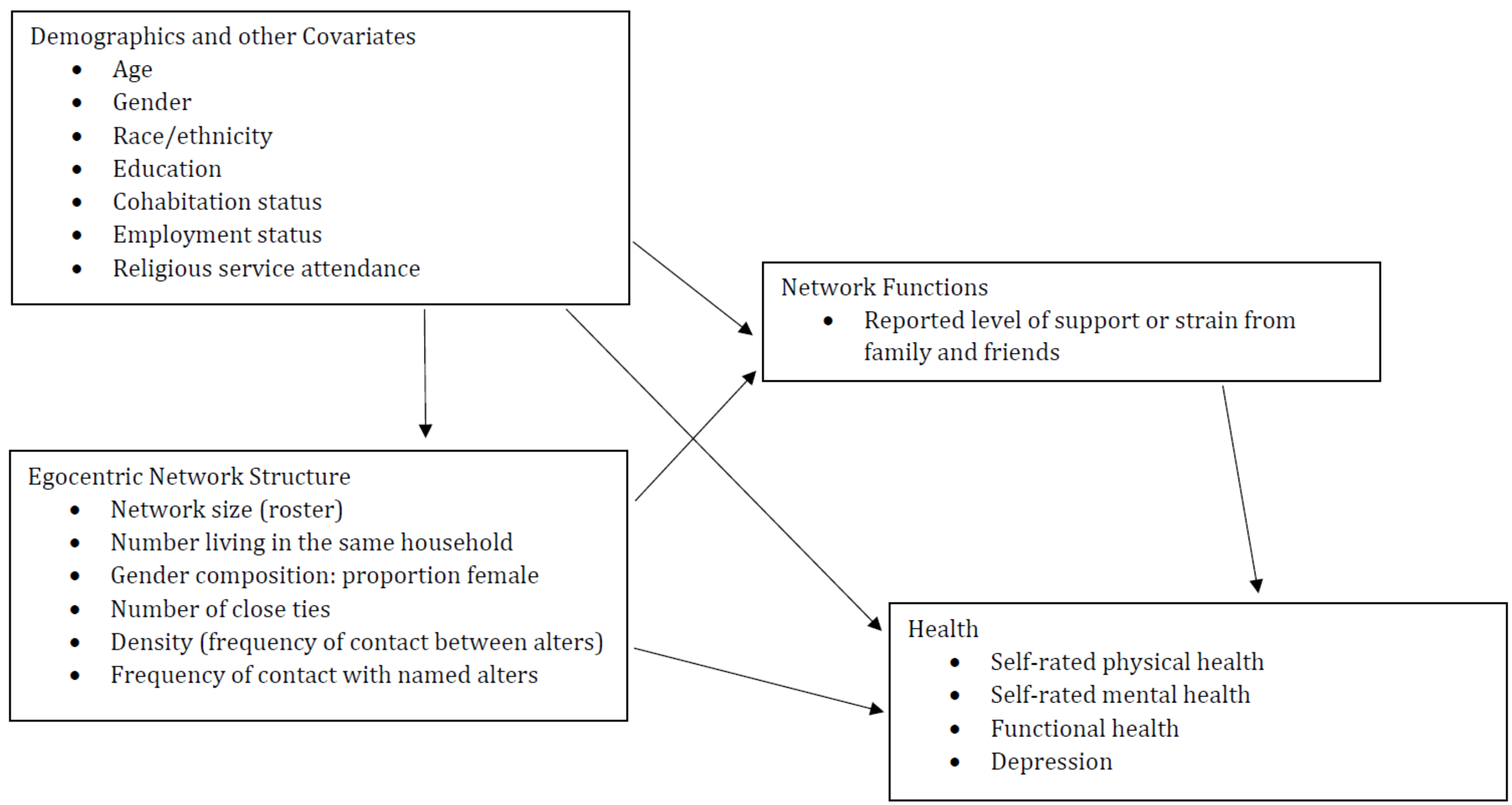
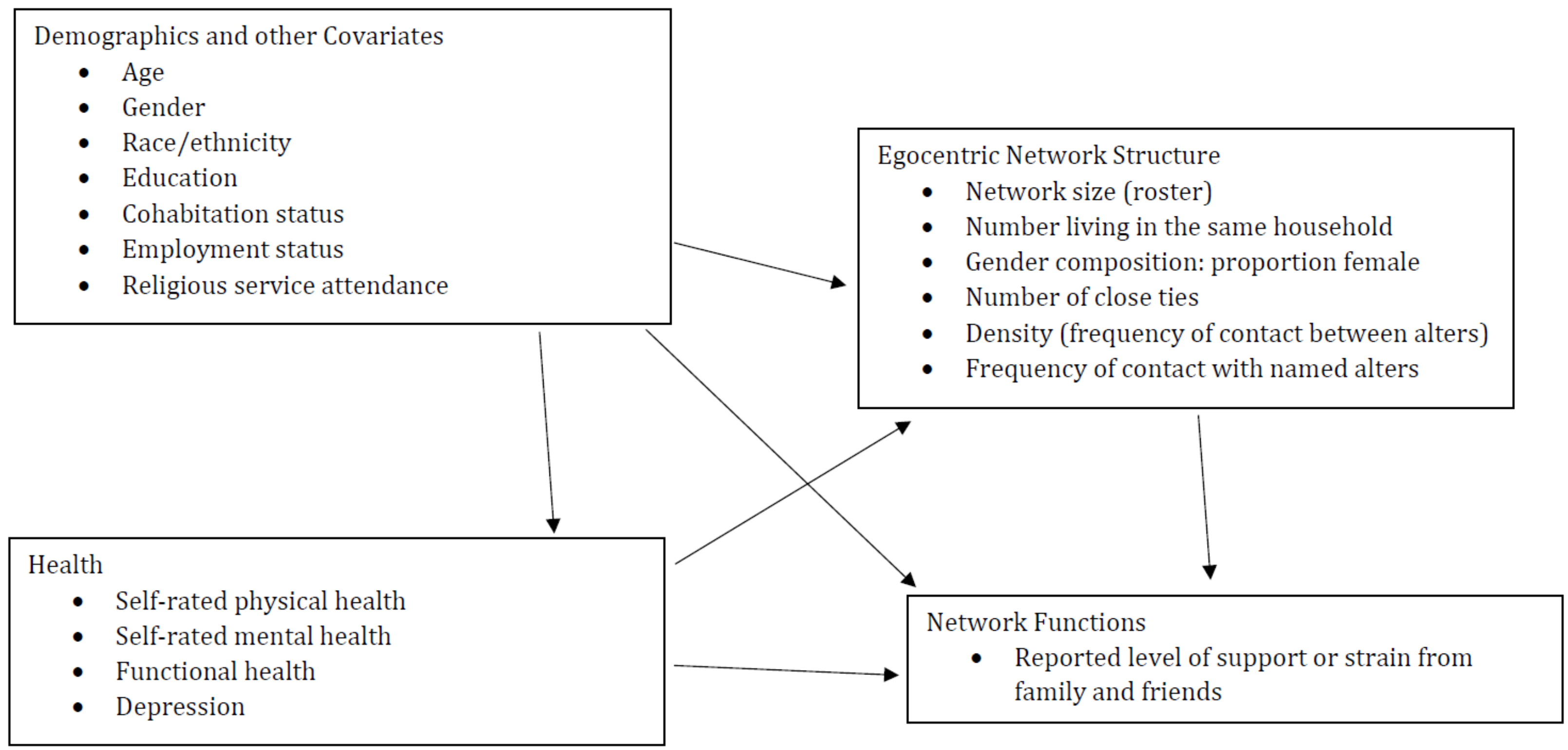


Figure 2. Conceptual Model of Health impacting Network Structure and Function.

Health also influences individuals' ability to form or maintain networks.



Deverts 2009, Mor-Barak and Miller 1991).

Research Questions

This study examines the association among social network characteristics of community-dwelling older adults with perceived social support and social strain and older adults' self-reported physical and mental health status as well as disability status and depression. The conceptual models are presented in Figures 1 and 2.

I seek to unpack the associations between older adults' social ties, levels of social support, and physical and mental health. My main research questions are as follows:

1. Do social network characteristics affect elderly physical or mental health?
2. Does elderly physical or mental health affect social network characteristics?
3. Does social support or social strain act to mediate any relationship between personal network characteristics and older adult health and well-being?

Accounting for baseline health and baseline network characteristics, I examine whether changes in networks and support impact future health, and whether changes in health impact future network characteristics. The aim of the study is to identify which specific network characteristics or whether social support affects older adult health. I assess three sets of hypotheses that correspond with the three research questions.

Hypotheses

Effect of Network Structure and Function on Health

The first set of hypotheses proposed are about how network structure and function are associated with poor health.

Hypothesis 1a: Network structure—network size, number living in the same household, proportion female, number of close ties, density, and the frequency of contact with named alters—will be negatively associated with poor health. Networks are beneficial for health.

Hypothesis 1b: Social support will be negatively associated with poor health. More support is beneficial for health.

Hypothesis 1c: Social strain will be positively associated with poor health. Strain from network ties is detrimental to health.

Effect of Health and Network Structure on Network Function

The second set of hypotheses are about how network structure and baseline health effect perceived social support and strain. A personal network can include supportive ties, thereby positively impacting perceived social support. But a network can also include non-supportive or negative ties as well.

Hypothesis 2a: Network structure will be positively associated with social support.

Hypothesis 2b: Network structure will be positively associated with social strain.

Poor health can make it more difficult to maintain relationships and also create stress on existing relationships. Because of this, the following hypotheses are proposed:

Hypothesis 2c: Poor health will be negatively associated with social support.

Hypothesis 2d: Poor health will be positively associated with social strain.

Effect of Health on Network Structure

The hypothesis for the third research question is about how baseline health is associated with aspects of network structure. Poor health can make it difficult to maintain relationships, as maintaining ties takes time and energy that may not be available after the prioritization of health needs.

Hypothesis 3: Poor health will be negatively associated with various aspects of network structure.

Data

To answer my research questions, I use the National Social Life, Health, and Aging Project (NSHAP). This survey uses a national area probability sample of community residing adults born between 1920 and 1947, ages 57 to 85 at the time of the Wave 1 interview. NSHAP has two waves, with five years between each wave, which will allow me to assess how social network characteristics affect health from time 1 to time 2, but also see how poor health affects the ability to maintain ties or loss of ties from one time to the next. NSHAP is a particularly good dataset to use to assess how poor health can impede the formation or maintenance of networks beyond family networks because NSHAP has two waves in addition to having more detailed information on physical and mental health beyond global health measures like self-rated physical and mental health. In addition to self-rated physical and mental health, I will also be using responses on activities of daily living (ADLs) and depressive symptoms.

NSHAP respondents were selected from the households screened by the Health and Retirement Study (HRS) in 2004. In Wave 1, 3,005 interviews were conducted between July 2005 and March 2006. For Wave 2, NSHAP re-interviewed the Wave 1 respondents and also non-interviewed respondents from Wave 1 who were eligible to participate in NSHAP but were not selected for interview out of the sample of households identified by HRS. In addition, the Wave 2 sample was extended to include cohabiting spouse and romantic partners who were at least 18 years of age and living with the respondent at the time of the Wave 2 interview. For Wave 2, 3,377 interviews were conducted between August 2010 and May 2011. Wave 3 is being planned and the projected number of interviews for Wave 3 is

2,352.

Comment on Missing Data

This study restricts analyses to only complete cases, but missingness from Wave 1 to Wave 2 should be addressed briefly. Among those who responded at Wave 1, 89.4% responded at Wave 2. Relative to other epidemiological surveys, Wave 2 of NSHAP missingness is low (Hawkley et al. 2014). However, nonresponse rates were higher among those with poorer cognitive function and poorer self-rated physical and mental health. This biases the health measures upward, as well as biases the estimates of coefficients between health measures and other covariates. To some degree, the sample weights provided with NSHAP (*weight_adj*) adjusts for nonresponse, including nonresponse due to mortality, as persons who were given a base weight in Wave 1 but died prior to Wave 2 were considered ineligible (O'Muircheartaigh et al. 2014). The weights account for unit-level nonresponse though, and not item-level missingness.

Description of Social Network Module of NSHAP

The NSHAP social network data is egocentric. The social network module for NSHAP permits respondents to identify network members important to the respondent, and then subsequently obtains information about those alters. A set of persons around each respondent are identified, as well as the relationships that link the respondents to other network members, and other network members to each other, providing a "local" sample from the larger social network around ego.

To collect egocentric network data, NSHAP employed name generators; the respondent enumerates relevant alters. The networks module starts off with the following text: "Now we are going to ask you some questions about your relationships with other people. We will begin by identifying some of the people you interact with on a regular basis." To assess several types of network members, NSHAP utilized four "rosters," or lists of people.

For Roster A, respondents were asked to list people with whom they discuss "important matters," thereby allowing enumeration of core confidantes. The following text was used to preface this roster:

> From time to time, most people discuss things that are important to them with others. For example, these may include good or bad things that happen to you, problems you are having, or important concerns you may have. Looking back over the last 12 months, who are the people with whom you most often discussed things that were important to you?

Respondents could name up to five core confidantes. If respondents named five, they were then prompted for any others. This allows us to identify if respondents had zero core contacts, or six or more core contacts.

Rosters B, C, and D capture other potentially important network members because of their relationship status to the respondent, but who were not named in Roster A by the respondent. Roster B included a spouse or romantic partner if the respondent had one but did not include that person in Roster A. For Roster C, respondents were asked the following: "(Besides the people you already listed), is there anyone (else) who is very important to you, perhaps someone with whom you feel especially close?" Any person identified in response to this question was listed in Roster C. Any remaining household members not included in Rosters A to C were added to Roster D.

Following the name generator questions to generate a list of alters, NSHAP then included questions to obtain information about each alter; these types of survey items are generally known as name interpreters. The respondent was asked to identify the type of relationship to each alter (e.g., kin, friend) and the gender of each alter. Other information recorded about the alters included whether the alter lives with ego, ego's frequency of contact with and emotional closeness to alter, ego's likelihood of discussing health matters with alter, and alter's frequency of contact with each of the alter alters listed in Rosters A, B, and C. The age of all alters living with ego was also asked.

Measures

For this study, I included measures for egocentric network structure, social network functions, health outcomes, and typical demographic and control variables. The following sections summarize how these variables were derived or coded.

Social Network Characteristics

Multiple measures for social network structure were used in this study to allow for the examination of which aspects of social network connectedness are impactful for health. The measures used were the following: egocentric network size, number of alters living in the same household as ego, percent female, closeness, density, and frequency of contact with alters.

All of the network structure measures were calculated from the roster data, then aggregated and merged to the main dataset for analyses. The most basic measure is egocentric network size. To calculate network size, I utilized the roster data. In Wave 1, the number of alters was calculated and included in the core dataset. However, this variable only included alters listed as core confidantes to the respondent, not the total number of alters reported by the respondent. Instead, I constructed another variable to indicate the number of alters in each respondent's network. The number of alters was calculated by taking the sum of alters in the network dataset for each respondent.

Each respondent responded to four different rosters: A, B, C, and D. For Roster A, up to five names can be entered for core confidantes whom the respondent discusses important matters to. Those who entered five were then asked if there were any others. For Roster B, respondents can name one spouse or current partner not named in roster A. For Roster C, anyone else important or close not mentioned in A can be named, but only one person can be named. For Roster D, all household members not captured in A, B, or C can be named, and there is no limit.

To construct a measure for the number of alters living with the respondent, I counted the number of alters reported by ego whom ego indicated as residing in the same household. Gender composition was calculated as the proportion of reported alters who are women.

To calculate closeness with alters, I used the responses for the question asking the respondent how close they feel to the person cited, which varied from not very close to extremely close. The responses were (1) not very close, (2) somewhat close, (3) very close, and (4) extremely close. To calculate a variable for a count of how many close alters a respondent has, first the variable measuring closeness was dummy coded to be an indicator for very close and extremely close alters.

The density measure captures the extent to which the members are connected to each other, or the frequency of contact between alters, expressed as a ratio of the number of actual ties to the number of theoretically possible ties. The density measure captured the number of existing ties between the alters of a respondent divided by the number of all possible pairs. This measure was constructed by first binary coding the variable asking about how frequently the respondent thinks the alters talk to each other. The variable responses ranged from (0) never to (8) every day. Any contact was re-coded as 1. Each respondent could have up to 7 alters for these sets of questions, because the respondent was only asked about the frequency of talking for alters in rosters A to C. After binary coding the set of 7 questions asking about the frequency of communication between alters 1 to 7 for each respondent, I summed all the ties reported between alters. The number of ties was divided by the number of pairs to capture the density for each personal network.

Frequency of contact with named alters was constructed by recoding the set of variables asking about the frequency of talking to alters. The responses for this variable ranged from (1) less than once a year to (8) every day and were asked only of those alters listed in rosters A to C, and so the maximum number of alters for this variable is seven. To use the variable as a continuous variable, the responses were recoded to reflect contact-days a year. The variable was recoded as follows: (1) less than once a year to 0.5 contact-days a year; (2) once a year to 1 contact-day a year; (3) a couple times a year to 2 contact-days a year; (4) once a month to 12 contact-days a year; (5) once every two weeks to 26 contact-days a year; (6) once a week to 52 contact-days a year; (7) several times a week to 182 contact-days a year; (8) every day to 365 contact-days a year. Then the number of days was summed across all alters to capture the total days a year of contact that ego has with all reported alters in ego's network. This sum can be quite large, so the sum was then re-scaled by dividing the value by 100 to reflect hundred-days a year so that the coefficients produced would be easier to interpret.

Social Network Functions

The functions of a network were operationalized as social support and social strain experienced from friends and family. Scales were constructed to capture the social support and social strain. The NSHAP survey included the reported level of support or strain from family and friends. There were eight variables in total—four each for family and friends. The survey questions used were the following for family:

- "How often can you open up to members of your family if you need to talk about your worries? Would you say hardly ever, some of the time, or often?"
- "How often can you rely on them for help if you have a problem? Would you say hardly ever, some of the time, or often?
- "How often do members of your family make too many demands on you? Would you say hardly ever, some of the time, or often"?
- "How often do they criticize you? Would you say hardly ever, some of the time, or often?"

The questions asked about friends were similar to the ones asked about family members:

- "How often can you open up to your friends if you need to talk about your worries? Would you say hardly ever, some of the time, or often?"
- "How often can you rely on them for help if you have a problem? Would you say hardly ever, some of the time, or often?"
- "How often do your friends make too many demands on you? Would you say hardly ever, some of the time, or often?"
- "How often do they criticize you? Would you say hardly ever, some of the time, or often?"

The response categories for each question were (1) hardly ever (or never), (2) some of the time, and (3) often.

In Wave 2, the response categories for hardly ever and never were in two separate categories. The question that offered the response options was phrased as follows: "Would you say never, hardly ever or rarely, some of time or often?" The categories "never" and "hardly ever or rarely" were collapsed to be consistent with the responses for these questions in Wave 1.

For the question asking how often the respondent can open up to the family, those who volunteered no family (only 18) were collapsed into the hardly ever or never category. This was done for Wave 2 as well. Also, in Wave 2, those who responded always were collapsed into the often category. This was done to maintain consistency of responses for this set of questions. Similar recoding was done for the question asking about frequency of opening up to friends in Wave 2.

The social support scale was created by summing the response for the four questions asking if the respondent could rely on or open up to family and friends. The response categories were re-coded so that 0 was hardly ever or never, 1 was some of the time, and 2 was often. The range of the scale was a minimum of 0 and a maximum of 8, since there were four questions and 2 was the maximum value for each response. Alpha reliability for this scale was 0.64.

The social strain scale was created by summing the responses for the four questions asking the extent to which the respondent's family and friends criticized or made demands on them. The response categories for this scale was recoded similarly to how the recoding was done for the social support questions, and the range for this measure was 0 to 8. Alpha reliability for this scale was 0.53.

General Health Status

Two measures were used for physical health and two for mental health. For physical health, the two measures were self-rated physical health and ADL disability status. The two measures used for mental health were self-rated mental health and depressive symptoms. For the survey question asking about self-rated physical health, the responses ranged from (1) poor to (5) excellent. The responses for poor and fair were collapsed to form an indicator variable for poor self-rated physical health. Similarly, for self-rated mental health, the responses ranged from (1) poor to (5) excellent. The responses for poor and fair were collapsed to form an indicator variable for poor self-rated mental health.

To measure disability status, a binary variable was constructed. The indicator variable employed self-reported level of difficulty with daily activities, or activities of daily living (ADLs). There were seven variables that measured the respondent's difficulty with activities of daily living (ADLs). Difficulty with the following activities were measured: walking one block, walking across the room, dressing, bathing or showering, eating, getting in or out of bed, using the toilet. The responses for these variables are as follows: (0) no difficulty, (1) some difficulty, (2) much difficulty, and (3) unable to do. The variables measuring difficulty walking a block, bathing/showering, and using the toilet, had a fourth response option "have never done." I collapsed these values with (3) unable to do. Most respondents responded that they did not have any difficult with any of the ADLs. Those who had some difficulty to complete inability to do any of the ADLs were coded as "1."

A measure for depression was constructed by building a scale using the Center for Epidemiologic Studies-Depression (CES-D) variables, which includes questions that ask how much respondents experienced the following: did not feel like eating; felt depressed; felt everything was an effort; sleep was restless; was happy; felt lonely; felt people were unfriendly; enjoyed life; felt sad; felt people disliked them; and could not get going. Responses varied from (1) rarely or none of the time to (4) most of the time. NSHAP used an existing 11-item short from of the CES-D.

To construct the NSHAP Depressive Symptoms Measure (NDSM), the variables measuring degree of happiness and enjoyment of life had to be reverse coded so that higher responses reflected higher levels of depression for all variables. The response categories of *occasionally* and *most of the time* were combined into one category denoting *much or most of the time;* this was necessary to achieve full comparability of the NDSM to the CES-D scale. *Rarely or none of the time* and *some of the time* were left as is. *Rarely or none of the time* was recoded from "1" to "0", *some of the time* was recoded from "2" to "1", and the combined category *much or most of the time* was assigned the value of "2." The scale was then created by summing all the items, producing a total score ranging from 0 to 22, with a higher score reflecting more depressive symptoms. Cronbach's alpha for this scale was 0.788.

An alternative measure for depression status was also constructed using the NDSM. A score of 9+ is the established cutpoint that formally identifies those with Frequent Depressive Symptoms (FDS), which warrants further clinical testing; scores of 8 or less were assigned a score of "0" for the binary variable. (Refer to Payne et al. 2014 for more details on the mental health measures of NDSM and FDS.)

Demographic and Other Covariates

NSHAP includes a number of other demographic and social engagement measures that potentially influence social networks and health, so they are also included in the analysis. Age was left as continuous. Gender was a dichotomous variable (male/female). I recoded this variable to construct an indicator for female. Race/ethnicity included four categories: White, Black, Hispanic non-Black, and other. I used White as the reference category.

A measure for cohabitation status was re-coded from a question asking about the respondent's marital status. The response categories for the survey question were married, living with a partner, separated, divorced, widowed, and never married. I collapsed the responses for married and living with a partner to cohabiting, and collapsed the other four categories to not cohabiting.

The variable for education consists of four categories: less than high school, high school/equivalent, vocational certification/some college/associate's degree, and bachelors or more. I dummy coded education to indicate college completion. Information on income was present in the data, but I did not use this variable because there was so much missing data, due to so many respondents not working, and so not reporting an income. Instead I used the variable for employment status, which included responses for whether the respondents worked for pay or not last week.

The variable for employment status also serves as a variable for social engagement, along with religious participation which was an ordinal measure that captured the estimated frequency of attending religious services. Responses ranged from never to several times a week. Other variables of social engagement (frequency of volunteer work, attendance at meetings of organized groups in the past year, and frequency of socializing with friends or relatives in the past year) were not used because of high levels of missing data.

Analytical Strategy

Data come from two waves of data collection. Models are estimated using ordinary least squares (OLS) and logistic lagged dependent variable regression models (also called “conditional change” models by Finkel 1995 or the “regressor variable method” by Allison 1990). These models account for prior values of the dependent variable before assessing the influences of other independent variables at time 1 on the dependent variable at time 2. All time-varying variables are lagged by one wave, thus independent variables at time 1 are used to predict changes in the outcome variable at time 2. Lagged independent variables help reduce (although not eliminate) the risk of endogeneity due to reverse causation, as it is not possible for outcome variables at time 2 to effect independent variables from a prior wave.

By controlling for prior values of the dependent variable when predicting current values of the dependent variable, the coefficients of the independent variables may be thought of as predicting change in the outcome variable between waves. The coefficients are interpreted as predicting changes in the outcome variable compared to what we would expect knowing the previous value of the dependent variable. The aim of the method is to examine the relationship between an independent variable at time 1 and a dependent variable at time 2 while controlling for the effects of that dependent variable at time 1. The dependent variable at time 1 is essentially treated as a control variable. All coefficients for the independent variables are net of effects from the lagged dependent variable on the dependent variable at time 2.

I chose not to use a change score method because the scores tend to be biased by regression towards the mean (Allison 1990). A change score method entails calculating the difference in the outcome variable from Wave 1 to Wave 2 and then calculating the difference for all independent and control variables from Wave 1 to Wave 2; the change from Wave 1 to Wave 2 for all variables are thus obtained. Analyses are then done by regressing the calculated difference in the outcome variable on the differences between waves for all the independent variables.

Conditional change modeling was chosen instead of fixed effects (FE) or random effects (RE) modeling because I am interested in temporal dependence in terms of how Wave 1 variables effect Wave 2 outcomes, not just whether the dependent variable is associated with the independent variables. Specifically, the model of temporal dependence that I am using is the lagged endogenous variable model, where the dependent variable is determined by a series of independent variables at a lag of time *t*-1, along with the lagged value of the dependent variable, as in:

$$Y_{it} = \alpha + \beta_1(Y_{i(t-1)}) + (\beta_2(X_{1i(t-1)}) + \beta_3(X_{2i(t-1)}) + \ldots + \beta_j(X_{ji(t-1)}) + \varepsilon_{it}$$

In this model, the lag value of *Y,* or the "lagged endogenous variable," has a direct effect on the value of *Y* at the next time point, along with effects specified from prior values of *X* as well. This model is equivalent to predicting the *change* in *Y* from its prior value. Because in this type of modeling, unlike fixed effects or random effects models, there is the absence of the unit-specific error term, it is assumed that *all* of the temporal dependence of responses over time is due to the causal mechanism linking the lagged endogenous variable and the lagged *X*'s to *Y.* The inclusion of the lagged *Y* term is meant to control for regression to the mean that would otherwise be present in the model if the lagged dependent variable was omitted.

Using the conditional change method allows us to take into account the baseline differences between respondents. For purposes of comparison, I include results of models without the lagged dependent variable or controls so we can see how much variation is accounted for by the lag, and what, if any, associations on the dependent variable at time 2 are left after accounting for the lag and other demographic control variables.

All analyses were done using Stata/SE 12.0. Results were weighted using *svyset* commands to incorporate the adjustment for nonresponse and correct for the sampling design. (For more details on weighting, refer to O'Muircheartaigh & Smith 2007.)

Sample Characteristics

Tables 1a and 1b present descriptive statistics for the sample. Table 1a presents descriptive statistics for the respondents included in the models with disability and depression status as health measures. Table 1b presents descriptive statistics for the respondents included in the models for self-rated physical and mental health.

In Wave 1, 26.9% of the sample was disabled. This percent increased to 32.6% in Wave 2. Self-rated measures show lower percentages of poor physical health than the percentage disabled. In Wave 1, 19.3% have poor self-rated physical health; this percent increased to 22.6% in Wave 2.

In Wave 1, 17.3% were depressed; this percentage remained the same in Wave 2. Lower percentages were observed when looking at the self-rated mental health measure instead of the CES-D measure. About eight percent (7.8%) of the sample reported poor self-rated mental health in Wave 1, and this percent increased to 11.1% in Wave 2.

The descriptive statistics for both analytic samples were very similar, with the exception of the health measures. The measures for network structure and social support also experienced very little change between waves. Perceived strain decreased from Wave 1 to Wave 2, but was low to begin with. The majority of the sample was female (53.7% in Table 1a), White (82.2%), college educated (56.5%), cohabiting (68.5%), and had an average age of 66.8 years.

Table 1a. Weighted Descriptive Statistics: NSHAP, 2005-2006 and 2010-2011 (N=1,658).

	Wave 1			Wave 2			Sig. difference
Variables	% or Mean	SD	Range	% or Mean	SD	Range	
Health Outcome							
Disabled	26.9			32.6			**
Depressed[1]	17.3			17.3			
Network structure							
Network size	4.802	(.051)	2 to 14	4.907	(.051)	2 to 14	**
Number living with ego	1.017	(.030)	0 to 11	0.964	(.030)	0 to 9	
Proportion female	0.603	(.007)	0 to 1	0.600	(.007)	0 to 1	
Number of close ties	3.688	(.044)	0 to 7	3.638	(.044)	0 to 7	
Density	0.831	(.008)	0 to 1	0.824	(.008)	0 to 1	
Frequency of contact with alters (hundred contact-days per year)	8.611	(.119)	0 to 22	8.596	(.119)	0 to 26	
Social Support and Strain							
Perceived support	5.449	(.050)	0 to 8	5.474	(.050)	0 to 8	
Perceived strain	0.929	(.034)	0 to 8	0.659	(.034)	0 to 8	***
Demographic and Control Variables (only W1)							
Age	66.826	(.229)	57 to 85				
Female	53.7						
Ethnicity							
White	82.2						
Black	9.8						
Hispanic	5.3						
Other	2.7						
College or higher	56.5						
Cohabiting	68.5						
Worked for pay last week	38.6						
Frequency of religious service attendance[2]	3.552	(.052)	0 to 6				

Note: Unweighted N = 1,658. All statistics are survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse. Two-tailed t-tests were conducted to examine the mean differences between 2006 (wave 1) and 2010 (wave 2) measures.

[1] Depressed = CES-D score of 9+.

[2] Responses were 0=never, 1=less than once a year, 2=about once or twice a year, 3=several times a year, 4=about once a month, 5=every week, and 6=several times a week.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

Table 1b. Weighted Descriptive Statistics: NSHAP, 2005-2006 and 2010-2011 (N=1,678).

	Wave 1			Wave 2			Sig. difference
Variables	% or Mean	SD	Range	% or Mean	SD	Range	
Health Outcome							
Poor Self-Rated Physical Health	19.3			22.6			*
Poor Self-Rated Mental Health	7.8			11.1			***
Network structure							
Network size	4.802	(.050)	2 to 14	4.911	(.054)	2 to 14	**
Number living with ego	1.019	(.029)	0 to 11	0.966	(.027)	0 to 9	
Proportion female	0.602	(.007)	0 to 1	0.600	(.007)	0 to 1	
Number of close ties	3.686	(.045)	0 to 7	3.635	(.046)	0 to 7	
Density	0.831	(.008)	0 to 1	0.824	(.008)	0 to 1	
Frequency of contact with alters (hundred contact-days per year)	8.589	(.117)	0 to 22	8.585	(.137)	0 to 26	
Social Support and Strain							
Perceived support	5.449	(.051)	0 to 8	5.465	(.045)	0 to 8	
Perceived strain	0.925	(.035)	0 to 8	0.661	(.028)	0 to 8	***
Demographic and Control Variables (only W1)							
Age	66.841	(.231)	57 to 85				
Female	53.6						
Ethnicity							
White	82.2						
Black	9.8						
Hispanic	5.4						
Other	2.6						
College or higher	56.6						
Cohabiting	68.5						
Worked for pay last week	38.3						
Frequency of religious service attendance	3.548	(.052)	0 to 6				

Note: Unweighted N = 1,678. All statistics are survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse. Two-tailed t-tests were conducted to examine the mean differences between 2006 (wave 1) and 2010 (wave 2) measures.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

Table 2a. Weighted Odds Ratios of Wave 1 Variables Predicting Wave 2 Disability and Depression from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,658).

	Disabled (W2)									Depressed (W2)								
	Model 1			Model 2			Model 3			Model 1			Model 2			Model 3		
Independent Variables from Wave 1	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.
Disabled (W1)							8.184	(1.244)	***									
Depressed (W1)																5.584	(1.294)	***
Network structure																		
Network size	1.028	(.056)		0.989	(.060)		1.034	(.074)		1.087	(.093)		1.041	(.086)		1.006	(.075)	
Number living with ego	0.868	(.058)	*	1.004	(.078)		0.958	(.077)		0.887	(.078)		1.008	(.087)		1.040	(.090)	
Proportion female	1.166	(.345)		0.831	(.229)		1.108	(.351)		1.779	(.591)		0.952	(.311)		0.903	(.330)	
Number of close ties	1.034	(.049)		1.039	(.057)		1.041	(.069)		0.959	(.067)		0.984	(.065)		1.038	(.068)	
Density	1.002	(.290)		0.891	(.236)		0.732	(.222)		1.075	(.395)		0.883	(.319)		0.841	(.346)	
Frequency of contact with alters (hundred contact-days per year)	1.022	(.018)		1.024	(.021)		1.007	(.024)		0.988	(.024)		0.988	(.025)		0.990	(.026)	
Social Support and Strain																		
Perceived support	0.933	(.030)	*	0.946	(.033)		0.963	(.040)		0.824	(.031)	***	0.797	(.031)	***	0.823	(.037)	***
Perceived strain	1.138	(.066)	*	1.196	(.076)	**	1.137	(.084)		1.234	(.062)	***	1.220	(.060)	***	1.151	(.066)	*
Demographic and Control Variables																		
Age				1.046	(.010)	***	1.046	(.011)	***				0.993	(.015)		0.995	(.013)	
Female				1.179	(.134)		1.041	(.148)					1.481	(.289)	*	1.429	(.318)	
Ethnicity (ref. = white)																		
Black				1.308	(.231)		1.292	(.253)					1.031	(.228)		0.890	(.214)	
Hispanic				0.692	(.186)		0.537	(.134)	*				1.086	(.301)		1.002	(.325)	
Other				0.391	(.182)	*	0.368	(.208)					1.055	(.505)		1.305	(.517)	
College or higher				0.699	(.077)	**	0.904	(.114)					0.522	(.086)	***	0.565	(.098)	**
Cohabiting				0.874	(.152)		0.989	(.186)					0.664	(.141)		0.680	(.169)	
Worked for pay last week				0.571	(.095)	***	0.682	(.131)					0.510	(.080)	***	0.548	(.088)	***
Frequency of religious service attendance				0.964	(.025)		0.984	(.029)					0.955	(.045)		0.981	(.048)	
Intercept	0.416	(.194)		0.042	(.036)	***	0.015	(.014)	***	0.301	(.162)	*	2.053	(2.170)		0.876	(.880)	
Likelihood Ratio		2.12			6.94			14.45			5.24			6.61			11.42	

Note: Unweighted N = 1,658. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse. Standard errors are for log odds.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

Table 2b. Weighted Odds Ratios of Wave 1 Variables Predicting Wave 2 Poor Self-Rated Physical and Mental Health from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,678).

	Poor Self-Rated Physical Health (W2)									Poor Self-Rated Mental Health (W2)								
	Model 1			Model 2			Model 3			Model 1			Model 2			Model 3		
Independent Variables from Wave 1	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.
Poor Physical Health (W1)							10.343	(1.738)	***									
Poor Mental Health (W1)																9.607	(1.970)	***
Network structure																		
Network size	0.968	(.067)		0.967	(.063)		0.965	(.073)		0.984	(.067)		0.976	(.067)		0.898	(.061)	
Number living with ego	1.005	(.098)		1.065	(.088)		1.031	(.103)		1.117	(.082)		1.176	(.101)		1.209	(.115)	
Proportion female	0.749	(.241)		0.594	(.186)		0.590	(.239)		1.976	(.741)		1.292	(.474)		1.100	(.468)	
Number of close ties	0.949	(.058)		0.974	(.059)		1.036	(.066)		0.854	(.071)		0.876	(.080)		0.932	(.085)	
Density	0.612	(.267)		0.488	(.204)		0.490	(.231)		0.758	(.348)		0.699	(.285)		0.835	(.349)	
Frequency of contact with alters (hundred contact-days per year)	1.030	(.017)		1.027	(.019)		1.004	(.022)		1.043	(.027)		1.037	(.028)		1.036	(.031)	
Social Support and Strain																		
Perceived support	0.913	(.023)	***	0.910	(.026)	**	0.923	(.033)	*	0.896	(.040)	*	0.856	(.044)	**	0.870	(.040)	**
Perceived strain	1.191	(.053)	***	1.215	(.053)	***	1.182	(.065)	**	1.211	(.056)	***	1.189	(.059)	***	1.140	(.070)	*
Demographic and Control Variables																		
Age				1.002	(.012)		1.017	(.011)					0.963	(.016)	*	0.976	(.015)	
Female				0.836	(.136)		0.922	(.168)					1.217	(.266)		1.205	(.263)	
Ethnicity (ref. = white)																		
Black				1.233	(.276)		1.086	(.306)					0.998	(.209)		0.946	(.220)	
Hispanic				1.513	(.509)		1.258	(.279)					0.994	(.314)		0.760	(.221)	
Other				0.360	(.208)		0.220	(.184)					0.116	(.105)	*	0.078	(.078)	*
College or higher				0.515	(.070)	***	0.579	(.090)	***				0.494	(.089)	***	0.550	(.102)	**
Cohabiting				0.763	(.122)		0.929	(.194)					0.693	(.182)		0.770	(.212)	
Worked for pay last week				0.457	(.076)	***	0.719	(.147)					0.473	(.123)	**	0.588	(.144)	*
Frequency of religious service attendance				0.986	(.037)		0.985	(.046)					0.934	(.053)		0.943	(.052)	
Intercept	0.771	(.472)		2.058	(2.482)		0.264	(.315)		0.175	(.114)	**	10.173	(15.515)		2.499	(3.598)	
Likelihood Ratio		3.87			5.64			16.29			6.53			11.33			14.49	

Note: Unweighted N = 1,678. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse. Standard errors are for log odds.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

Table 3a. Weighted Regression Coefficients of Wave 1 Variables Predicting Wave 2 Perceived Social Support and Strain from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,658).

	Perceived Social Support (W2)									Perceived Social Strain (W2)								
	Model 1			Model 2			Model 3			Model 1			Model 2			Model 3		
Independent Variables from Wave 1	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.
Perceived support (W1)							0.328	(.031)	***									
Perceived strain (W1)																0.307	(.028)	***
Health Outcome - Disability and Depression																		
Disabled	-0.149	(.122)		-0.158	(.118)		-0.125	(.123)		0.108	(.082)		0.092	(.086)		0.023	(.075)	
Depressed	-0.496	(.129)	***	-0.461	(.123)	***	-0.274	(.126)	*	0.300	(.090)	**	0.270	(.094)	**	0.182	(.072)	*
Network structure																		
Network size	0.073	(.046)		0.011	(.046)		0.0002	(.041)		0.047	(.028)		0.032	(.028)		0.029	(.025)	
Number living with ego	-0.158	(.056)	**	-0.045	(.063)		-0.041	(.057)		-0.019	(.033)		0.003	(.033)		-0.009	(.030)	
Proportion female	0.391	(.208)		-0.158	(.225)		-0.133	(.200)		0.302	(.117)	*	0.068	(.119)		0.042	(.121)	
Number of close ties	0.242	(.057)	***	0.217	(.054)	***	0.106	(.045)	*	-0.074	(.024)	**	-0.059	(.024)	*	-0.033	(.022)	
Density	-0.178	(.230)		-0.116	(.239)		-0.108	(.230)		-0.059	(.126)		-0.040	(.121)		-0.020	(.116)	
Frequency of contact with alters (hundred contact-days per year)	0.042	(.014)	**	0.039	(.012)	**	0.034	(.010)	***	0.008	(.009)		0.006	(.009)		-0.005	(.009)	
Demographic and Control Variables																		
Age				-0.025	(.006)	***	-0.010	(.006)					-0.007	(.005)		-0.001	(.005)	
Female				0.689	(.098)	***	0.497	(.103)	***				0.123	(.067)		0.093	(.062)	
Ethnicity (ref. = white)																		
Black				-0.705	(.178)	***	-0.607	(.168)	***				0.345	(.126)	**	0.277	(.110)	**
Hispanic				-0.955	(.230)	***	-0.755	(.217)	***				0.291	(.132)	*	0.267	(.123)	*
Other				-0.939	(.278)	***	-0.718	(.258)	**				0.446	(.340)		0.251	(.277)	
College or higher				-0.106	(.089)		-0.056	(.078)					0.020	(.077)		0.007	(.080)	
Cohabiting				-0.232	(.105)	*	-0.112	(.095)					-0.204	(.085)	*	-0.103	(.078)	
Worked for pay last week				0.058	(.108)		-0.119	(.106)					0.030	(.074)		0.002	(.069)	
Frequency of religious service attendance				0.066	(.022)	**	0.045	(.022)	*				0.002	(.012)		-0.005	(.013)	
Intercept	4.064	(.291)	***	6.054	(.481)	***	3.723	(.443)	***	0.447	(.201)	*	1.036	(.423)	*	0.425	(.444)	
R^2	0.1039			0.1679			0.2536			0.0273			0.0573			0.1691		

Note: Unweighted N = 1,658. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.
*p <.05, **p <.01, ***p <.001 (two-tailed tests).

Table 3b. Weighted Regression Coefficients of Wave 1 Variables Predicting Wave 2 Perceived Social Support and Strain from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,678).

	Perceived Social Support (W2)									Perceived Social Strain (W2)								
	Model 1			Model 2			Model 3			Model 1			Model 2			Model 3		
Independent Variables from Wave 1	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.
Perceived support (W1)							0.337	(.030)	***									
Perceived strain (W1)																0.308	(.029)	***
Health Outcome - Self-Rated Health																		
Poor Physical Health	-0.210	(.176)		-0.128	(.172)		-0.092	(.171)		0.172	(.076)	*	0.138	(.076)		0.091	(.069)	
Poor Mental Health	-0.043	(.211)		-0.055	(.198)		0.070	(.190)		0.241	(.149)		0.195	(.148)		0.138	(.130)	
Network structure																		
Network size	0.073	(.045)		0.012	(.047)		-0.001	(.042)		0.038	(.029)		0.023	(.027)		0.021	(.024)	
Number living with ego	-0.138	(.057)	*	-0.034	(.064)		-0.033	(.057)		-0.026	(.036)		-0.002	(.034)		-0.017	(.030)	
Proportion female	0.394	(.226)		-0.125	(.237)		-0.108	(.211)		0.281	(.117)	*	0.051	(.118)		0.032	(.118)	
Number of close ties	0.249	(.059)	***	0.224	(.055)	***	0.109	(.045)	*	-0.070	(.022)	**	-0.056	(.022)	*	-0.030	(.021)	
Density	-0.222	(.230)		-0.153	(.239)		-0.134	(.228)		-0.002	(.126)		0.021	(.119)		0.034	(.114)	
Frequency of contact with alters (hundred contact-days per year)	0.044	(.015)	**	0.040	(.013)	**	0.035	(.011)	**	0.008	(.009)		0.006	(.009)		-0.004	(.009)	
Demographic and Control Variables																		
Age				-0.026	(.007)	***	-0.010	(.006)					-0.006	(.005)		-0.001	(.005)	
Female				0.675	(.098)	***	0.485	(.103)	***				0.122	(.070)		0.081	(.067)	
Ethnicity (ref. = white)																		
Black				-0.732	(.187)	***	-0.617	(.173)	***				0.360	(.119)	**	0.279	(.098)	**
Hispanic				-0.973	(.227)	***	-0.768	(.213)	***				0.257	(.136)		0.233	(.123)	
Other				-0.895	(.284)	**	-0.689	(.263)	*				0.395	(.352)		0.212	(.283)	
College or higher				-0.084	(.092)		-0.036	(.083)					0.013	(.075)		0.006	(.076)	
Cohabiting				-0.208	(.108)		-0.086	(.099)					-0.207	(.085)	*	-0.104	(.079)	
Worked for pay last week				0.089	(.114)		0.156	(.112)					0.030	(.072)		0.001	(.068)	
Frequency of religious service attendance				0.077	(.022)	***	0.053	(.022)	*				-0.003	(.013)		-0.008	(.014)	
Intercept	3.951	(.296)	***	5.933	(.492)	***	3.536	(.443)	***	0.476	(.193)	*	1.023	(.430)	*	0.422	(.454)	
R^2	0.0947			0.1597			0.2508			0.0216			0.0498			0.1638		

Note: Unweighted N = 1,678. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.
*p <.05, **p <.01, ***p <.001 (two-tailed tests).

Table 4a. Weighted Regression Coefficients of Wave 1 Variables Predicting Wave 2 Network Structure from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,658).

	Network size (W2)			Number living with ego (W2)			Proportion female (W2)			Number of close ties (W2)			Density (W2)			Frequency of contact with alters (W2)		
Independent Variables from Wave 1	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.
Network structure (W1)																		
Network size	0.275	(.034)	***															
Number living with ego				0.451	(.047)	***												
Proportion female							0.469	(.024)	***									
Number of close ties										0.334	(.032)	***						
Density													0.272	(.037)	***			
Frequency of contact with alters (hundred contact-days per year)																0.450	(.025)	***
Health Outcome - Disability and Depression																		
Disabled	0.264	(.076)	***	0.118	(.042)	**	-0.010	(.013)		0.041	(.072)		-0.016	(.013)		0.116	(.183)	
Depressed	-0.134	(.120)		0.025	(.049)		0.012	(.015)		-0.235	(.125)		0.001	(.017)		-0.594	(.265)	*
Social Support and Strain																		
Perceived support	0.066	(.025)	*	-0.017	(.009)		0.004	(.003)		0.102	(.025)	***	0.002	(.003)		0.028	(.054)	
Perceived strain	0.030	(.037)		0.010	(.019)		0.005	(.004)		-0.024	(.033)		-0.004	(.004)		0.209	(.086)	*
Demographic and Control Variables																		
Age	-0.006	(.005)		-0.011	(.003)	***	0.00003	(.001)		-0.006	(.005)		-0.002	(.001)		0.0008	(.016)	
Female	0.114	(.065)		-0.129	(.041)	**	0.086	(.012)	***	0.308	(.082)	***	-0.038	(.012)	**	0.276	(.196)	
Ethnicity (ref. = white)																		
Black	-0.125	(.128)		0.147	(.080)		0.019	(.013)		-0.111	(.161)		0.062	(.020)	**	0.371	(.336)	
Hispanic	0.397	(.209)		0.373	(.114)	**	-0.024	(.020)		0.267	(.128)	*	0.033	(.022)		1.309	(.490)	**
Other	0.081	(.229)		0.294	(.158)		-0.035	(.043)		-0.154	(.275)		0.050	(.030)		0.918	(.705)	
College or higher	0.111	(.084)		-0.077	(.047)		0.020	(.011)		0.076	(.066)		-0.045	(.014)	**	-0.487	(.181)	**
Cohabiting	0.019	(.085)		0.186	(.065)	**	-0.043	(.012)	***	0.153	(.090)		0.058	(.014)	***	0.248	(.188)	
Worked for pay last week	0.184	(.104)		0.035	(.042)		-0.010	(.012)		-0.069	(.089)		-0.026	(.011)	*	0.026	(.225)	
Frequency of religious service attendance	0.006	(.023)		-0.003	(.012)		0.0001	(.003)		0.030	(.023)		0.003	(.003)		0.085	(.048)	
Intercept	3.299	(.464)	***	1.257	(.230)	***	0.265	(.064)	***	1.927	(.441)	***	0.715	(.085)	***	3.911	(1.170)	**
R^2	0.1107			0.3083			0.3540			0.2103			0.1504			0.2561		

Note: Unweighted N = 1,658. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.
*p <.05, **p <.01, ***p <.001 (two-tailed tests).

Table 4b. Weighted Regression Coefficients of Wave 1 Variables Predicting Wave 2 Network Structure from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,678).

	Network size (W2)			Number living with ego (W2)			Proportion female (W2)			Number of close ties (W2)			Density (W2)			Frequency of contact with alters (W2)		
Independent Variables from Wave 1	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.
Network structure (W1)																		
Network size	0.271	(.033)	***															
Number living with ego				0.443	(.045)	***												
Proportion female							0.465	(.024)	***									
Number of close ties										0.337	(.032)	***						
Density													0.266	(.037)	***			
Frequency of contact with alters (hundred contact-days per year)																0.452	(.025)	***
Health Outcome - Self-Rated Health																		
Poor Physical Health	0.110	(.120)		0.213	(.061)	***	-0.008	(.017)		-0.025	(.097)		0.045	(.015)	**	0.630	(.199)	**
Poor Mental Health	-0.003	(.192)		-0.046	(.100)		0.037	(.022)		0.121	(.172)		-0.042	(.023)		-0.008	(.363)	
Social Support and Strain																		
Perceived support	0.075	(.026)	**	-0.014	(.009)		0.004	(.003)		0.111	(.025)	***	0.002	(.003)		0.060	(.049)	
Perceived strain	0.038	(.035)		0.010	(.018)		0.004	(.004)		-0.019	(.033)		-0.004	(.004)		0.205	(.084)	*
Demographic and Control Variables																		
Age	-0.005	(.005)		-0.011	(.003)	***	0.0002	(.001)		-0.005	(.006)		-0.002	(.001)		0.004	(.016)	
Female	0.113	(.064)		-0.123	(.043)	**	0.086	(.012)	***	0.301	(.079)	***	-0.038	(.012)	**	0.330	(.206)	
Ethnicity (ref. = white)																		
Black	-0.156	(.129)		0.111	(.081)		0.021	(.013)		-0.131	(.171)		0.054	(.021)	*	0.270	(.357)	
Hispanic	0.397	(.209)		0.346	(.110)	**	-0.027	(.019)		0.276	(.129)	*	0.032	(.024)		1.285	(.451)	**
Other	0.060	(.236)		0.269	(.151)		-0.038	(.043)		-0.150	(.279)		0.048	(.028)		0.889	(.633)	
College or higher	0.074	(.081)		-0.088	(.047)		0.022	(.011)	*	0.072	(.068)		-0.043	(.014)	**	-0.402	(.178)	*
Cohabiting	0.040	(.084)		0.209	(.063)	**	-0.042	(.013)	***	0.167	(.092)		0.058	(.013)	***	0.328	(.187)	
Worked for pay last week	0.172	(.106)		0.041	(.042)		-0.009	(.013)		-0.032	(.089)		-0.019	(.012)		0.209	(.228)	
Frequency of religious service attendance	0.008	(.023)		-0.003	(.012)		0.0003	(.003)		0.030	(.022)		0.003	(.003)		0.093	(.046)	*
Intercept	3.235	(.484)	***	1.191	(.210)	***	0.255	(.067)	***	1.706	(.451)	***	0.709	(.088)	***	3.107	(1.227)	*
R^2	0.1062			0.3056			0.3514			0.2062			0.1514			0.2624		

Note: Unweighted N = 1,678. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.
$^*p<.05$, $^{**}p<.01$, $^{***}p<.001$ (two-tailed tests).

Results

The goal of this study was to examine the associations between network structure and function and health outcomes, while also observing whether baseline health was associated with network structure and/or function. Three sets of results are presented in the following sections. Table 2a presents the odds ratios from the residual change score models for disability and depression status regressed on network structure and social support/strain measures. Table 2b presents the same modeling strategy but using self-reported physical and mental health instead of disability and depression as outcome measures. These models assess the associations between network structure and function and later physical and mental health.

The next set of models assess social support/strain regressed on network structure and physical/mental health status. The models with disability/depression as the health measures is displayed in Table 3a, and the models with self-reported measures are displayed in Table 3b. The last set of models assess network structure regressed on health, with Table 4a presenting the models with disability/depression as the health measures, and Table 4b presenting models with self-reported physical/mental health measures.

Health Outcome

Two sets of results are presented. One set employs disability and depression status as outcome variables to examine how network structure and social support/strain are related to the onset of disability or depression five years from baseline. The second set of results parallels the first set, with poor self-rated physical and mental health as outcome measures. Tables 2a and 2b present three models for each outcome variable. Model 1 presents the odds ratios for network structure and network function without controls or the lagged dependent variables. Model 2 presents the odds ratios with controls, and Model 3 adds the lagged dependent variable.

From Model 3 for disability status in Table 2a, we can see that none of the network structure variables or social support/strain variables at time 1 (T1) predict disability status at time 2 (T2) once we control for disability at baseline or T1. Hypothesis 1a predicted that network structure would be negatively associated with poor health, but the results do not provide support for this hypothesis. The odds of disability status do increase with age (*OR*=1.046, *p*<.001), and Hispanics experience lower odds of disability compared to Whites (*OR*=0.537, *p*<.05). However, it is disability at T1 that is most important in predicting disability at T2 (*OR*=8.184, *p*<.001).

For depression, higher perceived social support from friends and family reduces the odds of depression onset at T2 (*OR*=.823, *p*<.001), controlling for baseline depression status at T1. Having an educational level of college (*OR*=.565, *p*<.01) and higher and being currently employed (*OR*=.548, *p*<.001) also reduces the odds of depression. Perceived social strain increases the odds of depression onset (*OR*=1.151, *p*<.05). However, none of the measures of network structure mattered for depression onset. This is inconsistent with the literature that finds that social ties matter for mental health. Hypotheses 1b and 1c are supported using this measure, but not 1a.

Similarly to the results for depression, in Table 2b, we see that perceived support decreases the odds of having poor self-rated physical health (*OR*=.923, *p*<.05) and mental health (*OR*=.870, *p*<.01), while perceived strain increases the odds of poor self-rated physical health (*OR*=1.182, *p*<.01) and mental health (*OR*=1.140, *p*<.05). Hypotheses 1b and 1c were also both supported when using self-rated physical and mental health as outcome measures. The models for poor self-rated physical and mental health are more comparable to the results for depression status as an outcome than disability onset, as none of the network structure and function variables mattered for disability onset.

Social Support and Strain

Tables 3a and 3b present the OLS regression models predicting perceived social support and perceived social strain in Wave 2 from Wave 1 health and network structure variables. The previous results from Tables 2a and 2b showed that social support and social strain matters more for the onset of depression than any of the measures for personal network structure. Both perceived support and perceived strain matter for the odds of poor self-rated mental and physical health. Tables 3a and 3b model social support and social strain as outcome variables to observe whether network structure impacts support. Network measures may not matter for predicting the onset of disability, depression, or self-rated physical/mental health, but they may impact support or strain, which we know matters for health.

The results in Table 3a indeed show that both the number of close ties (b=.106, p<.05) and the frequency of contact with other network members (b=.034, p<.001) increases perceived social support, although none of the network structure measures were significantly predictive of Wave 2 social strain. Table 3b, using the self-reported measures, show similar results, with the number of close ties (b=.109, p<.05) and the frequency of contact with alters (b=.035, p<.01) in Wave 1 positively associated with perceived social support in Wave 2. These results show that network structure may play a more indirect role in impacting health by impacting network functions instead, particularly social support.

Hypothesis 2a predicted that network structure would be positively associated with social support. There is support for this hypothesis with two of the network measures: the number of close ties and the frequency of contact with other network members. Hypothesis 2b, which predicted that network structure would be positively associated with social strain, was not supported by the findings.

Baseline depression is also associated with both perceived support and perceived strain. Being depressed in Wave 1 is negatively associated with perceived social support in Wave 2 (b=-0.274, p<.05) and positively associated with perceived social strain in Wave 2 (b=.182, p<.05). Hypotheses 2c and 2d are supported, but only with respect to depression. Neither baseline disability status or poor physical/mental health is associated with perceived social support and strain in Wave 2.

Other results show that being female and having higher levels of religious service attendance are both associated with higher perceived social support. Being non-White is associated with lower perceived social support in Wave 2, but higher perceived social strain.

Network Structure

The last set of models examine whether baseline health matters for network structure. The prior sets of models show that baseline network structure is not associated with health outcomes. The network function measures do predict later health outcomes. Some of the network structure variables are associated with social support though. This shows network structure's indirect relationship with health via social support.

Tables 4a and 4b present the results of the panel regression models for predictors of network structure in Wave 2. The results in Table 4a show that prior disability status is positively associated with network size (*b*=.264, *p*<.001) and the number of alters living with ego (*b*=.118, *p*<.01) at Wave 2 five years later. This is in contrast to Hypothesis 3, which predicted that poor health would be negatively associated with network structure, not positively associated. The positive associations observed could be explained by the mobilization hypothesis (Dunbar, Ford, and Hunt 1998), which asserts that individuals with disability or illnesses requiring care or support may have larger networks because of the need to mobilize one's network to obtain support. Depression is negatively associated with the frequency of contact with alters (*OR*=-0.594, *p*<.05), which is consistent with the expected direction of poor health negatively impacting personal network structure.

For poor physical health presented in Table 4b, we also observe a positive association with the number of alters living with ego at the 5-year follow-up (*b*=.213, *p*<.001). In addition, we also observe poor self-rated physical health positively associated with density (*b*=.045, *p*<.01) and the frequency of contact with alters (*b*=.63, *p*<.01). Cornwell (2009b) has found that older adults with poor health are less likely to have network bridging potential in later life. His finding may explain why we see a positive association between baseline poor self-rated physical health and network density.

Discussion and Conclusions

There is a growing body of research that documents the associations between network structure, social support, and health outcomes. One important finding in the literature has been the continued finding of the significance of social support to health outcomes. The results concerning the relationship between local network structure and well-being have been less consistent, although many studies do find that having more contacts with alters are beneficial. This study contributes to the literature by employing panel data to demonstrate causal relations between these relationships while differentiating between network structure and social support.

The three primary research questions for this study were as follows:

1. Do social network characteristics affect elderly physical or mental health?
2. Does elderly physical or mental health affect social network characteristics?
3. Does social support or social strain act to mediate any relationship between personal network characteristics and older adult health and well-being?

The results show that none of the social network structure measures are associated with physical or mental health during the five-year follow-up. These results are consistent regardless of whether we use disability status and depression status as outcome variables, or self-rated physical/mental health. These findings suggest that network structure is not directly related to changes in health, at least over a five-year period. Either the effects that network structure has on health are more short-term and fades over time, which is why no significant effects were detected, or the impacts on health from changes in network structure take longer to effect changes.

However, we do see that health does have an association with certain social network characteristics. Depression is associated with reduced contact with networks. Unexpectedly, poor health is associated with increases in social network size, number of household members, and density and frequency of contact with alters. This could be explained by the mobilization hypothesis, where the need for support generates larger networks to fill that need. This is contrary to some of the literature that asserts that poor health results in less dense networks among older adults in a cross-sectional study (Cornwell 2009a) or that poor health results in the formation of smaller networks among adolescents (Haas, Schaefer, and Kornienko 2010), although consistent with prior studies that find that elderly poor health is associated with lower network bridging potential (Cornwell 2009b).

The results show mixed results for the third research question on whether the social network functions of social support or strain act as mediators to the relationship between networks and health. The models do not show any mediation because there were no main effects observed between networks and health, and so there were no model effects to mediate per se. However, we do observe that networks, namely the number of close ties and the frequency of contact with alters, are related to social support in the models with social support/strain as outcome variables. We also see that social support/strain is associated with the odds of poor self-rated mental and physical health. In this way, network structure can have an indirect association with health outcomes through impacting the functions of a network, but the lagged dependent variable modeling strategy does not show statistical mediation.

Because no moderation or mediation effects were found, the effects of network structure and network function on health are largely independent. Both network structure and function may affect different aspects of health. The findings emphasize that personal network structure and network function are distinct concepts. Controlling for network structure, social support still matters, suggesting that the structural network characteristics may be less important for health than the functional characteristics of a network. Social support has direct relationships with health, indicating that the perceived quality of social ties are more important for health than the quantity or the structure of those ties. Adverse impact from baseline poor health can be mitigated by one's personal network, because local networks impact the perception of support, and social support was found to be protective.

A number of limitations should be considered. First, the lagged modeling approach can be used only to consider the possibility of causality, but more conclusive causal arguments cannot be drawn from this approach. Second, NSHAP only collects egocentric network data, so I cannot consider broader family structures beyond personal networks. Third, because NSHAP only has two waves, there are limitations when making arguments about any possible “feedback loops.”

STUDY 2: NETWORKS AND SPOUSAL BEREAVEMENT IN LATE LIFE

Overview to the Study

This study examined different components of network structure and network function to observe if any of these components can serve as a buffer to the negative effects to health from spousal loss, comparing the effects across different levels of spousal support. The sample of older adults was taken from the first and second waves of the National Social Life, Health, and Aging Project. The aim of the study was to determine which network components mediated the impact of spousal loss on the number of depressive symptoms, measured on the CES-D scale.

OLS regressions revealed that losing a spouse did have a positive association with the average number of depressive symptoms, but only for those with highly supportive spouses. Perceived strain was also positively associated with the number of depressive symptoms for respondents with high spousal support at baseline. None of the network function and network structure measures were associated with depressive symptoms for those with moderate or low spousal support at baseline. The findings imply that the negative association of spousal loss on depression in late life depends on how supportive the spouse was.

Introduction

Spousal bereavement is a major source of life stress. Researchers have found that spousal loss is related to the development of depressive symptoms in the elderly (Sikorski et al. 2014). While the grief process may subside in a few weeks or months for some, others experience depressive symptoms for much longer. The link between spousal loss and the development of depressive symptoms can be attributed to the loneliness experienced from spousal loss (Fried et al. 2015).

One major limitation of past research is not distinguishing supportive spouses from less supportive spouses. The development of depressive symptoms and feelings of loneliness may depend on how much a spouse is a source of support. Furthermore, loneliness may be mitigated if there are other sources of support that can help quell it, so it is important to investigate an older adult's personal network beyond their spouse.

This study queries the linkage of older adults' spousal loss to mental health, testing whether egocentric network characteristics and social support or strain act to buffer any adverse impacts from the loss. My study will investigate whether the development of depressive symptoms over time depend on whether the spouse was supportive before their loss, and whether other aspects of local network structure can mitigate the development of depressive symptoms from spousal loss.

I attempt to bring greater clarity by identifying different network components to the study and investigating those components so that we may find what specific aspects of a local network matter for spousal bereavement. Analyses examine associations of spousal loss, network structure, and social support/strain on depressive symptoms. Only the number of depressive symptoms is used as an outcome because spousal loss (widowhood) is not associated with changes in physical health across waves. [For reference, Table A in the appendix shows the models using inability to perform activities of daily living (ADLs) instead of depressive symptoms.]

Personal Social Networks as Potential Buffer from Effects of Spousal Loss on Depressive Symptoms

Bereavement is associated with worse physical and mental health (Helsing, Szklo, and Comstock 1981; Stroebe, Schut, and Stroebe 2007), and the effects can be long term (Das 2012). The psychosocial stress model posits that the loss of a spouse is associated with declines in psychosocial functioning when spousal loss is associated with the loss of meaningful spousal roles and functions, significant relationships, social support, or contacts (Siegel and Kuykendall 1990, Stroebe and Stroebe 1987). If spousal loss has adverse impacts on health because of the consequences of the loss of an important relationship, then the loss should not be as impactful if the relationship did not provide much support. My study investigates this question by presenting separate regression analyses for different levels of supportive spouses to find whether any differences exist in the relationship between spousal loss and mental health for those with supportive spouses compared to those without supportive spouses. I hypothesize that spousal loss has adverse effects, but that the effects are larger for those with supportive spouses.

Theories of social support posit both that social support itself is beneficial for well-being (main- or direct-effect model) and also beneficial by protecting individuals from adverse effects of stressful events (stress buffering model). The literature provides evidence supporting both processes (Cohen and Wills 1985, Kawachi and Berkman 2001). Supportive networks help individuals cope with stressful events and can be protective from the deterioration of health as a result of a crisis or momentous event (Albrecht and Goldsmith 2003), such as spousal loss. In this study, I hypothesize that support and networks will reduce the adverse consequences on mental health from spousal loss.

If social support provides buffers from stress, then the adverse impact from bereavement can be moderated by different levels of social ties and social support. The literature is contradictory in whether social support can act as a stress buffer as a consequence of spousal loss. Some studies find main effects of social support on depressive symptoms or psychological stress, but no buffering effect of social support on stress (Stroebe et al. 2005; Thoits 1982). In contrast, other studies have found that social support does indeed moderate the stress associated with spousal loss (Norris and Murrell 1990) or loss more generally (Siegel and Kuykendall 1990).

Many of these contradictory findings are due to different ways of measuring social support, as well as conflating social support—a function of a network—with measures of social network structure, such as number of close ties in a local network (Cohen et al. 1985; Smith and Christakis 2008). In this study, I use different ways of operationalizing social support and egocentric network characteristics to see which, if any, specific measures can serve as a buffer for the adverse effects from spousal loss.

My primary research questions are the following:

1. Does the negative impact from the loss of a spouse depend on whether the spouse was supportive or not?
2. Do social network characteristics or social support act as a buffer for any adverse impacts from spousal loss?

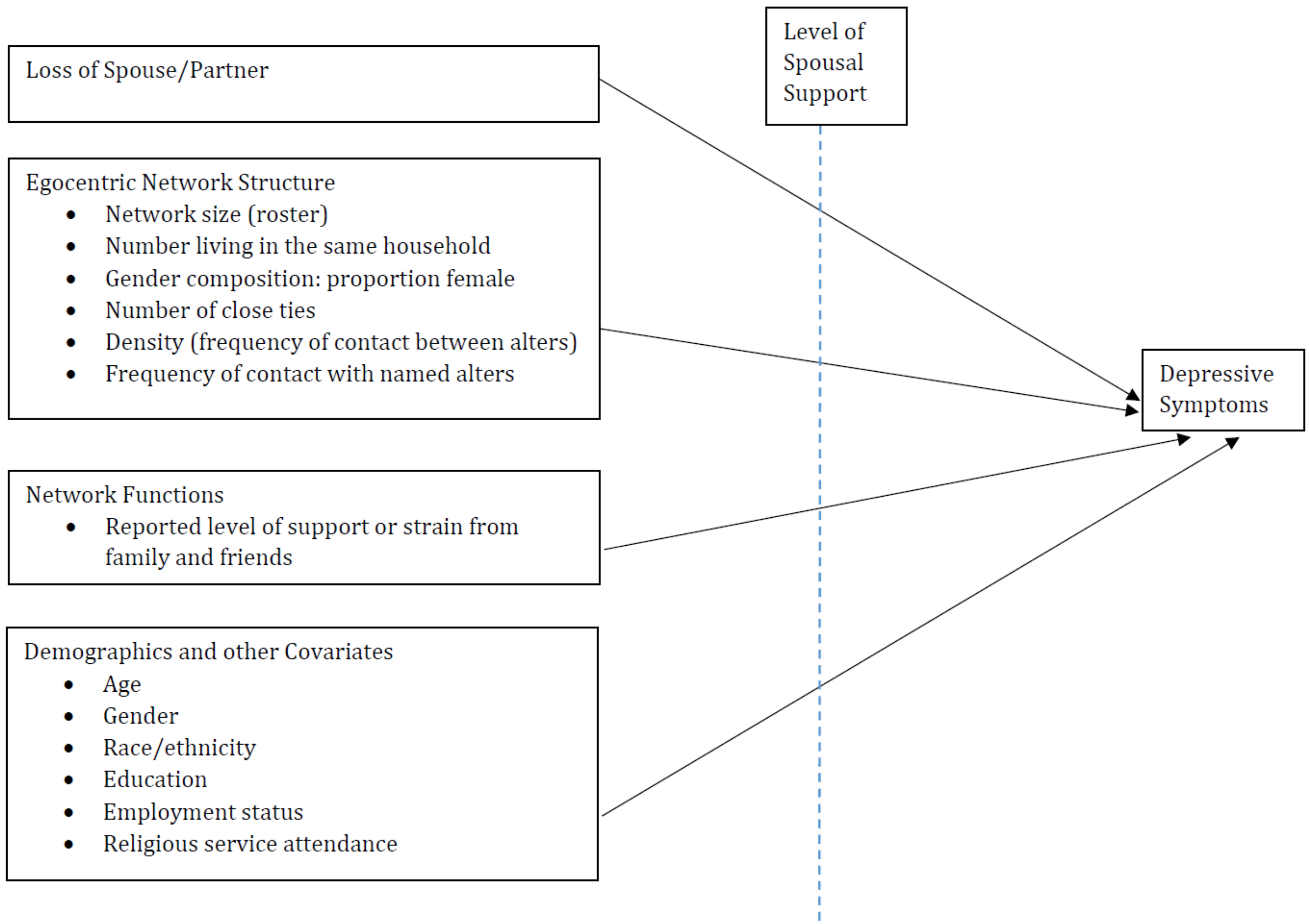
The conceptual model in Figure 3 summarizes the study.

Hypotheses

In this study, I investigate whether the initial level of support of the older adult's spouse matters in looking at negative associations with mental health. I also investigate whether other factors in a personal network can act to reduce the consequences of spousal loss. I propose the following hypotheses about the relationship between spousal bereavement, personal networks, and depression.

Figure 3. Conceptual Model for Effects of Spousal Loss by Different Levels of Support of Spouse/Partner.

The mental health impact from loss of a spouse depends on the level of support of the spouse/partner.



Hypothesis 1: Spousal loss will be associated with increases in depressive symptoms, but this increase will be greater for those who lost highly supportive spouses.

Hypothesis 2: Personal networks—network size, number living in the same household, proportion female, number of close ties, density, and the frequency of contact with named alters—will be negatively associated with depressive symptoms.

Hypothesis 3: Social support will be negatively associated with depressive symptoms.

Data

To answer my research questions, I use the National Social Life, Health, and Aging Project (NSHAP). This survey uses a national area probability sample of community residing adults born between 1920 and 1947, ages 57 to 85 at the time of the Wave 1 interview. NSHAP has two waves, with five years between each wave, which will allow me to assess how social network characteristics affect health from time 1 to time 2, but also see how poor health affects the ability to maintain ties or loss of ties from one time to the next. NSHAP is a particularly good dataset to use to assess how poor health can impede the formation or maintenance of networks beyond family networks because NSHAP has two waves in addition to having more detailed information on physical and mental health beyond global health measures like self-rated physical and mental health. For this study, I will be using data on depressive symptoms, and I also include a set of analyses using responses on activities of daily living (ADLs) in the appendix.

NSHAP respondents were selected from the households screened by the Health and Retirement Study (HRS) in 2004. In Wave 1, 3,005 interviews were conducted between July 2005 and March 2006. For Wave 2, NSHAP re-interviewed the Wave 1 respondents and also non-interviewed respondents from Wave 1 who were eligible to participate in NSHAP but were not selected for interview out of the sample of households identified by HRS. In addition, the Wave 2 sample was extended to include cohabiting spouse and romantic partners who were at least 18 years of age and living with the respondent at the time of the Wave 2 interview. For Wave 2, 3,377 interviews were conducted between August 2010 and May 2011. Wave 3 is being planned and the projected number of interviews for Wave 3 is 2,352.

Description of Social Network Module of NSHAP

The NSHAP social network data is egocentric. The social network module for NSHAP permits respondents to identify network members important to the respondent, and then subsequently obtains information about those alters. A set of persons around each respondent are identified, as well as the relationships that link the respondents to other network members, and other network members to each other, providing a "local" sample from the larger social network around ego.

To collect egocentric network data, NSHAP employed name generators; the respondent enumerates relevant alters. The networks module starts off with the following text: "Now we are going to ask you some questions about your relationships with other people. We will begin by identifying some of the people you interact with on a regular basis." To assess several types of network members, NSHAP utilized four "rosters," or lists of people.

For Roster A, respondents were asked to list people with whom they discuss "important matters," thereby allowing enumeration of core confidantes. The following text was used to preface this roster:

> From time to time, most people discuss things that are important to them with others. For example, these may include good or bad things that happen to you, problems you are having, or important

> concerns you may have. Looking back over the last 12 months, who are the people with whom you most often discussed things that were important to you?

Respondents could name up to five core confidantes. If respondents named five, they were then prompted for any others. This allows us to identify if respondents had zero core contacts, or six or more core contacts.

Rosters B, C, and D capture other potentially important network members because of their relationship status to the respondent, but who were not named in Roster A by the respondent. Roster B included a spouse or romantic partner if the respondent had one but did not include that person in Roster A. For Roster C, respondents were asked the following: "(Besides the people you already listed), is there anyone (else) who is very important to you, perhaps someone with whom you feel especially close?" Any person identified in response to this question was listed in Roster C. Any remaining household members not included in Rosters A to C were added to Roster D.

Following the name generator questions to generate a list of alters, NSHAP then included questions to obtain information about each alter; these types of survey items are generally known as name interpreters. The respondent was asked to identify the type of relationship to each alter (e.g., kin, friend) and the gender of each alter. Other information recorded about the alters included whether the alter lives with ego, ego's frequency of contact with and emotional closeness to alter, ego's likelihood of discussing health matters with alter, and alter's frequency of contact with each of the alter alters listed in Rosters A, B, and C. The age of all alters living with ego was also asked.

Measures

The measures used include depressive symptoms as an outcome variable, and various social support, network structure, and demographic and control variables as independent variables. The sample was restricted to those who had a spouse or partner in Wave 1 to capture the impact from spousal loss.

Depressive Symptoms Outcome

A measure for depression was constructed by building a scale using the Center for Epidemiologic Studies-Depression (CES-D) variables, which includes questions that ask how much respondents experienced the following: did not feel like eating; felt depressed; felt everything was an effort; sleep was restless; was happy; felt lonely; felt people were unfriendly; enjoyed life; felt sad; felt people disliked them; and could not get going. Responses varied from (1) rarely or none of the time to (4) most of the time. NSHAP used an existing 11-item short from of the CES-D.

To construct the NSHAP Depressive Symptoms Measure (NDSM), the variables measuring degree of happiness and enjoyment of life had to be reverse coded so that higher responses reflected higher levels of depression for all variables. The response categories of *occasionally* and *most of the time* were combined into one category denoting *much or most of the time;* this was necessary to achieve full comparability of the NDSM to the CES-D scale. *Rarely or none of the time* and *some of the time* were left as is. *Rarely or none of the time* was recoded from “1” to “0”, *some of the time* was recoded from “2” to “1”, and the combined category *much or most of the time* was assigned the value of “2.” The scale was then created by summing all the items, producing a total score ranging from 0 to 22, with a higher score reflecting more depressive symptoms. Cronbach’s alpha for this scale was 0.788.

Spousal Support Level

A binary variable was constructed to indicate high spousal support versus moderate or low spousal support during Wave 1. Two questions were used to create this indicator variable—the questions asking if the respondent could rely on or open up to his/her spouse/partner. The survey questions concerning support from partner were prefaced with the following instruction: "For this next set of questions, I'd like you to think about your relationship with (NAME OF SPOUSE/PARTNER)." A battery of questions were asked, but the ones used to measure the level of spousal support were the following:

- "How often can you open up to (NAME) if you need to talk about your worries? Would you say hardly ever, some of the time, or often?"
- "How often can you rely on (NAME) for help if you have a problem? Would you say hardly ever, some of the time, or often?"

The response categories were *hardly ever or never, some of the time,* and *often.* Responses for often for both questions were flagged as 1 to indicate that the respondent had a highly supportive spouse during Wave 1. Other responses for the questions on whether the respondent could rely on or open up to a spouse were coded as 0 for this measure to indicate moderate or low spousal support in Wave 1. This constructed variable was used to produce separate regression models for each level.

Loss of Spouse or Partner

This was an indicator variable for those respondents who had a change in their marital status from married or cohabited in Wave 1 to widowed in Wave 2. Those who were married or living with a partner in Wave 1 who reported that they were widowed in Wave 2 were coded as "1" for this variable. All other married or cohabiting respondents were coded as "0" (including respondents who were married or cohabiting in Wave 1 but divorced in Wave 2, as this study focused on consequences of bereavement).

Social Network Functions: Social Support and Strain

The functions of a network were operationalized as social support and social strain experienced from friends and family. Scales were constructed to capture the social support and social strain. The NSHAP survey included the reported level of support or strain from family and friends. There were eight variables in total—four each for family and friends. The survey questions used were the following for family:

- "How often can you open up to members of your family if you need to talk about your worries? Would you say hardly ever, some of the time, or often?"
- "How often can you rely on them for help if you have a problem? Would you say hardly ever, some of the time, or often?
- "How often do members of your family make too many demands on you? Would you say hardly ever, some of the time, or often"?
- "How often do they criticize you? Would you say hardly ever, some of the time, or often?"

The questions asked about friends were similar to the ones asked about family members:

- "How often can you open up to your friends if you need to talk about your worries? Would you say hardly ever, some of the time, or often?"
- "How often can you rely on them for help if you have a problem? Would you say hardly ever, some of the time, or often?"
- "How often do your friends make too many demands on you? Would you say hardly ever, some of the time, or often?"
- "How often do they criticize you? Would you say hardly ever, some of the time, or often?"

The response categories for each question were (1) hardly ever (or never), (2) some of the time, and (3) often.

In Wave 2, the response categories for hardly ever and never were in two separate categories. The question that offered the response options was phrased as follows: "Would you say never, hardly ever or rarely, some of time or often?" The categories "never" and "hardly ever or rarely" were collapsed to be consistent with the responses for these questions in Wave 1.

For the question asking how often the respondent can open up to the family, those who volunteered no family (only 18) were collapsed into the hardly ever or never category. This was done for Wave 2 as well. Also, in Wave 2, those who responded always were collapsed into the often category. This was done to maintain consistency of responses for this set of questions. Similar recoding was done for the question asking about frequency of opening up to friends in Wave 2.

The social support scale was created by summing the response for the four questions asking if the respondent could rely on or open up to family and friends. The response categories were re-coded so that 0 was hardly ever or never, 1 was some of the time, and 2 was often. The range of the scale was a minimum of 0 and a maximum of 8, since there were four questions and 2 was the maximum value for each response. Alpha reliability for this scale was 0.64.

The social strain scale was created by summing the responses for the four questions asking the extent to which the respondent's family and friends criticized or made demands on them. The response categories for this scale was recoded similarly to how the recoding was done for the social support questions, and the range for this measure was 0 to 8. Alpha reliability for this scale was 0.53.

Network Structure: Social Network Characteristics

Multiple measures for social network structure were used in this study to allow for the examination of which aspects of social network connectedness are impactful for health. The measures used were the following: egocentric network size, number of alters living in the same household as ego, percent female, closeness, density, and frequency of contact with alters.

All of the network structure measures were calculated from the roster data, then aggregated and merged to the main dataset for analyses. The most basic measure is egocentric network size. To calculate network size, I utilized the roster data. In Wave 1, the number of alters was calculated and included in the core dataset. However, this variable only included alters listed as core confidantes to the respondent, not the total number of alters reported by the respondent. Instead, I constructed another variable to indicate the number of alters in each respondent's network. The number of alters was calculated by taking the sum of alters in the network dataset for each respondent.

Each respondent responded to four different rosters: A, B, C, and D. For Roster A, up to five names can be entered for core confidantes whom the respondent discusses important matters to. Those who entered five were then asked if there were any others. For Roster B, respondents can name one spouse or current partner not named in roster A. For Roster C, anyone else important or close not mentioned in A can be named, but only one person can be named. For Roster D, all household members not captured in A, B, or C can be named, and there is no limit.

To construct a measure for the number of alters living with the respondent, I counted the number of alters reported by ego whom ego indicated as residing in the same household. Gender composition was calculated as the proportion of reported alters who are women.

To calculate closeness with alters, I used the responses for the question asking the respondent how close they feel to the person cited, which varied from not very close to extremely close. The responses were (1) not very close, (2) somewhat close, (3) very close, and (4) extremely close. To calculate a variable for a count of how many close alters a respondent has, first the variable measuring closeness was dummy coded to be an indicator for very close and extremely close alters.

The density measure captures the extent to which the members are connected to each other, or the frequency of contact between alters, expressed as a ratio of the number of actual ties to the number of theoretically possible ties. The density measure captured the number of existing ties between the alters of a respondent divided by the number of all possible pairs. This measure was constructed by first binary coding the variable asking about how frequently the respondent thinks the alters talk to each other. The variable responses ranged from (0) never to (8) every day. Any contact was re-coded as 1. Each respondent could have up to 7 alters for these sets of questions, because the respondent was only asked about the frequency of talking for alters in rosters A to C. After binary coding the set of 7 questions asking about the frequency of communication between alters 1 to 7 for each respondent, I summed all the ties reported between alters. The number of ties was divided by the number of pairs to capture the density for each personal network.

Frequency of contact with named alters was constructed by recoding the set of variables asking about the frequency of talking to alters. The responses for this variable ranged from (1) less than once a year to (8) every day and were asked only of those alters listed in rosters A to C, and so the maximum number of alters for this variable is seven. To use the variable as a continuous variable, the responses were recoded to reflect contact-days a year. The variable was recoded as follows: (1) less than once a year to 0.5 contact-days a year; (2) once a year to 1 contact-day a year; (3) a couple times a year to 2 contact-days a year; (4) once a month to 12 contact-days a year; (5) once every two weeks to 26 contact-days a year; (6) once a week to 52 contact-days a year; (7) several times a week to 182 contact-days a year; (8) every day to 365 contact-days a year. Then the number of days was summed across all alters to capture the total days a year of contact that ego has with all reported alters in ego's network. This sum can be quite large, so the sum was then re-scaled by dividing the value by 100 to reflect hundred-days a year so that the coefficients produced would be easier to interpret.

Demographic and Other Covariates

NSHAP includes a number of other demographic and social engagement measures that potentially influence social networks and health, so they are also included in the analysis. Age was left as continuous. Gender was a dichotomous variable (male/female). I recoded this variable to construct an indicator for female. Race/ethnicity included four categories: White, Black, Hispanic non-Black, and other. I used White as the reference category.

The variable for education consists of four categories: less than high school, high school/equivalent, vocational certification/some college/associate's degree, and bachelors or more. I dummy coded education to indicate college completion. Information on income was present in the data, but I did not use this variable because there was so much missing data, due to so many respondents not working, and so not reporting an income. Instead I used the variable for employment status, which included responses for whether the respondents worked for pay or not last week.

The variable for employment status also serves as a variable for social engagement, along with religious participation which was an ordinal measure that captured the estimated frequency of attending religious services. Responses ranged from never to several times a week. Other variables of social engagement (frequency of volunteer work, attendance at meetings of organized groups in the past year, and frequency of socializing with friends or relatives in the past year) were not used because of high levels of missing data.

Interaction Variable for Spousal Loss and Level of Spousal Support

An interaction variable was generated by multiplying the indicator variables for the loss of a spouse or partner from Wave 1 to Wave 2 and high spousal support in Wave 1.

Analytical Strategy

All analysis for this study is restricted to those who were married or living with a partner during Wave 1 since partner loss is the theoretical focus of this study. In order to take advantage of the panel design of my study and strengthen the casual inferences that can be made from the findings, I employed ordinary least squares (OLS) and logistic lagged dependent variable regression models (also called "conditional change" models by Finkel 1995 or the "regressor variable method" by Allison 1990). These models account for prior values of the dependent variable before assessing the influences of other independent variables at time 1 on the dependent variable at time 2. All time-varying variables are lagged by one wave, thus independent variables at time 1 are used to predict changes in the outcome variable at time 2. Lagged independent variables help reduce (although not eliminate) the risk of endogeneity due to reverse causation, as it is not possible for outcome variables at time 2 to effect independent variables from a prior wave.

By controlling for prior values of the dependent variable when predicting current values of the dependent variable, the coefficients of the independent variables may be thought of as predicting change in the outcome variable between waves. The coefficients are interpreted as predicting changes in the outcome variable compared to what we would expect knowing the previous value of the dependent variable. The aim of the method is to examine the relationship between an independent variable at time 1 and a dependent variable at time 2 while controlling for the effects of that dependent variable at time 1. The dependent variable at time 1 is essentially treated as a control variable. All coefficients for the independent variables are net of effects from the lagged dependent variable on the dependent variable at time 2.

I chose not to use a change score method because the scores tend to be biased by regression towards the mean (Allison 1990). A change score method entails calculating the difference in the outcome variable from Wave 1 to Wave 2 and then calculating the difference for all independent and control variables from Wave 1 to Wave 2; the change from Wave 1 to Wave 2 for all variables are thus obtained. Analyses are then done by regressing the calculated difference in the outcome variable on the differences between waves for all the independent variables.

Conditional change modeling was chosen instead of fixed effects (FE) or random effects (RE) modeling because I am interested in temporal dependence in terms of how Wave 1 variables effect Wave 2 outcomes, not just whether the dependent variable is associated with the independent variables. Specifically, the model of temporal dependence that I am using is the lagged endogenous variable model, where the dependent variable is determined by a series of independent variables at a lag of time *t*-1, along with the lagged value of the dependent variable, as in:

$$Y_{it} = \alpha + \beta_1(Y_{i(t-1)}) + (\beta_2(X_{1i(t-1)}) + \beta_3(X_{2i(t-1)}) + \ldots + \beta_j(X_{ji(t-1)}) + \varepsilon_{it}$$

In this model, the lag value of *Y,* or the "lagged endogenous variable," has a direct effect on the value of *Y* at the next time point, along with effects specified from prior values of *X* as well. This model is equivalent to predicting the *change* in *Y* from its prior value. Because in this type of modeling, unlike fixed effects or random effects models, there is the absence of the unit-specific error term, it is assumed that *all* of the temporal dependence of responses over time is due to the causal mechanism linking the lagged endogenous variable and the lagged *X*'s to *Y.* The inclusion of the lagged *Y* term is meant to control for regression to the mean that would otherwise be present in the model if the lagged dependent variable was omitted.

Using the conditional change method allows us to take into account the baseline differences between respondents. For this study, OLS regression models were used to predict depressive symptoms in Wave 2 with independent variables from Wave 1, including depressive symptoms from Wave 1 as the lagged dependent variable, spousal loss, social support/strain, network structure, and other demographic and control variables. The models were run separately for respondents with high spousal support in Wave 1, and respondents with moderate or low spousal support in Wave 1.

Using an interaction to test for social support as a potential moderator did not produce any significant results, but the results for these models are shown for reference.

Table 5. Weighted Regression Coefficients of Wave 1 Variables Predicting Wave 2 Depressive Symptoms (CES-D) from Residual Change Score Models with Interaction: NSHAP, 2005-2006 and 2010-2011 (N=1,117).

	Depressive Symptoms (W2)								
	Model 1			Model 2			Model 3		
Independent Variables from Wave 1	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.
Depressive Symptoms (W1)				0.507	(.034)	***	0.479	(.033)	***
Loss of Spouse/Partner from W1 to W2	0.539	(.700)		0.767	(.725)		0.635	(.734)	
Indicator for High Spousal Support in W1	-0.748	(.256)	**	0.270	(.227)		0.311	(.234)	
Interaction of High Spousal Support with Spousal Loss	1.468	(.853)		1.187	(.887)		1.103	(.879)	
Social Support and Strain									
Perceived support							-0.081	(.065)	
Perceived strain							0.348	(.108)	**
Network structure									
Network size							0.017	(.141)	
Number living with ego							0.139	(.166)	
Proportion female							-0.287	(.640)	
Number of close ties							-0.061	(.096)	
Density							0.952	(.669)	
Frequency of contact with alters (hundred contact-days per year)							-0.052	(.035)	
Demographic and Control Variables									
Age							0.026	(.020)	
Female							0.406	(.219)	
Ethnicity (ref. = white)									
Black							-0.368	(.308)	
Hispanic							-0.0004	(.426)	
Other							0.296	(.638)	
College or higher							-0.545	(.305)	
Worked for pay last week							-0.075	(.203)	
Frequency of religious service attendance							0.034	(.071)	
Intercept	4.569	(.309)	***	1.708	(.243)	***	0.108	(1.561)	
R^2	0.0240			0.2791			0.3066		

Note: Unweighted N = 1,117. All analyses restricted to to those who were married or living with a partner during wave 1. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

The interaction may not be significant because the sample sizes are rather small after restricting the analyses to just those who were married or cohabiting in Wave 1. However, the direction of the interaction effect is as theoretically expected, even without statistical significance. An alternative that was employed was to model how spousal loss impacts depressive symptoms during Wave 2 separately for those with high spousal support in Wave 1 and those with moderate and low spousal support in Wave 1.

All analyses were done using Stata/SE 12.0. Results were weighted using *svyset* commands to incorporate the adjustment for nonresponse and correct for the sampling design. (For more details on weighting, refer to O'Muircheartaigh & Smith 2007.)

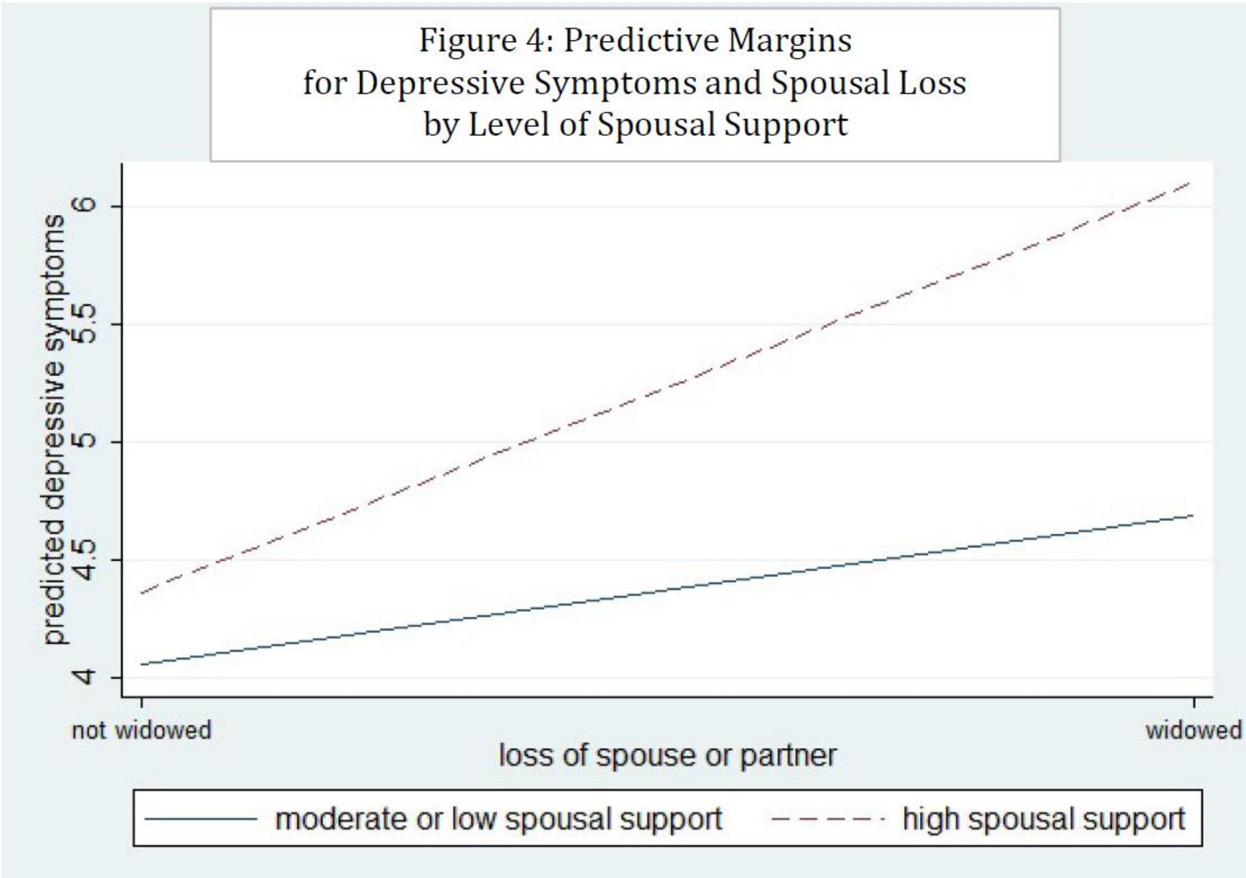
Results

Results of Models testing Interaction

Table 5 shows the results for OLS models predicting Wave 2 depressive symptoms from Wave 1 variables. In these models, the interaction between high spousal support and spousal loss is not significant, although Figure 4 shows that for those with high spousal support vs. moderate/low spousal support, spousal loss has a stronger impact on increasing depressive symptoms. However, because the interaction effect is not statistically significant, the following sections will discuss the results of the OLS models that were run separately for high vs. moderate/low spousal support.

Results of Models with Separate Regressions for Level of Spousal Support

Table 6 shows descriptive statistics for the separate models for high and moderate/low spousal support. Two-tailed *t*-tests show statistically significant differences in the number of depressive symptoms between those with high spousal support and those with moderate or low spousal support in each wave.



The percent of respondents losing a spouse or partner from Wave 1 to Wave 2 is also significantly different between respondents with different levels of spousal support in Wave 1. About 17% of respondents with moderate or low spousal support lost a spouse or partner from Wave 1 to Wave 2, compared to only 10% of respondents with high spousal support. It is unclear from the data whether this large difference is due to more friction in less supportive relationships or if the perceived low support may be due to the spouse having frail health and unable to provide support but also more likely to experience mortality between waves. There is no information in the datasets about spousal health, but comparing average strain between respondents with highly supportive spouses and respondents with spouses who are perceived to be not highly supportive, we do observe a

Table 6. Weighted Descriptive Statistics: NSHAP, 2005-2006 and 2010-2011 (N=1,117).

	Wave 1 % or Mean			Wave 2 % or Mean		
Variables	High Spousal Support in Wave 1	Moderate or Low Spousal Support in Wave 1	Sig.	High Spousal Support in Wave 1	Moderate or Low Spousal Support in Wave 1	Sig.
Health Outcome						
Depressive Symptoms	3.642	5.563	***	4.019	4.659	***
Loss of Spouse/Partner				9.9%	16.8%	***
Network structure						
Network size	4.903	4.724		4.983	4.737	
Number living with ego	1.287	1.335		1.197	1.076	
Proportion female	0.559	0.580		0.557	0.564	
Number of close ties	3.881	3.395	***	3.784	3.395	**
Density	0.869	0.839		0.855	0.847	
Frequency of contact with alters (hundred contact-days per year)	9.041	8.931		8.882	8.529	
Social Support and Strain						
Perceived support	5.579	4.729	***	5.569	4.950	***
Perceived strain	0.819	0.858		0.553	0.609	
Demographic and Control Variables (only W1)						
Age	65.665	66.879	*			
Female	43.1%	47.4%				
Ethnicity						
White	86.3%	82.3%				
Black	5.2%	13.4%				
Hispanic	5.9%	4.0%				
Other	2.6%	0.4%				
College or higher	59.6%	56.8%				
Worked for pay last week	42.0%	38.5%				
Frequency of religious service attendance	3.721	3.083	***			
N	826	291		826	291	

Note: Unweighted N = 1,117. All analyses restricted to to those who were married or living with a partner during wave 1. All descriptive statistics are survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse. Two-tailed t-tests were conducted on unweighted values to examine the mean differences between high and not high spousal support for each wave.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

small difference. The average strain in Wave 1 for respondents with highly supportive spouses is 0.819; the average strain is higher for respondents with spouses who provide low/moderate support, with a mean of 0.858. We also see this in the average strain in Wave 2, where the average strain for respondents with moderate/low spousal support (0.609) is higher than the average for respondents with high spousal support (0.553). This could imply greater friction among respondents with moderate or low spousal support, but this difference may not be big enough to influence the higher percentage of spousal loss.

Table 7. Comparison of Changes in Average Depressive Symptoms by Level of Spousal Support and Spousal Loss: NSHAP, 2005-2006 and 2010-2011.

	Wave 1 Depressive Symptoms	Wave 2 Depressive Symptoms	Change in Average Depressive Symptoms from Wave 1 to Wave 2
Not Widowed			
High Spousal Support in wave 1	3.632	3.821	0.189
Moderate/Low Spousal Support in wave 1	5.638	4.569	-1.069
Widowed			
High Spousal Support in wave 1	3.736	5.827	2.091
Moderate/Low Spousal Support in wave 1	5.189	5.108	-0.081

Note: All analyses restricted to to those who were married or living with a partner during wave 1. All statistics are survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.

We also observe changes in depressive symptoms from Wave 1 to Wave 2 between the different levels of Wave 1 spousal support. Depressive symptoms increased for those with high spousal support (from 3.642 to 4.019), but decreased for those with moderate or low spousal support (from 5.563 to 4.659), as shown in Table 6. To see the changes over time in average depressive symptoms by both spousal support and spousal loss, we can compare means for four groups for both waves: high spousal support and widowed, high spousal support and not widowed, moderate or low spousal support and widowed, and moderate or low spousal support and not widowed. These statistics are presented in Table 7.

We see that respondents with high spousal support experienced increases in average depressive symptoms from Wave 1 to Wave 2, regardless of whether they lost a spouse or not; both values of changes are positive. Respondents with moderate/low spousal support experienced decreases in average depressive symptoms between waves regardless of spousal loss; we can see this with both the values of change being negative. However, spousal loss does impact everyone adversely by increasing the average

Table 8. Weighted Regression Coefficients of Wave 1 Variables Predicting Wave 2 Depressive Symptoms from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,117).

	Depressive Symptoms (W2)											
	High Spousal Support in Wave 1						Moderate and Low Spousal Support in Wave 1					
	Model 1			Model 2			Model 1			Model 2		
Independent Variables from Wave 1	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.
Depressive Symptoms (W1)	0.502	(.040)	***	0.482	(.042)	***	0.502	(.064)	***	0.493	(.058)	***
Loss of Spouse/Partner from W1 to W2	1.776	(.556)	**	1.768	(.570)	**	0.327	(.723)		0.397	(.715)	
Social Support and Strain												
Perceived support				-0.080	(.084)					-0.126	(.123)	
Perceived strain				0.336	(.130)	*				0.259	(.163)	
Network structure												
Network size[1]				0.189	(.169)					-0.361	(.237)	
Number living with ego				0.058	(.197)					0.299	(.232)	
Proportion female				-0.077	(.869)					-0.450	(.699)	
Number of close ties[1]				-0.195	(.143)					0.191	(.157)	
Density				1.173	(.859)					0.502	(1.156)	
Frequency of contact with alters (hundred contact-days per year)				-0.054	(.042)					-0.002	(.090)	
Demographic and Control Variables												
Age	0.027	(.024)		0.030	(.025)		0.010	(.029)		0.005	(.029)	
Female	0.071	(.282)		0.336	(.245)		0.430	(.383)		0.718	(.457)	
Ethnicity (ref. = white)												
Black	0.463	(.537)		0.222	(.511)		-0.899	(.588)		-0.904	(.591)	
Hispanic	0.066	(.526)		-0.125	(.466)		1.084	(1.202)		0.593	(1.200)	
Other	0.895	(.660)		0.350	(.652)		0.102	(1.043)		-0.151	(1.144)	
College or higher	-0.612	(.343)		-0.608	(.346)		-0.224	(.393)		-0.142	(.375)	
Worked for pay last week	0.152	(.266)		0.163	(.266)		-0.685	(.376)		-0.765	(.384)	
Frequency of religious service attendance	0.059	(.085)		0.060	(.089)		-0.040	(.120)		0.008	(.110)	
Intercept	0.259	(1.753)		-0.559	(1.934)		1.513	(1.905)		2.550	(2.357)	
R^2	0.2795			0.2990			0.3257			0.3483		
N	826						291					

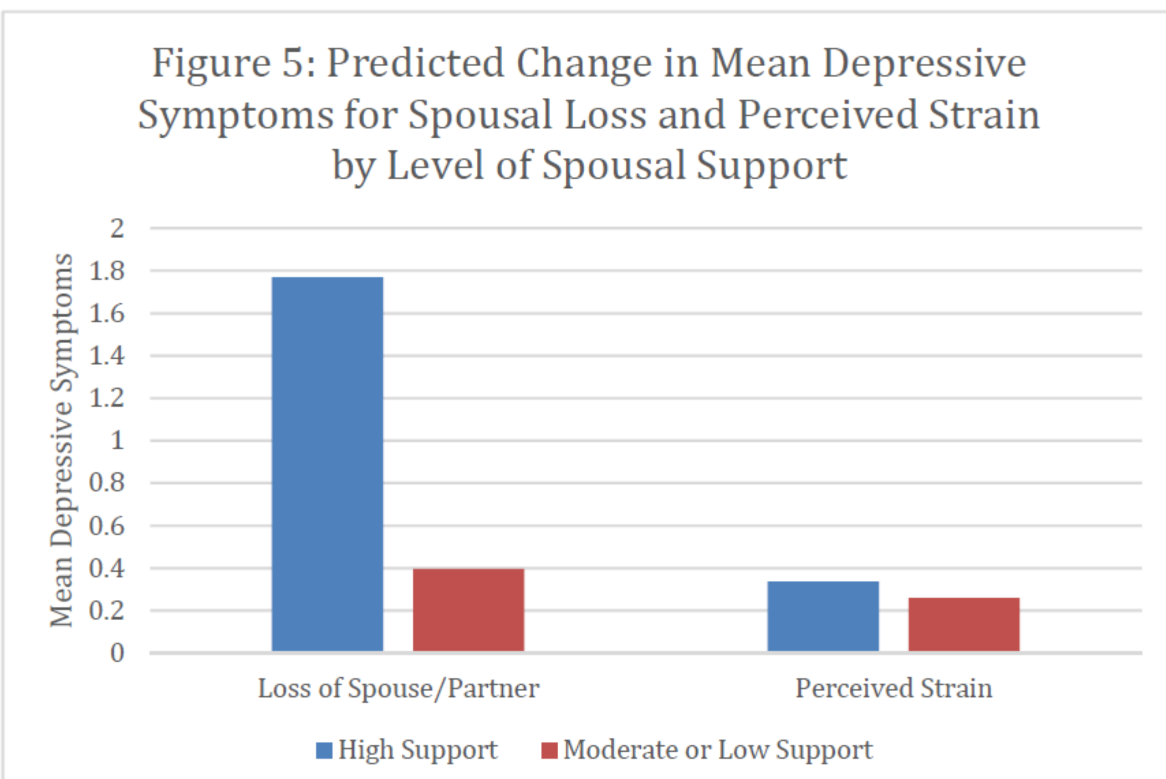
Note: Unweighted N = 1,117. All analyses restricted to to those who were married or living with a partner during wave 1. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.

[1] When network size and number of close ties are modeled just with the lagged dependent variable as the only other independent variable, the signs of the coefficients are the same.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

depressive symptoms for respondents with high spousal support (2.091 increase instead of just 0.189), and diminishing the decreases in average depressive symptoms for respondents with moderate/low spousal support (a decrease of just 0.081 for those who lost their spouse compared to a decrease of 1.069).

Table 8 presents the results for the lagged dependent variable panel regression models predicting Wave 2 depressive symptoms from Wave 1 social support/strain and network measures, separately for respondents with high spousal support in Wave 1, and moderate and low spousal support. Controlling for baseline depressive symptoms in Wave 1, depressive symptoms in Wave 2 are positively associated with the loss of spouse/partner from Wave 1 to Wave 2 and perceived social strain, but only for respondents with high spousal support in Wave 1. Figure 5 shows the predicted change in mean depressive symptoms for spousal loss and perceived strain by level of spousal



support. For respondents with high spousal support in Wave 1, losing a spouse or partner was associated with an increase in the mean for depressive symptoms in Wave 2. Perceived strain was also associated with an increase in depressive symptoms. For respondents with moderate or low spousal support in Wave 1, losing a spouse or partner did not significantly impact depressive symptoms in Wave 2. Perceived social support and strain and network structure also do not significantly predict depressive symptoms in Wave 2 for respondents with moderate and low spousal support in Wave 1.

Discussion

This study began with the expectation that spousal loss has adverse impacts on mental health, but that personal social networks can buffer that adverse impact (although inconsistencies on the protective effects of support remain in the literature). The question remained on whether the adverse impact depends on how supportive the spouse is in the first place, and whether other sources of support or social contact could ameliorate any adverse effects from spousal loss.

The results show that spousal loss is only associated with the mental health of those with supportive spouses. The loss of support from losing a supportive spouse matters. However, if the spouse is not supportive, then losing the spouse does not appear to be related to mental health, perhaps because there is no significant loss of an important tie. Hypothesis 1 was only partially supported. Spousal loss was not associated with increases in depressive symptoms for all widow(er)s, but only for those who lost a highly supportive spouse.

In addition, social support or network characteristics do not appear to mitigate the adverse impact of the loss of a spouse on depression for those with supportive spouses.

The results do not support Hypotheses 2 and 3, which predict that various aspects of personal networks and social support would be negatively associated with depressive symptoms, thereby serving to help shield individuals from the negative effects of spousal bereavement. This finding is contrary to literature showing that there is a buffering effect from support (Hays et al. 2001; Krause 1986), but consistent with other studies that do not find a protective effect from social support or network characteristics from spousal loss (Lin, Woelfel, and Light 1985).

This study provides new information on which types of spousal loss matter. Widowed individuals with poor preloss relationships with their spouse or partners do not experience the negative effects of spousal loss. However, the sample size for those respondents who reported moderate or low spousal support in Wave 1 were relatively low, at 291 respondents. It may be that this small sample size does not provide enough power to detect any effects.

We observe in the descriptive statistics that moderate or low spousal support is associated with later decreases in depressive symptoms, but also higher rates of spousal loss. Future research can delve into why lower spousal support is associated with higher rates of spousal loss. One possibility is that frail older adults who can only provide low support because of their poor physical health are also at increased risk of experiencing mortality.

STUDY 3: THE ROLE OF PERSONAL SOCIAL NETWORKS IN LATER-LIFE ALCOHOL AND CIGARETTE USE

Overview of the Study

Health behaviors, whether preventive or risky, impact the health of older adults. This study examines the social network factors that influence health risk behaviors—specifically cigarette use and alcohol consumption—over time in a sample of older adults in the United States. Smoking and drinking were examined as dependent variables, as well as prevalence of heavy drinking or smoking for those who do engage in alcohol consumption or cigarette use. Independent variables included demographic characteristics and control variables, baseline use and prevalence of heavy use, and social network characteristics.

Findings show that personal networks can have protective effects on smoking or drinking; however, for current smokers and drinkers, personal networks are enabling. Having more support or being able to discuss issues of health with others serve to reduce the adoption of health-compromising behaviors. Health-compromising behaviors may not necessarily always be adopted as a coping mechanism, but may be a pro-social activity that is increased when there are others in the network who also engage in similar activities.

Introduction

Researchers have studied the linkages between social relationships and health risk behaviors. Social relationships may buffer the impact of stress on health by providing social support but also by influencing health behavior (Cohen and Wills 1985). In addition to influencing health behaviors, social support from social relationships may reduce the adoption of health-risk behaviors used as a coping mechanism and as such be protective (Wills and Cleary 1996).

However, social relationships can also be enabling if individuals are surrounded by others who engage in health-compromising behaviors like smoking (Cutler and Glaeser 2007). Individuals can adopt or continue certain behaviors through social influence. Health-compromising behaviors like smoking and drinking are not necessarily a coping mechanism, but could be a pro-social activity. In this study, I investigate how personal social networks are related to smoking and drinking behavior over time.

Background

Among the general population, including older adults, health status and health risk behaviors are linked. Older adults with poor health practices and who engage in negative health behaviors, such as smoking cigarettes and excessive alcohol consumption, experience worse health (Breslow and Breslow 1993). Consuming more than three drinks a day and smoking are associated with elevated cardiovascular risks (Mukamal 2006). Longitudinal studies link future health with poor health practices as well (Wiley and Camacho 1980). Therefore, understanding the predictors of health risk behaviors is important.

Researchers posit a relationship between support networks and health behaviors, particularly impacting health risk behaviors such as smoking or heavy drinking (Heaney and Israel 1995). Health-related support systems can provide health regulation which keeps individuals from engaging in health risk behaviors, encourages quitting health risk behaviors (Gulliver et al. 1995, Hanson et al. 1990), or promotes avoiding relapse (Havassy 1991). Some of the theories explaining the role of social networks in influencing health behaviors suggest that health regulation is largely due to the social control that can happen in a personal network (Berkman et al. 2000), or the stress buffering that social support provides (Cohen and Wills 1985), reducing the reliance on substances to help individuals cope with stressful events.

Understanding the prevalence of cigarette and alcohol use is important because excessive use or substance abuse have adverse health consequences and higher health costs (Sturm 2002). A recent study by Peirce et al. (2000) documents a relationship between one's social network (measured as social contact), social support, depression, and alcohol use. Peirce et al. highlighted a feedback loop. Social contact was positively related to perceived social support, which was negatively related to depression. Depression was positively related to alcohol use, which results in decreased contact with family and friends. In this model, social contact and social support can potentially reduce alcohol dependence by reducing depression. However, depression can elevate alcohol dependence, which compromises the protective support structure. By extending the model to include other measures of a personal social network and to include measures on not just use, but also prevalence of heavy use by existing users, this study examines if all network characteristics are consistently protective. Furthermore, the focus of this study is on older adults, and there exists limited research on health risk behaviors for that population. Much of the literature on smoking and drinking as self-medication have been largely focused on adolescents or adults moreso than on the elderly (examples include Baker et al. 2004 on cigarette use among adolescents, Kassel et al. 2003 on smoking for stress reduction among adults, Thoits 1995 on a review of the literature that includes a summary on coping strategies, and Wills and Vaughan 1989 on substance use among adolescents as coping).

Evidence also suggests that, irrespective of whether there are regulating ties or not in a network, that the size or "connectedness" of a network is inversely associated with health risk behaviors (Berkman et al. 2000). Broadening the measures for network characteristics of individuals to include other measures in addition to network size can elucidate which specific network characteristics matter, and how they matter.

In this study, I first look at which health behavior—smoking, drinking, and heavy use for current users—impacts poor physical health. Then, I examine network characteristics as well as social support and having health discussion partners to see which specific aspects of these factors matter for smoking or drinking behavior for older adults. The following research questions were examined:

1. Do smoking and drinking behaviors compromise physical health?
2. Do social network factors influence smoking or drinking behavior in older adults over time?
3. Do these factors differ for prevalence versus heavy use?

The dependent variable for the first set of models was poor self-rated physical health, and the independent variables included baseline self-rated physical health, whether respondent was a smoker or drinker, the level of use for current smokers and drinkers, and demographic and other covariates. The dependent variables for the second set of models examined include whether or not the respondent drinks or smokes, and prevalence for heavy use for older adults who did engage in those behaviors. Independent variables included demographic characteristics and other controls, baseline smoking or drinking behavior, baseline status as a heavy user, social network characteristics, social support, and the likeliness of discussing health with alters.

Figure 6 presents a conceptual model for health risk behaviors impacting self-rated physical health. The impacts on health justify looking into what network characteristics

Figure 6. Conceptual Model for Impact of Alcohol and Cigarette Use on Physical Health.

Health behaviors influence health. Because NSHAP has only two waves, we can study this relationship by examining how health behaviors in wave 1 influences health in wave 2.

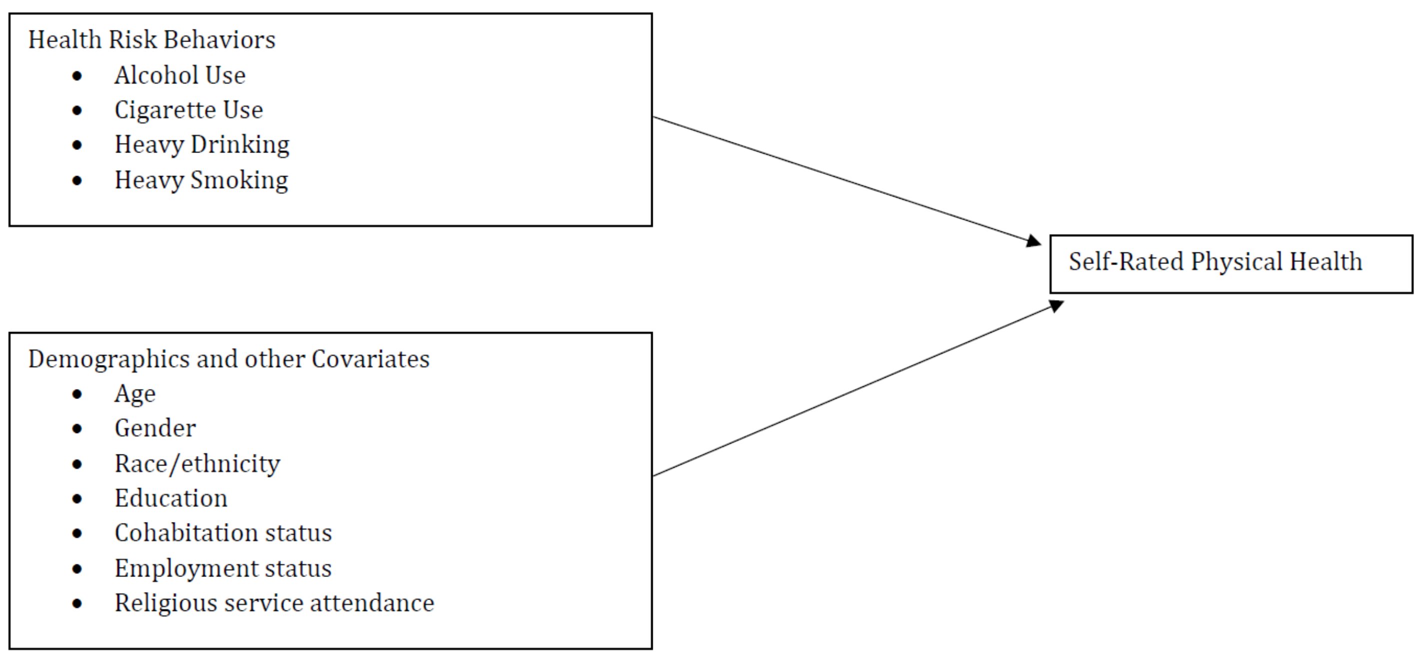
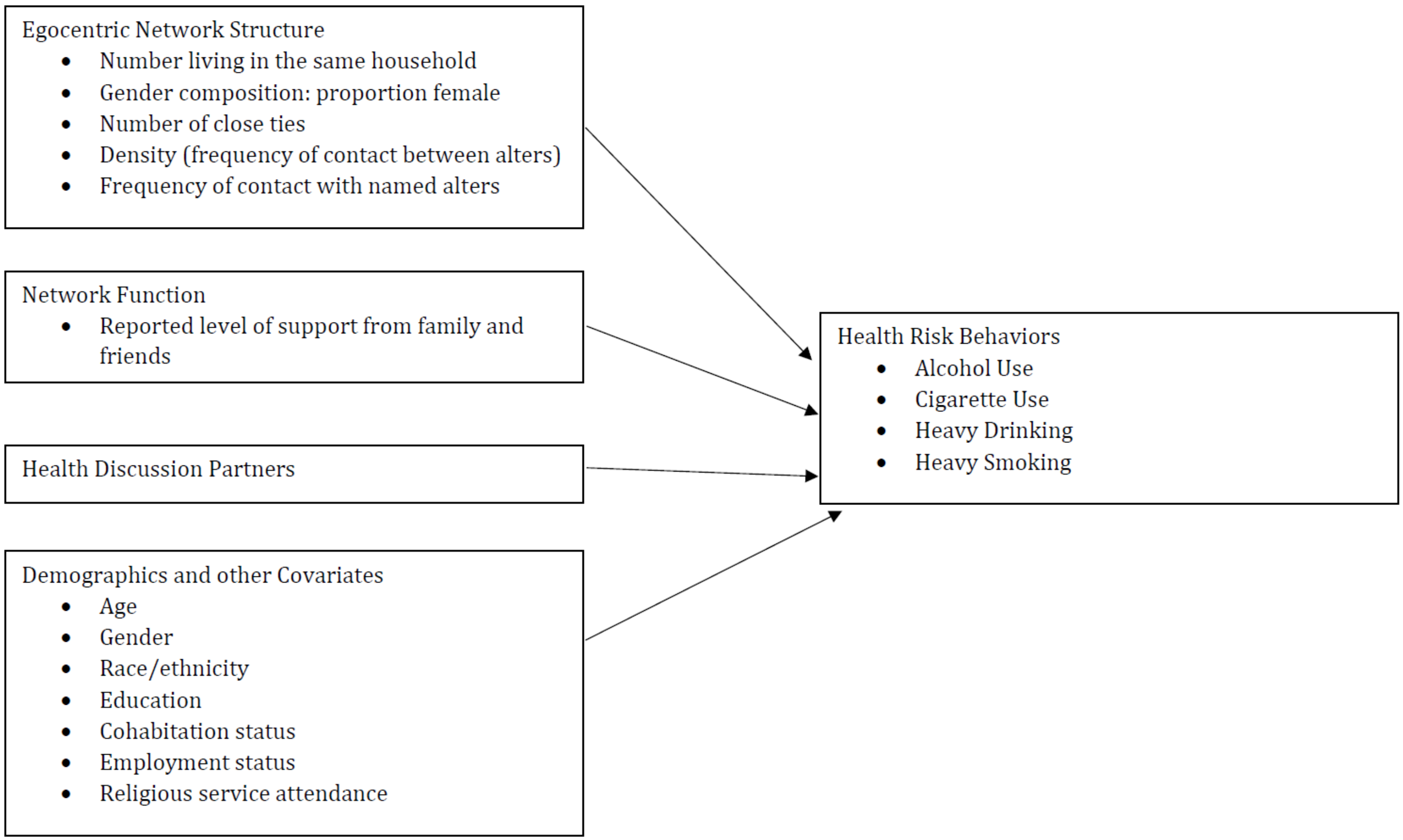


Figure 7. Conceptual Model for Networks Impacting Alcohol and Cigarette Use.

Social networks can influence health risk behaviors.



impact health behaviors, and this conceptual model is presented in Figure 7.

Hypotheses

I propose the following hypotheses about the associations between social networks and both smoking/drinking prevalence and heavy use.

Hypothesis 1: Smoking and drinking will be associated with poor physical health.

Hypothesis 2: Various social network factors will be negatively associated with smoking/drinking.

Hypothesis 3: Social support will be negatively associated with smoking/drinking.

Hypothesis 4: Discussing health with partners will be negatively associated with smoking/drinking.

Generally, I hypothesize that social networks and social support are protective, reducing the likelihood of engaging in health-compromising behaviors.

Data

This study uses data from the National Social Life, Health, and Aging Project (NSHAP). This survey uses a national area probability sample of community residing adults born between 1920 and 1947, ages 57 to 85 at the time of the Wave 1 interview. NSHAP has two waves, with five years between each wave. NSHAP respondents were selected from the households screened by the Health and Retirement Study (HRS) in 2004. In Wave 1, 3,005 interviews were conducted between July 2005 and March 2006. For Wave 2, NSHAP re-interviewed the Wave 1 respondents and also non-interviewed respondents from Wave 1 who were eligible to participate in NSHAP but were not selected for interview out of the sample of households identified by HRS. In addition, the Wave 2 sample was extended to include cohabiting spouse and romantic partners who were at least 18 years of age and living with the respondent at the time of the Wave 2 interview. For Wave 2, 3,377 interviews were conducted between August 2010 and May 2011. Wave 3 is being planned and the projected number of interviews for Wave 3 is 2,352.

The present study examined only that portion of the NSHAP sample that responded in both Wave 1 and Wave 2 to the questions used in this analysis. The final sample included 1,922 persons. The sample used to model prevalence of heavy use in this study was restricted to those who responded that they smoked or consumed alcohol and also responded to the question on prevalence of both. The sample size for to look at prevalence for current drinkers was 926 respondents, and 196 for the models for prevalence of current smokers.

Description of Social Network Module of NSHAP

The NSHAP social network data is egocentric. The social network module for NSHAP permits respondents to identify network members important to the respondent, and then subsequently obtains information about those alters. A set of persons around each respondent are identified, as well as the relationships that link the respondents to other network members, and other network members to each other, providing a "local" sample from the larger social network around ego.

To collect egocentric network data, NSHAP employed name generators; the respondent enumerates relevant alters. The networks module starts off with the following text: "Now we are going to ask you some questions about your relationships with other people. We will begin by identifying some of the people you interact with on a regular basis." To assess several types of network members, NSHAP utilized four "rosters," or lists of people.

For Roster A, respondents were asked to list people with whom they discuss "important matters," thereby allowing enumeration of core confidantes. The following text was used to preface this roster:

> From time to time, most people discuss things that are important to them with others. For example, these may include good or bad things that happen to you, problems you are having, or important concerns you may have. Looking back over the last 12 months, who are the people with whom you most often discussed things that were important to you?

Respondents could name up to five core confidantes. If respondents named five, they were then prompted for any others. This allows us to identify if respondents had zero core contacts, or six or more core contacts.

Rosters B, C, and D capture other potentially important network members because of their relationship status to the respondent, but who were not named in Roster A by the respondent. Roster B included a spouse or romantic partner if the respondent had one but did not include that person in Roster A. For Roster C, respondents were asked the following: "(Besides the people you already listed), is there anyone (else) who is very important to you, perhaps someone with whom you feel especially close?" Any person identified in response to this question was listed in Roster C. Any remaining household members not included in Rosters A to C were added to Roster D.

Following the name generator questions to generate a list of alters, NSHAP then included questions to obtain information about each alter; these types of survey items are generally known as name interpreters. The respondent was asked to identify the type of relationship to each alter (e.g., kin, friend) and the gender of each alter. Other information recorded about the alters included whether the alter lives with ego, ego's frequency of contact with and emotional closeness to alter, ego's likelihood of discussing health matters with alter, and alter's frequency of contact with each of the alter alters listed in Rosters A, B, and C. The age of all alters living with ego was also asked.

Variables

The dependent variables examined include whether or not the respondent drinks or smokes, and baseline status as heavy user for older adults who did engage in those behaviors. Independent variables included demographic characteristics and other controls, baseline smoking or drinking behavior, baseline status as heavy user, social network characteristics, social support, and the likeliness of discussing health with alters. All independent variables were measured at Wave 1, while all dependent variables were measured at Wave 2. The variables were measured as follows.

Poor Self-Rated Physical Health

For the survey question asking about self-rated physical health, the responses ranged from (1) poor to (5) excellent. The responses for poor and fair were collapsed to form an indicator variable for poor self-rated physical health.

Drinking Status

The indicator for drinking status constructed from the responses for two survey questions. The first question for the respondent was as follows: "Do you ever drink any alcoholic beverages such as beer, wine, or liquor?" For those who responded "no," they were asked a follow-up question: "Have you ever drunk alcohol?" If the respondent answered "yes" to the first question, or "yes" to the follow-up, then they were asked on average, how many days per week have they had any alcohol to drink in the last three months. Those who responded to this question, or who did not respond to this question when asked, but did indicate that they drink alcoholic beverages in the prior question, were flagged as "1" for the indicator variable for drinking status. Those who responded that they did not drink alcohol to the first question were flagged as "0." Missing responses for both questions were kept as missing.

Smoking Status

Smoking status was established by the question asking if the respondent smokes cigarettes.

Heavy Drinking

Status of heavy drinking was a derived measure. The measure for drinks per week was calculated by multiplying the responses for reported days per week drinking and reported drinks per day. The U.S. Centers for Disease Control and Prevention (CDC) definition for heavy drinking was used to calculate an indicator variable. The CDC defines heavy drinking as 15 or more drinks per week for men, and 8 or more drinks per week for women.

Heavy Smoking

Status of heavy smoking was a derived measure from the question asking respondents who currently smoked cigarettes to report the cigarettes per day they smoked. The CDC defines heavy smoking as 25 or more cigarettes per day, but the natural cut-point for older adults and for this dataset was one or more packs a day, or 20 or more cigarettes a day. This study defines heavy smoking as 20 or more cigarettes per day.

Network Structure

Multiple measures for social network structure were used in this study. The measures used were the following: number of alters living in the same household as ego, proportion female, number of close ties, density, and frequency of contact with alters. All of the network structure measures were calculated from the roster data, then aggregated and merged to the main dataset for analyses.

Each respondent responded to four different rosters: A, B, C, and D. For Roster A, up to five names can be entered for core confidantes whom the respondent discusses important matters to. Those who entered five were then asked if there were any others. For Roster B, respondents can name one spouse or current partner not named in roster A. For Roster C, anyone else important or close not mentioned in A can be named, but only one person can be named. For Roster D, all household members not captured in A, B, or C can be named, and there is no limit.

To construct a measure for the number of alters living with the respondent, I counted the number of alters reported by ego whom ego indicated as residing in the same household. Gender composition was calculated as the proportion of reported alters who are women.

To calculate closeness with alters, I used the responses for the question asking the respondent how close they feel to the person cited, which varied from not very close to extremely close. The responses were (1) not very close, (2) somewhat close, (3) very close, and (4) extremely close. To calculate a variable for a count of how many close alters a respondent has, first the variable measuring closeness was dummy coded to be an indicator for very close and extremely close alters.

The density measure captures the extent to which the members are connected to each other, or the frequency of contact between alters, expressed as a ratio of the number of actual ties to the number of theoretically possible ties. The density measure captured the number of existing ties between the alters of a respondent divided by the number of all possible pairs. This measure was constructed by first binary coding the variable asking about how frequently the respondent thinks the alters talk to each other. The variable responses ranged from (0) never to (8) every day. Any contact was re-coded as 1. Each respondent could have up to 7 alters for these sets of questions, because the respondent was only asked about the frequency of talking for alters in rosters A to C. After binary coding the set of 7 questions asking about the frequency of communication between alters 1 to 7 for each respondent, I summed all the ties reported between alters. The number of ties was divided by the number of pairs to capture the density for each personal network.

Frequency of contact with named alters was constructed by recoding the set of variables asking about the frequency of talking to alters. The responses for this variable ranged from (1) less than once a year to (8) every day and were asked only of those alters listed in rosters A to C, and so the maximum number of alters for this variable is seven. To use the variable as a continuous variable, the responses were recoded to reflect contact-days a year. The variable was recoded as follows: (1) less than once a year to 0.5 contact-days a year; (2) once a year to 1 contact-day a year; (3) a couple times a year to 2 contact-days a year; (4) once a month to 12 contact-days a year; (5) once every two weeks to 26 contact-days a year; (6) once a week to 52 contact-days a year; (7) several times a week to 182 contact-days a year; (8) every day to 365 contact-days a year. Then the number of days was summed across all alters to capture the total days a year of contact that ego has with all reported alters in ego's network. This sum can be quite large, so the sum was then re-scaled by dividing the value by 100 to reflect hundred-days a year so that the coefficients produced would be easier to interpret.

General Perceived Social Support

A scale was constructed to capture general perceived social support. The NSHAP survey included the reported level of support from family and friends. There were four variables in total—two each for family and friends. The survey questions used were the following for family:

- "How often can you open up to members of your family if you need to talk about your worries? Would you say hardly ever, some of the time, or often?"
- "How often can you rely on them for help if you have a problem? Would you say hardly ever, some of the time, or often?

The questions asked about friends were similar to the ones asked about family members:

- "How often can you open up to your friends if you need to talk about your worries? Would you say hardly ever, some of the time, or often?"
- "How often can you rely on them for help if you have a problem? Would you say hardly ever, some of the time, or often?"

The response categories for each question were (1) hardly ever (or never), (2) some of the time, and (3) often.

In Wave 2, the response categories for hardly ever and never were in two separate categories. The question that offered the response options was phrased as follows: "Would you say never, hardly ever or rarely, some of time or often?" The categories "never" and "hardly ever or rarely" were collapsed to be consistent with the responses for these questions in Wave 1.

For the question asking how often the respondent can open up to the family, those who volunteered no family (only 18) were collapsed into the hardly ever or never category. This was done for Wave 2 as well. Also, in Wave 2, those who responded always were collapsed into the often category. This was done to maintain consistency of responses for this set of questions. Similar recoding was done for the question asking about frequency of opening up to friends in Wave 2.

The social support scale was created by summing the response for the four questions asking if the respondent could rely on or open up to family and friends. The response categories were re-coded so that 0 was hardly ever or never, 1 was some of the time, and 2 was often. The range of the scale was a minimum of 0 and a maximum of 8, since there were four questions and 2 was the maximum value for each response. Alpha reliability for this scale was 0.64.

Average Likeliness of Discussion Health with Health Discussion Partners

This variable was derived from two questions: network size and health discussion. Network size was a derived measure. To calculate network size, I constructed a variable to indicate the number of alters in each respondent's network. The number of alters was calculated by taking the sum of alters in the network dataset for each respondent. The question on health discussion partners asked the respondent if they would talk about their health problems to each alter they cited. The responses were (1) not likely, (2) somewhat likely, and (3) very likely. Scores of zero were assigned to those respondents who did not respond to this question for any of their alters (three from Wave 1; four from Wave 2). I summed the responses across all alters for each ego. Then I generated an average likeliness score by taking that sum and dividing by network size. The final derived measure of average likeliness of discussing health with alters ranges from 0 to 3.

Demographic and Other Covariates

Age was left as continuous. Gender was a dichotomous variable (male/female). I recoded this variable to construct an indicator for female. Race/ethnicity included four categories: White, Black, Hispanic non-Black, and other. I used White as the reference category.

A measure for cohabitation status was re-coded from a question asking about the respondent's marital status. The response categories for the survey question were married, living with a partner, separated, divorced, widowed, and never married. I collapsed the responses for married and living with a partner to cohabiting, and collapsed the other four categories to not cohabiting.

The variable for education consists of four categories: less than high school, high school/equivalent, vocational certification/some college/associate's degree, and bachelors or more. I dummy coded education to indicate college completion. Information on income was present in the data, but I did not use this variable because there was so much missing data, due to so many respondents not working, and so not reporting an income. Instead I used the variable for employment status, which included responses for whether the respondents worked for pay or not last week.

The variable for employment status also serves as a variable for social engagement, along with religious participation which was an ordinal measure that captured the estimated frequency of attending religious services. Responses ranged from never to several times a week. Other variables of social engagement (frequency of volunteer work, attendance at meetings of organized groups in the past year, and frequency of socializing with friends or relatives in the past year) were not used because of high levels of missing data.

Methods

Data come from two waves of data collection. In order to take advantage of the panel design of my study and strengthen the casual inferences that can be made from the findings, I employed logistic lagged dependent variable regression models (also called "conditional change" models by Finkel 1995 or the "regressor variable method" by Allison 1990). These models account for prior values of the dependent variable before assessing the influences of other independent variables at time 1 on the dependent variable at time 2. All time-varying variables are lagged by one wave, thus independent variables at time 1 are used to predict changes in the outcome variable at time 2. Lagged independent variables help reduce (although not eliminate) the risk of endogeneity due to reverse causation, as it is not possible for outcome variables at time 2 to effect independent variables from a prior wave.

By controlling for prior values of the dependent variable when predicting current values of the dependent variable, the coefficients of the independent variables may be thought of as predicting change in the outcome variable between waves. The coefficients are interpreted as predicting changes in the outcome variable compared to what we would expect knowing the previous value of the dependent variable. The aim of the method is to examine the relationship between an independent variable at time 1 and a dependent variable at time 2 while controlling for the effects of that dependent variable at time 1. The dependent variable at time 1 is essentially treated as a control variable. All coefficients for the independent variables are net of effects from the lagged dependent variable on the dependent variable at time 2. Using this method allows us to take into account the baseline differences between respondents.

I chose not to use a change score method because the scores tend to be biased by regression towards the mean (Allison 1990). A change score method entails calculating the difference in the outcome variable from Wave 1 to Wave 2 and then calculating the difference for all independent and control variables from Wave 1 to Wave 2; the change from Wave 1 to Wave 2 for all variables are thus obtained. Analyses are then done by regressing the calculated difference in the outcome variable on the differences between waves for all the independent variables.

Conditional change modeling was chosen instead of fixed effects (FE) or random effects (RE) modeling because I am interested in temporal dependence in terms of how Wave 1 variables effect Wave 2 outcomes, not just whether the dependent variable is associated with the independent variables. Specifically, the model of temporal dependence that I am using is the lagged endogenous variable model, where the dependent variable is determined by a series of independent variables at a lag of time *t*-1, along with the lagged value of the dependent variable, as in:

$$Y_{it} = \alpha + \beta_1(Y_{i(t-1)}) + (\beta_2(X_{1i(t-1)}) + \beta_3(X_{2i(t-1)}) + \ldots + \beta_j(X_{ji(t-1)}) + \varepsilon_{it}$$

In this model, the lag value of *Y,* or the "lagged endogenous variable," has a direct effect on the value of *Y* at the next time point, along with effects specified from prior values of *X* as well. This model is equivalent to predicting the *change* in *Y* from its prior value. Because in this type of modeling, unlike fixed effects or random effects models, there is the absence of the unit-specific error term, it is assumed that *all* of the temporal dependence of responses over time is due to the causal mechanism linking the lagged endogenous variable and the lagged *X*'s to *Y.* The inclusion of the lagged *Y* term is meant to control for regression to the mean that would otherwise be present in the model if the lagged dependent variable was omitted.

All analyses were done using Stata/SE 12.0. Results were weighted using *svyset*

Table 9. Weighted Descriptive Statistics: NSHAP, 2005-2006 and 2010-2011 (N=1,922).

	Wave 1			Wave 2		
Variables	% or Mean	SD	Range	% or Mean	SD	Range
Outcome Variables						
Poor Self-Rated Physical Health	20.9			23.5		
Respondent Currently Drinks	62.4			56.3		
Heavy Drinking *(n=926)*	13.4			14.9		
Respondent Currently Smokes	14.4			12.9		
Heavy Smoking *(n=196)*	54.3			46.2		
Network structure						
Number living with ego	1.023	(.030)	0 to 11	0.965	(.026)	0 to 12
Proportion female	0.603	(.008)	0 to 1	0.599	(.007)	0 to 1
Number of close ties	3.637	(.049)	0 to 7	3.625	(.047)	0 to 7
Density	0.828	(.007)	0 to 1	0.825	(.008)	0 to 1
Frequency of contact with alters (hundred contact-days per year)	8.554	(.099)	0 to 22	8.548	(.131)	0 to 26
Perceived support	5.407	(.048)	0 to 8	5.450	(.046)	0 to 8
Health Discussion Partners						
Average Likeliness of Discussing Health	2.446	(.013)	0 to 3	2.428	(.012)	0 to 3
Demographic and Control Variables (only W1)						
Age	67.130	(.243)	57 to 85			
Female	53.0					
Ethnicity						
White	81.7					
Black	9.6					
Hispanic	6.2					
Other	2.5					
College or higher	55.5					
Cohabiting	67.7					
Worked for pay last week	38.3					
Frequency of religious service attendance	3.466	(.058)	0 to 6			

Note: Unweighted N = 1,922. All statistics are survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse. Two-tailed t-tests were conducted to examine the mean differences between 2006 (wave 1) and 2010 (wave 2) measures. No differences were found.

commands to incorporate the adjustment for nonresponse and correct for the sampling design. (For more details on weighting, refer to O'Muircheartaigh & Smith 2007.)

Results

Table 9 presents descriptive statistics for all study variables by wave. Over 20% of the sample in each wave reported poor self-rated physical health. Over half reported that they currently consumed alcohol; of current drinkers, 13.4% reported heavy drinking. Over

Table 10. Weighted Odds Ratios of Wave 1 Variables Predicting Wave 2 Poor Self-Rated Physical Health from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,922).

	Poor Self-Rated Physical Health (W2)											
	Respondent Currently Drinks or Smokes						Heavy Drinking or Smoking					
	Model 1			Model 2			Model 1			Model 2		
Independent Variables from Wave 1	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.
Poor Self-Rated Physical Health (W1)	10.297	(1.416)	***	10.379	(1.489)	***	12.343	(2.992)	***	4.750	(2.035)	***
Respondent Currently Drinks	0.693	(.121)	*									
Respondent Currently Smokes				2.675	(.422)	***						
Heavy Drinking							1.189	(.405)				
Heavy Smoking										1.251	(.705)	
Demographic and Control Variables												
Age	1.013	(.009)		1.021	(.010)	*	1.020	(.017)		1.030	(.025)	
Female	0.860	(.141)		0.933	(.158)		0.646	(.172)		0.825	(.371)	
Ethnicity (ref. = white)												
Black	1.091	(.268)		1.045	(.257)		0.935	(.360)		1.068	(.612)	
Hispanic	1.268	(.228)		1.381	(.247)		0.852	(.335)		3.990	(3.343)	
Other	0.235	(.196)		0.203	(.187)		0.262	(.344)		0.361	(.579)	
College or higher	0.697	(.101)	*	0.685	(.097)	*	0.888	(.223)		0.681	(.340)	
Cohabiting	0.943	(.148)		0.973	(.155)		0.775	(.213)		0.673	(.297)	
Worked for pay last week	0.848	(.150)		0.834	(.146)		0.955	(.263)		0.442	(.191)	
Frequency of religious service attendance	0.929	(.038)		0.970	(.041)		0.883	(.069)		1.040	(.097)	
Intercept	0.161	(.118)	*	0.051	(.039)	***	0.068	(.079)	*	0.087	(.176)	
Likelihood Ratio	31.35			28.47			12.83			2.41		
N	1922			1922			926			196		

Note: Unweighted N = 1,922. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

Table 11. Weighted Odds Ratios of Wave 1 Variables Predicting Wave 2 Drinking and Smoking Behavior from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,922).

	Drinking (W2)						Smoking (W2)					
	Respondent Drinks			Heavy Drinking			Respondent Smokes			Heavy Smoking		
Independent Variables from Wave 1	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.	Odds	SE	Sig.
Respondent Currently Drinks (W1)	29.972	(4.198)	***									
Heavy Drinking (W1)				23.674	(9.124)	***						
Respondent Currently Smokes (W1)							84.589	(22.158)	***			
Heavy Smoking (W1)										27.170	(16.432)	***
Network characteristics and social support												
Number living with ego	1.015	(.079)		0.759	(.121)		0.679	(.120)	*	1.561	(.336)	*
Proportion female	1.212	(.409)		0.431	(.335)		1.793	(1.361)		12.743	(14.267)	*
Number of close ties	1.128	(.071)		1.531	(.233)	**	0.865	(.098)		1.231	(.286)	
Density	1.016	(.385)		0.559	(.388)		1.545	(.588)		0.701	(.613)	
Frequency of contact with alters (hundred contact-days per year)	0.935	(.026)	**	0.935	(.047)		1.028	(.041)		1.038	(.079)	
Perceived Social Support	1.061	(.043)		1.060	(.085)		1.000	(.078)		0.754	(.098)	*
Health Discussion Partners												
Average Likeliness of Discussing Health	0.995	(.187)		0.890	(.319)		0.555	(.143)	*	0.954	(.394)	
Demographic and Control Variables												
Age	1.001	(.013)		0.947	(.028)		0.988	(.023)		1.020	(.042)	
Female	0.934	(.169)		0.699	(.192)		0.685	(.185)		1.547	(.860)	
Ethnicity (ref. = white)												
Black	0.654	(.141)		0.510	(.289)		1.693	(.395)	*	0.182	(.119)	*
Hispanic	0.926	(.236)		1.111	(.446)		1.499	(.541)		0.040	(.048)	*
Other	1.024	(.597)		4.367	(4.295)		1.187	(.729)		0.024	(.048)	
College or higher	1.654	(.311)	**	0.560	(.151)	*	0.755	(.158)		1.564	(.832)	
Cohabiting	0.882	(.177)		0.961	(.288)		1.280	(.382)		0.670	(.424)	
Worked for pay last week	1.445	(.229)	*	0.952	(.284)		0.582	(.181)		1.569	(.752)	
Frequency of religious service attendance	0.894	(.032)	**	0.779	(.067)	**	1.024	(.066)		0.902	(.127)	
Intercept	0.130	(.169)		10.782	(23.904)		0.344	(.666)		0.015	(.052)	
Likelihood Ratio		37.8			5.32			27.08			4.47	
N		1922			926			1922			196	

Note: Unweighted N = 1,922. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).

14% (14.4%) reported that they currently smoked cigarettes. Of current smokers, about half were heavy smokers.

Results of the models are presented in tables 10 to 11. Table 10 presents the predictors for having poor self-rated health in Wave 2. Both cigarette use and alcohol consumption were associated with the odds of poor self-rated physical health at Wave 2, even though heavy smoking and heavy drinking by current users did not predict the odds of poor self-rated physical health at time 2. As presented in Table 10, respondents who smoked in Wave 1 have 2.675 times (p<.001) the odds of poor self-rated physical health in Wave 2, controlling for baseline self-rated physical health. The odds of poor self-rated physical health was lower for respondents who reported current alcohol consumption (OR=0.693, p<.05).

In Table 11, two sets of models are presented: logistic regression models predicting change in prevalence of drinking or smoking in Wave 2 from network characteristics, social support, and average likeliness of discussing health with alters in Wave 1, controlling for baseline drinking or smoking; and logistic regression models predicting prevalence of heavy drinking or heavy smoking with the same independent variables. The lag terms for all models are extremely large, suggesting that habits are persistent over time.

Controlling for baseline rates of current drinking, we can see that the odds of drinking is .935 times the odds of not drinking for each hundred increase in contact-days with alters in the respondent's personal network (p<.01). More contact-days with alters is associated with lower odds of drinking. However, none of the network variables are protective when it comes to prevalence of heavy drinking for those respondents who engaged in alcohol consumption. The number of close ties is predictive of higher odds of heavy drinking (*OR*=1.531, *p*<.01).

In Wave 2, the odds of not smoking is .679 times the odds of smoking for each additional alter living with ego (*p*<.05), controlling for baseline smoking behavior in Wave 1. But even though the odds of smoking are lower for those with higher number of alters living in the same household, the number of alters living in the same household increases the odds of being a heavy smoker for current smokers (*OR*=1.561, *p*<.01). Having a higher proportion of women in ego's network is also associated with higher odds of heavy smoking for current smokers (*OR*=12.743, *p*<.05).

Discussing health and perceived social support are both protective of smoking. Higher average likeliness of discussion health is associated with lower odds of smoking at Wave 2 (*OR*=0.555, *p*<.05). For current smokers, higher perceived social support is associated with lower odds of heavy use at Wave 2 (*OR*=0.754, *p*<.05).

Discussion

Smoking was found to be positively associated with poor physical health, lending partial support for Hypothesis 1. However, drinking was negatively associated with poor self-rated health, contradicting Hypothesis 1. As indicated by the models for cigarette and alcohol use, which included demographics, controls, baseline health behavior, and social network characteristics, networks do influence smoking and drinking behavior. Having more contact with others in a personal network reduces odds of drinking, but having more close ties increases the odds of heavy drinking. The evidence for Hypothesis 2 is inconsistent.

Smoking is predictive of higher odds of poor self-rated health at Wave 2, and so the influence of personal networks on smoking behavior has greater consequences than the influence of personal networks on drinking behavior. Higher number of alters living with the respondent has protective effects on smoking, but for current smokers, it actually increases the odds of smoking more heavily. This measure is both protective but also encouraging for this health risk behavior. We unfortunately do not have information on whether any of the alters smoked, so we cannot investigate whether having higher numbers of alters living in the same household increases the odds for heavy use because of the social nature of that activity. What is curious is why having higher proportions of females in a personal network is associated with much higher odds of heavy smoking for current smokers.

There are other network variables that are protective of smoking behavior of older adults. Discussing health with alters reduces odds of being a current smoker. For current smokers, support reduces the odds of heavy smoking. Hypotheses 3 and 4 are both supported by the results. Having more support or being able to discuss issues of health with others serve to reduce the adoption of health-compromising behaviors.

We see inconsistent results with some of the network structure variables that are associated with smoking and drinking. The probability of drinking is reduced by having more frequent contact with alters and the probability of smoking is reduced by having more alters living in the same household; this may be related to similar stress buffering processes as with social support and discussing health with alters, or perhaps the association is a result of social regulation from ties.

In contrast, heavy use is positively associated with a couple of the network structure variables. More close ties are associated with higher odds of heavy drinking, and more alters living with ego are associated with higher odds of heavy smoking. Health-compromising behaviors may not necessarily always be adopted as a coping mechanism, but may be a pro-social activity that is increased when there are others in the network who also engage in similar activities. Unfortunately, we cannot examine whether this is so using NSHAP because the data does not have information on the smoking and drinking behavior of alters. With information on the behavior of alters, we can further examine whether heavy users are connected to others in the network who also smoke and drink. We would be able to compare social influence processes with behavior regulation processes. Perhaps behavior regulation is more dominant when it comes to engaging in smoking or drinking, but social influence is more dominant when it comes to levels of use by current users.

CONCLUSION

The importance of social ties and social connections for the health of older adults has been firmly established in the literature. This dissertation is situated in this body of research and contributes to the literature by utilizing multiple ways to measure both networks and health in order to carefully distinguish network structure and function. In this dissertation, I examined how social networks and health are related. Utilizing panel data allows me to incorporate a time dimension to the analyses to look at change over time.

In Study 1, I find that network structure is not directly associated with health. Baseline network structure is associated with later social support though, and baseline social support and strain is associated with later health. Although network structure does not have a direct relationship with health, it can be indirectly related via functions of a network like social support and strain. However, baseline health is associated with later local network structure. Depression is associated with reduced contact with networks. Unexpectedly, poor physical health is associated with increases in a number of network structure variables.

Findings from Study 2 demonstrated that spousal loss is associated with the mental health, but only for those with spouses who were supportive. Losing a spouse who was not supportive is not related to mental health. In both cases, social networks were not protective of the impact to mental health from losing a supportive spouse. This study provides new information on which types of spousal loss matter for mental health.

Study 3 elucidated how networks is related to health-compromising behaviors, namely smoking and drinking. Networks are not necessarily always protective of health-compromising behaviors. Network structure variables are protective by reducing the adoption of smoking and drinking behavior. However, for current smokers and drinkers, the network structure variables are enabling for heavy use. This study also found that discussing health with alters and having social support is protective. This study lends some support to structural theories of social influence which point to the role networks play in influencing individual behavior.

Overall, my dissertation findings point to the importance of social support over aspects of network structure in regards to health. Network structure's association with health is largely indirect, either through influencing the functions of a network, or through influencing individual health behaviors.

There are some limitations to the data used. Although the measures for social network structure were derived from the social network roster data, the measures for social support used for this dissertation was not specific to particular alters, but was a more general perception of support. It is quite possible that I would have arrived at different results if information on the level of support from each alter was available. In future research, compiling more specific information on the types and level of support and strain from each alter would be useful, as well as information on the health behaviors of each alter. The findings for this dissertation were also limited by the availability of only two waves of data. Any feedback loops can be surmised from the research design but not directly observed unless there was a third wave of data.

Policy interventions for the elderly oftentimes operate on the premise that social ties affect health. However, in my dissertation, I do not find any direct ways in which social ties affect health. Knowing more information on how different aspects of personal networks matter for health can be helpful in informing policy. If social network structure does not directly impact health, but influences health via other pathways, then policy focusing on increasing opportunities for social engagement alone for older adults will not be enough to see the desired health benefits. Furthermore, not all ties are beneficial for health. In fact, some social ties may be detrimental for health. This is why it's important to take a clear look as to which social network characteristics matter for health outcomes and to pay more attention to the substance of network ties rather than the mere existence of the ties themselves. Efforts to enhance the social relationships of older adults should be focused on ways to cultivate and strengthen supportive ties more specifically rather than expanding network ties more generally.

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APPENDIX

Table A. Weighted Regression Coefficients of Wave 1 Variables Predicting Wave 2 Inability to Perform Activities of Daily Living (ADLs) from Residual Change Score Models: NSHAP, 2005-2006 and 2010-2011 (N=1,117).

	Inability to perform Activities of Daily Living (W2)[1]											
	High Spousal Support in Wave 1						Moderate and Low Spousal Support in Wave 1					
	Model 1			Model 2			Model 1			Model 2		
Independent Variables from Wave 1	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.
Inability to perform Activities of Daily Living (W1)[1]	0.905	(.099)	***	0.898	(.101)	***	0.639	(.086)	***	0.644	(.088)	***
Loss of Spouse/Partner from W1 to W2	-0.025	(.279)		-0.015	(.278)		0.244	(.359)		0.220	(.357)	
Social Support and Strain												
Perceived support				-0.032	(.053)					-0.003	(.037)	
Perceived strain				0.092	(.080)					0.004	(.083)	
Network structure												
Network size				-0.041	(.075)					0.050	(.096)	
Number living with ego				0.120	(.084)					-0.124	(.097)	
Proportion female				-0.135	(.422)					0.337	(.595)	
Number of close ties				0.088	(.087)					-0.015	(.111)	
Density				-0.485	(.447)					0.468	(.372)	
Frequency of contact with alters (hundred contact-days per year)				0.010	(.027)					-0.006	(.037)	
Demographic and Control Variables												
Age	0.007	(.012)		0.009	(.011)		0.055	(.016)	**	0.054	(.015)	***
Female	0.084	(.147)		0.063	(.137)		-0.171	(.181)		-0.196	(.200)	
Ethnicity (ref. = white)												
Black	0.544	(.319)		0.446	(.334)		-0.045	(.256)		-0.025	(.288)	
Hispanic	-0.535	(.355)		-0.567	(.372)		0.023	(.470)		0.091	(.508)	
Other	0.533	(.727)		0.417	(.698)		0.426	(.553)		0.432	(.521)	
College or higher	0.108	(.178)		0.079	(.156)		-0.256	(.192)		-0.251	(.206)	
Worked for pay last week	0.042	(.166)		0.014	(.167)		-0.024	(.222)		-0.018	(.233)	
Frequency of religious service attendance	-0.023	(.053)		-0.027	(.055)		-0.005	(.046)		-0.003	(.049)	
Intercept	-0.014	(.926)		0.131	(1.147)		-2.937	(1.156)	*	-3.410	(1.142)	**
R^2	0.3845			0.3904			0.3764			0.3803		
N	826						291					

Note: Unweighted N = 1,117. All analyses restricted to to those who were married or living with a partner during wave 1. The model estimates survey design adjusted and weighted to account for the probability of selection, with poststratification adjustments for nonresponse.

[1] Inability to perform Activities of Daily Living (ADLs) range from 0 to 21, with 0 indicating no disability, and 21 indicating inability to perform all ADLs.

*p <.05, **p <.01, ***p <.001 (two-tailed tests).