Multimorbidity at Midilfe: An Analysis of Morbidity Patterns and Life Course Socioeconomic Cofactors

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DISSERTATION

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A dissertation project can be a lonely process. It requires long hours toiling in isolation, staving off fatigue and feelings of self-doubt and tolerating the discomforting notion that, although you understand a great deal about your topic of choice, your comprehension is embarrassingly limited. I have found that the only real antidote to this discomfort is the support of loved ones – whether life partners, friends, family, academic mentors, or pets. I worked hard on this project. I learned a literature, an analytic approach, and sophisticated statistical techniques. The most important lesson for me, however, was that the only real way to advance was to ask for help and lean on people who cared for me and who I trusted and for whom I also cared.

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TABLE OF CONTENTS

CHAPTER 1. INTRODUCTION 1
A. Background 1
B. Purpose 3

CHAPTER II. CONCEPTUAL FRAMEWORK AND RELATED LITERATURE 4
A. Cumulative advantage and disadvantage theory 4
B. Life course social determinants and pathways to health 8
C. Related literature 13
1. Strategies for assessing multimorbidity 13
2. Prevalence and patterns of multimorbidity 15
3. Cofactors of multimorbidity 18
D. Research hypotheses 21

III. METHOD 24
A. Sample 24
B. Human subjects protections 27
C. Measures 27
1. Morbidity and multimorbidity 27
2. Functional health and well-being: Short Form Health Survey (SF-12) 28
3. Life course individual and household 29
4. Individual educational attainment 31
5. Parental educational attainment 31
6. Adult household income trajectory 31
7. Household net worth 34
8. Home ownership 35
9. Race or ethnicity 35
10. Demographic variables 35
11. Additional control variables 35
D. Analysis plan 37
1. Latent variable mixture models 39
2. Mixed regression models 47
3. Evaluation of research questions and hypothesis tests 48

CHAPTER IV. RESULTS 52
A. Chronic Health Conditions 52
B. Covariates and control variables 54
1. Participant educational attainment 55
2. Parental educational attainment 55
3. Household size adjusted net worth at 40 and 50 years old in $1,000 increments 55
4. Adult household size adjusted annual income 55
5. Home ownership 56
6. Race and/or ethnicity 56

TABLE OF CONTENTS (continued)

7. Gender 56
8. Age 56
9. Body mass index 57
10. Heath insurance 57
11. Binge drinking 57
12. Current smoking 57
13. Early adult health conditions 57
14. Functional health and well-being: Short Form Health Survey (SF-12) 62

C. Mixed regression models 62

D. Patterns of accumulation of chronic health conditions at midlife 67
1. Latent class analysis results 67
2. Latent Class Descriptions 71

E. Relationship between accumulation at 40 and 50 years of age 75
1. Latent transition analyses 75

F. Life course socioeconomic characteristics and race and midlife patterns of accumulation of chronic health conditions 80
1. A three step latent transition analysis with covariates 80

G. Patterns of morbidity and perceived functional health and well-being Overall physical and mental health 88
1. Distal Outcomes 88

H. Summary 90

CHAPTER V. DISCUSSION 91

A. General summary and hypotheses 91

B. Cumulative disadvantage, life course determinants of health, and morbidity at midlife.. 95

D. Limitations 99

E. Questions for future research 102

F. Implications for policy and practice 105

CITED LITERATURE 108

APPENDICES 131

Appendix A Mixed regression models 132

Appendix B Bivariate Perason tests of residual associations 142

VITA 143

LIST OF TABLES

TABLE PAGE

I. CHRONIC HEALTH CONDITIONS 53

II. COVARIATE AND CONTROL VARIABLES 58

III. AGE IN YEARS AT FOUR TIME POINTS BY INCOME IN DOLLARS ($1,000 INCREMENTS) AND LOG TRANSFORMED DOLLARS ($1,000 INCREMENTS)....................63

IV. SIX MIXED REGRESSION MODELS....................64

V. FIT STATISTICS FOR SELECTION OF THE BEST FITTING MIXED REGRESSION MODEL....................66

VI. OBSERVED AND ESTIMATED INCOME AT FOUR AGES....................68

VII. FIT STATISTICS FOR CROSS-SECTIONAL LATENT CLASS MODELS.....69

VIII. ESTIMATED PROBABILITY OF TRANSITIONING (T) BETWEEN MORBIDITY STATUSES FROM 40 TO 50 YEARS 78

IX. MULTINOMIAL LOGISTIC REGRESSION RELATING SOCIO ECONOMIC CLASS TO MORBIDITY STATUS AT 40 (REFERENCE = LOW MORBIDITY CLASS) 82

X. COVARIATE EFFECTS ON TRANSITION PROBABILITIES 85

XI MEAN SFPCS AND SFMCS SCORES BY LATENT CLASS ASSIGNMENT....................89

LIST OF FIGURES

FIGURE		PAGE
1.	Life course and social determinants of health	12
2.	Conceptual relationship of indicator variables to latent class variable	41
3.	Conceptual relationship of indicator variables, covariates, and transition in the transition analysis	42
4.	Latent class membership by estimated conditional probabilities of reporting chronic health conditions: 40 years old	72
5.	Latent class membership by estimated conditional probabilities of reporting chronic health conditions: 50 years old	74
6.	Latent status membership by estimated conditional probabilities of chronic health conditions	76

LIST OF ABBREVIATIONS

AIC	Akaike Information Criteria
ACA	Patient Protection and Affordable Care Act
BIC	Bayesian Information Criteria
BICadj	Sample Size Adjusted Bayesian Information Criteria
BLS	Bureau of Labor Statistics
BMI	Body Mass Index
CAD	Cumulative Advantage and Disadvantage
ECP	Estimated Conditional Probabilities
EBE	Empirical Bayes Estimates
HPA	Hypothalamic-Pituitary-Adrenal
LCA	Latent Class Analyses
LTA	Latent Transition Analysis
NLSY79	The National Longitudinal Survey of Youth-1979
OR	Odds Ratios
SEP	Socioeconomic Position
SF-12	Short Form Health Survey
SFPCS	Short Form Physical Health Composite Scale Scores
SFMCS	Short Form Mental Health Composite Scale Scores

SUMMARY

Multimorbidity, commonly understood as the presence of multiple chronic health conditions within an individual, has received considerable research attention. One predominant focus of this research is ascertaining the prevalence, patterns, and cofactors of multimorbidity in older, clinical, and special populations. Relatively less effort has concentrated on midlife (40 to 65 years of age), the point when a significant number of individuals develop multiple chronic medical conditions. Although general population surveys report multimorbidity prevalence rates of over 15% for those at midlife, the patterns, if any, by which health conditions accumulate within individuals and the cofactors related to accumulation have yet to be identified. For a number of reasons, understanding accumulation and related cofactors is germane to health social work policy and practice. Multimorbidity is relatively prevalent at midlife and beyond; it has demonstrable links to social and economic factors; it creates pervasive difficulties for coordination of care; and it is associated with multiple deleterious health outcomes. Drawing on the theory of cumulative advantage and disadvantage (CAD) across the life course, a theory consistent with the social determinants of health framework, the current research focused on the relationship between life course social and economic factors and the onset and progression of multimorbidity. It examines five questions:

1. Are there discernible patterns of accumulation of chronic health conditions at two points during midlife (approximately 40 and 50 years of age)?
2. How do patterns of accumulation at an earlier point in time (i.e., 40 years of age) relate to those at a later time (i.e., 50 years of age)?
3. Do life course individual and household socioeconomic characteristics predict midlife patterns of accumulation of chronic health conditions?

4. Does race or ethnicity relate to patterns of accumulation of chronic health conditions?
5. How do these patterns contribute to self-reported functional health and well-being?

Using a set of responses to questions about the presence of 12 chronic health conditions at two points in time as indicator variables, two latent class analyses (LCA) classified individuals into morbidity patterns when they were about 40 years old and again when they were about 50. After developing these cross sectional pictures of morbidity, a latent transition analysis (LTA) modeled the temporal relationship between morbidity patterns of individuals when they were 40 and once more when they were 50. To do this, it classified individuals into morbidity patterns or statuses at 40. It then related morbidity status at 40 to morbidity status at 50. Introduction of covariates related indicators of life course individual socioeconomic position and race or ethnicity to morbidity patterns at 40. Additionally, they conditioned the relationship of patterns at 40 to those at 50.

Findings suggest a mixture of stability and change in morbidity at midlife. At both time points, four discernible patterns of morbidity were identified. There was a large Low Morbidity status of individuals who reported few health conditions. Two smaller statuses were also observed, one whose members reported arthritis and the other whose members tended to report hypertension. The final status consisted of individuals who were truly multi-morbid (i.e., reporting two or more conditions on average). This small status was described by an elevated propensity for reporting chronic lung disease and heart disease. Between 40 and 50, this heart and lung status was static. Individuals classified in this status at 40 remained there and no new individuals transitioned to this status. The majority of transitions were from the low morbidity status into the Arthritis or the Hypertension status, though the majority of those in the Low Morbidity status at 40 remained there at 50. It was not uncommon for individuals to transition from the Hypertension status to the Arthritis status. In addition to qualitative differences in the types of chronic health conditions associated with each status, there were also quantitative differences in the average number of health conditions members of each status reported. Members of the Low-Morbidity and Hypertension and statuses reported less than one chronic health condition on average. Members of the Arthritis status reported on average more than one chronic health condition but tended not report over two conditions. Finally, those in the Heart and Lung status expressed true multimorbidity and reported just over three health conditions on average. Viewing this as a continuum, one might understand the first two statuses as low morbidity statuses, the Arthritis status as moderate morbidity status, and the Heart and Lung status as a high morbidity status. After conditioning on control variables, covariates representing social and economic position, in particular, income and wealth were related to morbidity status. Members of the Low-Morbidity status reported on average appreciably better physical and psychological functioning than their counterparts in the three other morbidity statuses.

These results underscore the importance of identifying individuals with multiple chronic health conditions and coordinating their care to improve function and well-being and manage or avoid the complications that emerge frequently in a care system built around treating the single condition. Developing a medical framework that can manage multimorbidity will require changes to health policy and practice. More importantly perhaps, the links between multimorbidity and social and economic position urges us to extend our thinking for how social policy interventions may attenuate this relationship. Potentially, this could be accomplished directly with interventions to improve social and economic position of individuals, families, and communities. Alternatively, policy could intervene by addressing the myriad of mediating factors (e.g., community violence, affordable access to fresh food, safe and secure recreational spaces, affordable and safe housing, and curtailing and cleaning up environmental toxins).

CHAPTER 1. INTRODUCTION

A. Background

Multimorbidity, commonly understood as the co-occurrence of two or more chronic medical conditions, has garnered considerable recent research interest (e.g., Agborsangaya, Lau, Lahtinen, & Johnson, 2012; Barnett et al., 2012; Roberts, Rao, Bennett, Loukine, & Jayaraman, 2015; Swartz, 2011). The reasons for this are straightforward. There is an increasing awareness that multimorbidity is relatively common and becoming more so (Paez, Zhao, & Hwang, 2009). Incidence in clinical and older (i.e., >65 years) populations may be well over 50 percent (Fortin, Bravo, Hudon, Vanasse, & Lapointe, 2005; Marengoni, Winbald, Karp, & Fratigliona, 2008). Even general population surveys report prevalences of 4 and 15 percent for respondents between 20 and 39 and 40 and 59 years of age, respectively (Taylor et al., 2010).

Accumulating multiple chronic medical conditions places onerous burdens on individuals, including physical limitations, overall reduced quality of life, increased mortality, and psychological distress (Fortin et al., 2006; Kadam, Croft, N Staffordshire Group, & Consortium Group, 2007; Menotti et al., 2001; Walker, 2007). Further, simultaneous treatment of multiple conditions exposes inadequacies in medical systems of care which may compound the burden of multimorbidity. Treatment in the presence of numerous health conditions is, for instance, associated with services that are neither cost- nor medically effective and result in fractured coordination of care, avoidable hospitalizations, and preventable complications (Tinetti, Bogardus, & Agostini, 2004; Wolff, Starfield, & Anderson, 2002).

In part, these problems may emerge from prioritization of treatment of the single condition which has driven the evolution of many medical care systems (Tinetti & Fried, 2004). Traditionally, standard of care guidelines have prioritized treating single morbidities such as chronic obstructive pulmonary disease or hypertension with limited guidance for care modifications when co-occurring conditions are present (Boyd et al., 2005; Lugtenberg, Burgers, Clancy, Westert, & Schneider, 2011). Given this focus, it is perhaps unsurprising that systems of care experience difficulty managing the complex medical and organizational issues introduced when patients have multimorbidity. Indeed, the dearth of consistent evidence supporting the effectiveness of case management, a major tool for coordinating complex care arrangements and difficult treatment adherence programs required in cases of multimorbidity, may indicate a current lack of capacity to remediate these inadequacies (cf., Smith, Soubhi, Fortin, Hudon, & O'Dowd, 2011).

In addition to these unfortunate individual consequences and system of care difficulties, evidence suggests that social and economic policies, processes, and conditions have demonstrable links to multimorbidity. Researchers have observed independent effects of community economic deprivation (Barnett et al., 2012; Robert, 1998; Robert & Lee, 2002), individual income (Agborsangaya et al., 2012; Salisbury, Johnson, Purdy, Valderas, & Montgomery, 2011), educational attainment (Gold, Michael, & Whitlock, 2006), and experiences of interpersonal and structural discrimination (Williams, Mohammed, Leavell, & Collins, 2010) on the relative likelihood of reporting multiple chronic medical conditions. Predictably, this research generally reports that diminished community and individual socioeconomic capacities are associated with increased likelihood of multimorbidity. For any given population, then, a foreseeable consequence of these links is the concentration of health problems within communities and individuals who experience relatively higher levels of economic and social duress for protracted periods (Gijsen et al., 2001; Mays, Cochran, & Barnes, 2007).

B. Purpose

In spite of this recognition, gaps remain in our understanding of the influence that social and economic factors have on the accumulation of chronic medical conditions. Research has tended to focus on either special populations such as criminal justice (Swartz, 2011), children with feeding problems (Berlin, Lobato, Pinkos, Cerezo, & LeLeiko, 2011), or on older populations (John, Kerby, & Hagan Hennessy, 2003). With notable exceptions (e.g., Luchenski, Quesnel, Vallee, & Lynch, 2008), the vast majority of this research has examined the association between point in time measures of social factors and multimorbidity (e.g., Andrade, Bensenor, Viana, Andreoni, &Wang, 2010). The study described below proposes to partially fill these gaps. It examined the accumulation patterns of multiple medical conditions for a sample of individuals at two points at midlife. It used measures of life course socioeconomic circumstances and race or ethnicity as model covariates. This examination resulted in a description of morbidity patterns that emerge at midlife and related these patterns to a set of predictor variables representing life course social and economic position.

CHAPTER II. CONCEPTUAL FRAMEWORK AND RELATED LITERATURE

A. Cumulative advantage and disadvantage theory

The theory of cumulative advantage and disadvantage (CAD) informs this research. Introduced by Merton (1968), CAD is the primary sociological conceptual framework used to understand the Matthew Effect in science (Zuckerman, 1988; Zuckerman, 2010). Named for a famous passage in the Gospel of Matthew "For unto everyone that hath shall be given, and he shall have abundance; but from him that hath not shall be taken away even that which he hath", this effect describes the frequent observation that professional prestige and recognition concentrate within a disproportionally small number of scientists (Merton, 1988). In its original formulation, CAD posited that initial differences in quality of training and available research resources result in early academic successes, often in the form of well-regarded and frequently cited publications. These successes in turn trigger an accelerating process of future scientific productivity, evaluated quality of research, and formal recognition by the academy. As such, academicians' career trajectories tend to diverge early and form disparate patterns in which a very few elite scientists at a limited number of institutions garner the vast majority of available research resources, professional prestige, and influence in their respective fields. In describing the consequences of accumulation processes, Merton (1988) noted that between 1961 and 1980, 0.3 percent of peer reviewed publications in the physical and biological sciences were cited 100 times or more while 58 percent were cited only once. Further, of the $4.4 billion dollars the federal government provided for academic research in 1981, 28 percent was concentrated in ten universities. Although it acknowledged that countervailing processes must exist to temper rates of inequitable accumulation, this early version of CAD placed considerable emphasis on accumulation having “a direct and causal relationship on future levels of accumulation” (DiPrete & Eirich, 2006, p. 272; Merton, 1988).

Researchers in various disciplines have generalized CAD for use in analysis of accumulation and disparity formation processes to a broad range of topics, including unemployment trajectories (Heckman & Borjas, 1980), childhood behavior problems and IQ (Duncan, Brooks-Gunn, Klebanov, 1994), and criminal offending careers (Sampson & Laub, 1997). A repeated conclusion of this work is that irrespective of substantive area, prior exposure to advantage or disadvantage increases the likelihood of even greater advantage or disadvantage. Given its demonstrated utility in multiple social science domains, CAD has been advanced as a general explanatory mechanism that underpins the temporal and social processes that generate inequality (Dannefer, 2003; DiPrete & Eirich, 2006).

More recent analyses of accumulation have modified CAD to incorporate social and economic structural factors that potentially influence the rate at which disparities between individuals and groups evolve (Dannefer, 2003). An examination of research on the development of health disparities over the life course, the main topic of this research, points to at least four prominent factors. They are:

- status markers such as race or gender on which disparity generating processes (e.g., interpersonal and structural discrimination) operate (Farmer & Ferraro, 2005; Quiñones, Liang, Bennett, Xu, & Ye, 2011);
- characteristics like educational attainment that regulate access to material resources and health knowledge (Dupre, 2008; Herd, Goesling, & House, 2007; Phelan, Link, & Tehranifar, 2010);

- community level socioeconomic conditions that help form the political, economic, and social context in which individuals live and that also regulate levels of risk and opportunity along multiple dimensions (Robert, Cagney, & Weden, 2010);
- and parallel processes of accumulation over the life course such as income or wealth that establish levels, timing, and duration of exposures to health risks and protections (Shuey & Willson, 2008).

With respect to this last point, recent research suggests that the rates, patterns, or trajectories by which these parallel processes develop are related to variation in a number of health outcomes such as incidence of atherosclerosis (Lemelin et al., 2009), binge drinking (Cerdá, Johnson-Lawrence, & Galea, 2011), and cardiovascular disease mortality (Johnson-Lawrence, Kaplan, & Galea, 2013). Using Alameda County Study participant household income data collected during four waves over 20 years, Johnson-Lawrence et al. (2013), for example, reported that four observed income trajectories (consistently low, consistently moderate to low, increasing, and high incomes) were differentially related to cardiovascular disease mortality. Specifically, there appeared to be a graded relationship such that respondents reporting consistently low incomes experienced the highest risk of mortality from cardiovascular disease during the 20 year interval, followed by those in the moderate-low pattern, and finally those in the increasing and high groups.

An analysis of morbidity patterns at midlife fits naturally within a CAD framework. Multimorbidity is a cumulative process, one in which current morbidities may contribute directly or indirectly to future ones (Valderas, Starfield, Sibbald, Salisbury, & Roland, 2009). Cataracts are a direct consequence of diabetes; certain chemotherapies to treat breast cancer increase risk of congestive heart failure (Jensen, 2006; Valderas et al., 2009). Moreover, like other health outcomes, multimorbidity has demonstrable associations with indicators of status and socioeconomic position all of which possibly influence accumulation (Agborsangaya et al., 2012; Barnett et al., 2012). With some exceptions (e.g., Quiñones et al., 2011), however, research has yet to examine the timing, patterning, or progression of accumulation of multiple chronic medical conditions within individuals. Nor has it investigated the relationship between these aspects to potentially relevant cofactors such as status markers, education, or parallel processes of accumulation.

For the current purposes, research informed by or consistent with CAD is a useful guide for the selection of cofactors for a model of multimorbidity accumulation. Persistent or recurring experiences of individual or household poverty, for instance, is reliably and positively associated with likelihood of reporting specific chronic illnesses such as coronary heart disease or functional impairments such as problems with daily activities (Lynch, Kaplan, & Shema, 1997; Singh-Manoux, Ferrie, Chandola, & Marmot, 2004).

This research also provides insight about the different roles these cofactors might occupy in a model of multimorbidity. The relative contributions of income and education to a health outcome, two of the most commonly used indicators of socioeconomic position, vary depending on current levels of accumulation of health problems. Specifically, evidence suggests that educational attainment asserts its greatest protection against onset of both general (e.g., functional impairments) and particular (e.g., hypertension or heart attack) health problems. After onset, however, income plays a greater role in governing their progression (Dupre, 2008; Herd et al., 2007; Zimmer & House, 2003). Finally, at least with respect to onset of health conditions, race--or more accurately the social forces whose health consequences are based on racial categories--may moderate the effect of social and economic cofactors. Evidence supports the claim, for example, that educational attainment is less protective against onset of health problems for African Americans compared to their White counterparts (Farmer & Ferraro, 2005).

Finally, the guidance offered by CAD is consistent with other frameworks like life course (Ben-Shlomo & Kuh, 2002) and fundamental causes (Phelan et al., 2010) used to investigate the social patterning of health. Like these frameworks, CAD accommodates social and economic factors that regulate exposure to risk and opportunity (Dannefer, 2003). One additional conceptual benefit of CAD is an explicit requirement that an individual's prior health status influences future ones. Specific to the current goal, this means that number of health conditions an individual has accumulated at an earlier point in time should have a significant and positive correlation with future accumulation. Moreover, the empirical base suggests that individual and household social and economic characteristics contribute to both onset and progression for varied health outcomes. The contributions of these factors are at times dependent on status markers such as race.

B. Life course social determinants and pathways to health

A substantial literature describes the relationship between social and economic policies, processes, and conditions to mental and physical health. A general aim of the research in this literature is to describe the putative pathways or mechanisms that link life course social and economic determinants to a broad range of psychological and physical health outcomes (Marmot & Wilkinson, 2005). The research described in this proposal will not specifically test these pathways. As such, an exhaustive review is beyond the current scope. Nevertheless, a cursory discussion of these pathways serves to place the current research in a larger context in which health is understood as an outcome of a complex set of relationships between time, social structures and processes, physical environments, human agency and behavior, physiological and psychological characteristics, and, more recently, genetic predispositions (Glass & McAtee, 2006). In addition to providing the conceptual back drop for the current research, the content of the discussion is consistent with the proposition that cumulative disadvantage over the life course may result in clustering of chronic health conditions within a limited number of individuals.

From the perspective of this conceptual framework, socioeconomic factors are understood as fundamental or basic causes of health outcomes (Phelan et al., 2010). In support of this idea, is the frequent observation that the uneven distribution of chronic illnesses, infectious diseases, mortality rates, and other health outcomes correlate tightly with social hierarchy (Marmot & Wilkinson, 2005). Individuals and groups with the bulk of material, political, and educational resources tend to have longer and healthier lives (Marmot & Wilkinson, 2005). This observation extends across cultures, societies, and historical periods. As early as the 12th century, for instance, the predecessors to modern social scientists noted the negative relationship between social status and mortality rates (Antonovsky, 1967). In 1848, Engels used the term "social murder" to describe the social and economic policies that created physically and psychologically toxic and at times fatal conditions in tenement housing during the English industrial revolution (Engels, 1993).

This framework posits further that social and economic factors are not direct causes of health. Rather, they regulate exposure to the risks and protections, resources and deprivations, and opportunities and impediments which, upon interaction with individual psychology and physiology, manifest as illness or well-being (Glass & McAtee, 2006). A common example, the physiological responses to experiences of chronic stress, describes one dominant path or mechanism by which social and economic factors might project their effects onto health.

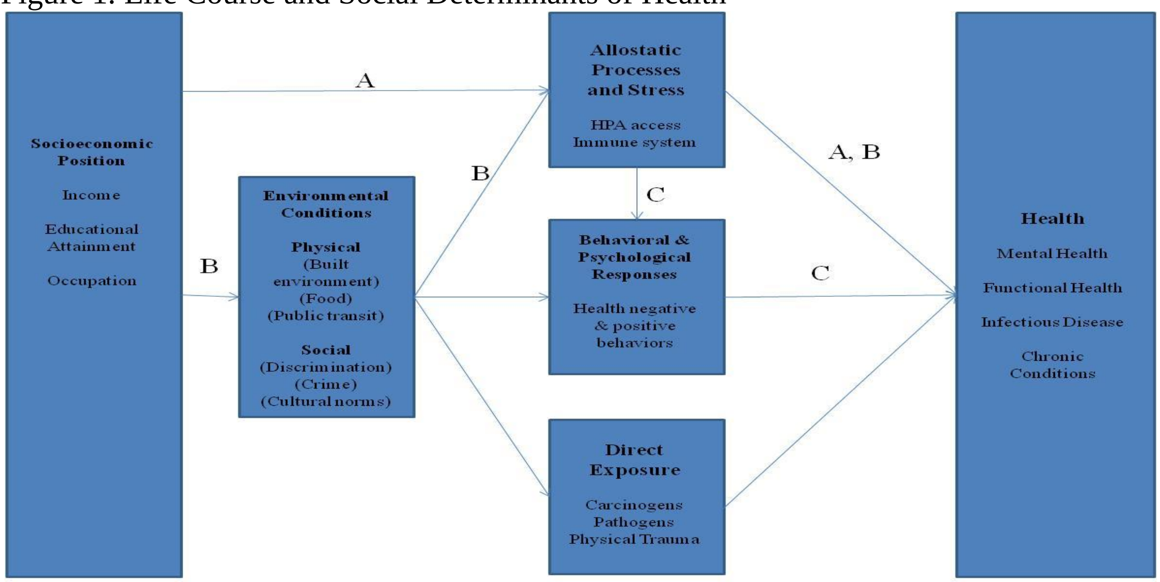
Human physiology is equipped to adapt to an array of physical and social stressors. In response to these, regulatory body systems maintain internal homeostasis and also marshal resources to respond to the external environment. In order to prepare for perceived physical threats or other stressors, for instance, there is an increase in blood pressure, redirected attention to the source of the threat, and a temporary suspension of the digestive system (McEwen, 1998). Largely governed by the hypothalamic-pituitary-adrenal (HPA) axis but also including the autonomic nervous, metabolic, and immune systems, responses like this accommodate constantly changing conditions while still maintaining bodily homeostasis. Termed allostasis, these processes of accommodation and maintenance, are the primary mechanisms by which the body adapts to external stressors (McEwen, 1998). During the course of a life, these mechanisms regulate bodily systems, so that the individual can respond to stressors and insults from the social and physical environment. Like any bodily mechanism, however, there are limits to the allostatic machinery. Over time, it may succumb to the general "wear and tear" (McEwen, 1998, p. 171) of responding to a chronically stressful environment. In this circumstance, individuals exposed to multiple or high levels of chronic stress may experience dysregulation in the responses of the HPA axis and its allied systems leading to a loss of effectiveness (Seeman, Epel, Gruenewald, Karlamangla, & McEwen, 2010). This dysregulation is associated with numerous negative health outcomes. In fact, the same mechanisms dedicated to maintaining bodily health and integrity are, in certain circumstances, associated with exacerbating and possibly even causing ill health. Researchers have discovered an association between chronically elevated levels of the hormone glucocorticoid, an indicator of a dysregulated stress response, and such health problems obesity (Incollingo Rodriguez et al., 2015).), hypertension, diabetes (Brindley & Rolland, 1989), loss of bone density (Michelson, 1996), cardiovascular disease (Bjorntorp, 1990), depressed immune responses (Dhabhar & McEwen, 1997), and differential breast cancer mortality between African American and White women (Gehlert et al., 2010).

Socioeconomic position may influence health through allostatic processes in a number of ways. It may lead directly to allostatic dysregulation. In this scenario, we might imagine that long term financial deprivation leads to recurring challenges in acquiring basic necessities such as housing, groceries, or child care (e.g., Shippee, Wilkinson, & Ferraro ,2012). The effect of exposure to these chronic stressors may accumulate over time, wearing out allostatic mechanisms, and eventually degrading health (Pearlin, Schieman, Fazio, & Meersman, 2005). Alternatively, SEP's effect on the allostatic process may proceed through mediated paths. SEP plays direct and substantial role in selection of individuals' social and physical communities (Sampson & Sharkey, 2008). Once selected, these communities may then confer varying levels of risk for experiencing stressors that, in turn, may prompt degradation of the allostatic system. Communities, for example, differ in the extent to which residents experience exposure to stressors such as rates of violent crime. Finally, behavioral and psychological responses to stress may mediate the effects of both SEP and allostatic processes on health. One adaptive response to chronic stress is heavy consumption of alcohol or other drugs such as nicotine, all of which have deleterious health consequences (McEwen & Wingfield, 2003).

Another dominant pathway by which SEP may influence health outcomes is through access to resources, such as medical treatment and health knowledge (Phelan et al., 2010). Link, Northridge, Phelan, & Ganz (1998) observed a positive relationship between educational attainment, family income, and use of pap smear and mammography screenings for early detection of cervical and breast cancers. Similar sorts of unequal use of or access to care have been reported for other health outcomes including diabetes retinal scans (Gulliford et al., 2009) and access to lung cancer treatment (Jack, Gulliford, Ferguson, & Moller, 2006).

The preceding discussion offered a sketch of some potential pathways down which SEP might project its effects onto health. It is depicted in Figure 1 below.

Figure 1. Life Course and Social Determinants of Health



The discussion was not intended to be exhaustive. As such, it omitted other pathways by which SEP may influence health. SEP may also govern the availability of fresh produce (Morland, Wing, Roux, & Poole, 2002), safe and convenient locations for exercise (Saelens, Sallis, Black, & Chen, 2003), and exposure to environmental toxins (Oyana & Margai, 2010). Despite these shortcomings, this discussion suggested the numerous avenues by which SEP might affect health. Given this, the clustering of multiple chronic health conditions in individuals with prolonged experiences in lower socioeconomic strata is not an unrealistic expectation.

C. Related literature

The following section reviews overlapping literatures that focus on aspects relevant to multimorbidity: strategies for assessing multimorbidity, its prevalence and patterns, and its associated cofactors. This review presents evidence that at midlife multimorbidity is not uncommon and, at least in older individuals and possibly those at midlife, discernible clusters of health conditions are present. It will further suggest a number of cofactors that may relate to the uneven distribution of onset and accumulation of midlife multimorbidity across members of a population.

1. Strategies for assessing multimorbidity

A relatively well-established definition of multimorbidity is the occurrence within one individual of two or more acute or chronic health conditions (Valderas et al., 2009). Unlike comorbidity, no disease or disorder need act as the primary or reference condition. Strict co-occurrence is not required, although when no temporal overlap is present, a time frame in which the conditions develop may be defined (Valderas et al., 2009).

Despite a shared definition, there is no uniformly adopted standard for assessing multimorbidity (Diederichs, Berger, & Bartels, 2011). One straightforward technique often seen in survey research is the use of a list of common medical conditions. Then, based on survey respondents' self-reports, researchers create a summary score. Depending on the analytic plan, these scores may take the form of a count (e.g., Andrade et al., 2010) or an ordered categorical variable (e.g., Taylor et al., 2010) in which some pre-determined number of conditions, typical two or more, is set as a threshold for multimorbidity.

Several potential limitations confront this strategy. The number of reportable conditions is constrained to items on a list. Any list must likely omit important conditions (Guthrie, Watt, Wyke, & Mercer, 2012). Additionally, measures of the overall severity of impact of multimorbidity on individuals are regularly absent (e.g., Agborsangaya et al., 2012; Barnett et al., 2012). Perhaps in response to these concerns, a recent systematic review recommended the creation of core health conditions for inclusion in any study on multimorbidity (Diederichs et al., 2011). Based on four health condition criteria - protracted duration, ongoing management, severity of impact, and high prevalence in older populations, the review identified eleven core conditions - cancer, diabetes mellitus, depression, hypertension, myocardial infarction, chronic ischemic heart disease, heart arrhythmias, congestive heart failure, stroke, chronic obstructive pulmonary disease, and arthritis – for inclusion in this core.

Diederichs et al. (2011) also examined a number indices developed to count the number of diseases and disorders in an individual and assess some aspect of cumulative health impact. The Charlson Index, for instance, collects information on the presence of 19 chronic health conditions and calculates a weighted score based on each reported condition and an estimated one year mortality rate for each condition. Higher scores are indicative of a greater number of health conditions and higher likelihood of early mortality (Charlson, Pompei, Ales, & MacKenzie, 1987). Other indices deploy other weighting schemes to calculate the level of disability or limitation in physical function resulting from the number and kinds of health conditions (e.g., Groll, To, Bombardier, & Wright, 2005; Verbrugge, Lepkowski, & Imanaka, 1989). Indices provide a convenient way to quantify the overall impact of multimorbidity. Despite this convenience, aggregating “complex reality into single indicators,” is always accompanied by the risk of over simplifying the “complexity of the phenomenon of multimorbidity” (Diederichs et al., 2011, p. 307). In particular, use of a single index score might blind an analysis to clusters or patterns of conditions collecting within individuals. If these clusters exist and are identified, there is the potential to develop interventions around them.

An additional common limitation to research on multimorbidity is question wording in surveys that makes it impossible to distinguish between conditions that truly co-occur or that occur sequentially without overlap. The National Survey of Drug Use and Health, for instance, asks respondents if they have ever had lung cancer or high blood pressure (SAMHSA, 2012). Alternative question wording may help address this issue. The survey of the Health Quality Council of Alberta, used in Agborsangaya et al. (2012), frames questions in the present tense (e.g., Do you have any of the following chronic conditions or diseases?), thus focusing respondents' attention on current conditions.

Another limitation is an unavoidable consequence of survey design. Measurement error is always a potential threat as mistakes or inaccuracies in self-report inherent in the social survey method (Tourangeau, Rips, & Rasinski, 2000) and have been observed in the presence of self-reported health conditions (Molenaar, Van Ameijden, Grobbee, & Numans, 2007). Although impossible to have perfect confidence in self-reports, accuracy appears to increase when conditions have sudden and life threatening onset or are chronic and require regular management (Okura, Urban, Mahoney, Jacobsen, & Rodeheffer, 2004). These types of conditions (e.g., heart attack and diabetes) are the ones the research described in this proposal will use, thus partially ameliorating concerns of accuracy.

2. Prevalence and patterns of multimorbidity

Differences in populations of interest, definitions of a chronic health condition, number of conditions assessed, and methods of assessment create the potential for considerable variability in prevalence estimates for mulitmorbidity (Fortin, Hudon, Haggerty, van den Akker,

& Almirall, 2010). A recent review of 39 studies reported, for instance, three predominant data sources (self-reports, medical records, and physician reports) and a wide range (4-102; *M* = 18.5) of assessed conditions (Diederichs et al., 2011). Despite this heterogeneity in method, a number of studies described below have concluded that multimorbidity is relatively common, a finding that is robust across populations.

In older populations, this is perhaps expected. In Sweden, an analysis of medical records and physician reports determined that 55 percent of a sample of elderly patients (*M* = 84.6 years) had two or more chronic medical conditions, of which hypertension (38%), dementia (21%), and heart failure (18%) were most common (Marengoni et al., 2008). Similarly, using administrative claims data, a study of Medicare beneficiaries who were 65 years or older revealed that 65 and 43 percent had two and three or more chronic medical conditions, respectively (Wolff et al., 2002). In a large population based U.S. study of Medicaid found that 50 percent of adults under and 65 years of age and 62 percent of adults between 65 and 74 years of age were multi-morbid (Salive, 2013)

Though less common, research has also observed relatively high prevalence rates in younger age groups. One study of primary care patients in Portugal examined 147 conditions and reported that 58 percent of 35 to 49 year olds and 81 percent of 50 to 64 year olds were multi-morbid (Prazeres & Santiago, 2015). Another recent study in Scotland of 1.7 million primary care patients, reported that 11 percent of those between 25 and 44 years of age and 30 percent of those between 45 and 64 had two or more chronic health conditions from a list of 40 (Barnett et al., 2012). Two general population surveys, one from the Canadian province of Alberta and the other from Australia, contained slightly lower estimates. Approximately nine and 26 percent, respectively, of 25 to 44 and 45 to 64 year old respondents in the Canadian study had two or more of 16 possible conditions (Agborsangay et al., 2012). The Australian study produced even lower estimates. Defined as two or more health conditions from a list of seven, multimorbidity prevalence for 20 to 39 year olds was four percent and 15 percent for 40 to 59 year olds (Taylor et al., 2010). In part, it is possible that these lower estimates reflect surveys that contained questions about fewer conditions, 16 and seven, respectively. Whether or not this is the case, all three studies reported that at midlife a non-trivial number of individuals report having multiple chronic health conditions.

In older populations, discernible clusters of chronic medical conditions exist. Studies on clustering or grouping typically rely on some type of data reduction technique such as cluster or factor analysis. A recent analysis of administrative data for patients 65 years or older from the German single payer health care system, produced three principal components, the first consisting of cardiovascular and metabolic disorders; another of anxiety, depression, and somatoform disorders; and a final one of neuropsychiatric disorders, including Parkinson's Disease and dementia to describe patterns of multimorbidity (Schäfer et al., 2010). Researchers assigned patients to a pattern if they had three or more conditions belonging to a principal component factor. Based on this grouping scheme, over half of all patients expressed at least one distinct pattern of multimorbidity (Schäfer et al., 2010). Using cluster analysis, multiple disease and disorder clusters have been observed in older members of U.S. veteran and Native American populations (Cornell et al., 2007; John et al., 2003). These include clusters of cardiopulmonary diseases; metabolic disorders; neurovascular disorders and diseases; dual diagnosis clusters of substance use and mental health problems; groups of diseases of the liver such as Hepatitis B, Hepatitis C, and chronic liver disease; those consisting of a mixture of mood and anxiety disorders; and ones in which obesity combines with osteoarthritis, low back pain, and enlarged prostate.

To date, one study, a survey of working Australians, has examined clusters of health problems in adults at midlife (Holden et al., 2011). Based on responses to 22 health conditions, a factor analysis identified six factors. The two factors with the highest eigenvalues were one in which arthritis, osteoporosis, other chronic pain, bladder problems, and irritable bowel had the highest loadings and another with high loadings for asthma and chronic obstructive pulmonary disease. These results should be considered tentative. The response rate was low (22 percent), and potential survey respondents were limited to individuals who were at work during the time of the survey, thus disallowing any potential inferences about rates of multimorbidity in individuals who were unemployed or worked at home. Further, the analysis did not relate these clusters to potential explanatory variables.

3. Cofactors of multimorbidity

As discussed earlier, research has linked the onset and progression of several health outcomes to numerous factors, including individual level socioeconomic position, status markers, characteristics regulating access to resources, and community social and economic conditions. With some exceptions (e.g., Quiñones et al., 2011; Luchenski et al., 2008) most research on multimorbidity has used cross sectional designs. This necessarily eliminates inferring an ordered relationship between cofactors and accumulation of health conditions. Keeping this limitation in mind, cross sectional analyses nevertheless suggest that the same factors associated with onset and progression of other health outcomes are also relevant to the accrual of multiple chronic health conditions.

Unsurprisingly age is the most consistent and strongest cofactor related to reporting multiple chronic medical conditions. In any given population, older members report higher numbers of chronic health conditions (Agborsangay et al., 2012; Barnett et al., 2012; Prazeres & Santiago, 2015; Taylor et al., 2010). In addition to age, a number of studies have linked indicators of individual social and economic position to mulitmorbidity. In general, this research finds a significant independent effect of educational attainment and individual and household income on the number of chronic health conditions individuals report and the severity of the associated health consequences such as functional limitations (Andrade et al., 2010; Nagel et al., 2008; Neeleman, Ormel, Bijl, 2001; van den Akker, Buntinx, Metsemakers, Roos, & Knottnerus, 1998). Status markers, primarily race, also have independent associations with a number of health conditions (Gold et al., 2006; Mathur, Hull, Badrick, & Robson, 2011).

The bulk of this research consistently demonstrates that location in lower socioeconomic strata places individuals at increased risk for expressing multimorbidity. Moreover, members of racial and ethnic minorities such as African Americans and Hispanics in the U.S. are more likely to have multimorbidity (Quiñones et al., 2011). Research modeling joint effects has further concluded that race and ethnicity shape the relationship between individual socioeconomic characteristics and multimorbidity. Gold et al. (2006), for example, reported a significant interaction effect between race and both income and education on Charlson Index scores. Education and income were negatively associated with levels of multimorbidity. These effects, however, were more pronounced for African American and Hispanic respondents compared to their White counterparts.

Two studies have attempted to account for life course factors and multimorbidity. Both present conclusions that are consistent with cross sectional analyses. In a recent study using data from the Health and Retirement Study, Tucker-Seeley, Li, Sorensen, & Subramanian (2011) modeled the relationship between life course indicators of socioeconomic position and a point in time measure of multimorbidity for a sample of individuals who were at least 50 years old during the 2004 data collection wave. Three measures assessed life course socioeconomic position: (1) a dichotomous variable indicating if respondents experienced financial hardship before they were 16 years old, (2) educational attainment, and (3) respondents' mean annual income from the time they were 20 through age 50. During the 2004 wave, respondents reported how many from a list of six chronic conditions they had. Thus, although strictly cross sectional in the outcome, there is an attempt to model the relationship between accumulation of deprivation from adolescence into adulthood and number of reported chronic health problems at midlife or old age. In addition to age and after covariate adjustment, the experience of early economic hardship was significantly and positively associated with reporting more chronic health conditions, an effect which was vitiated as average earnings during adulthood increased. Interestingly, the covariate representing race was not statistically significant. It was, however, never entered in a model without the covariates for social class such as early childhood deprivation, so it is unclear if the effects of race were present but mediated completely by social class.

Also using data from the Health and Retirement Study, Quiñones et al. (2011) modeled the accumulation of chronic health conditions. At each of seven interview waves over 11 years, respondents who were between 48 and 103 years old (*M* = 64) at the start of the study reported if they had received a physician diagnosis for each of seven conditions. Three findings of interest emerged. Across all three racial and ethnic categories, education and income were both negatively associated with baseline reports of chronic conditions and accumulation across time. On average African Americans reported more chronic health conditions at the first data collection wave than both White and Hispanic respondents. Finally, both African American and Hispanic respondents accumulated fewer conditions over time than White respondents. This finding is of interest, as numerous studies report that African Americans report higher rates of negative health outcomes than their White counterparts (Williams, 2012). In part, this result may have been a consequence of the means by which the study deployed statistical controls. The study modeled and found a significant positive association between utilization of care and likelihood of reporting health conditions. A race by utilization interaction term, however, was not created. This could explain higher accumulation for White respondents, as they had, on average more doctors' visits than African American respondents. As a consequence, it is possible that White respondents had higher rates of accumulation than African American ones because they experienced more medical surveillance.

D. Research hypotheses

Taken together, the preceding review supports several conclusions:

1. multimorbidity is not uncommon at midlife;
2. at least in older populations and possibly by midlife, patterns of accumulation exist;
3. socioeconomic factors are related to numerous health outcomes, including accumulation of multiple chronic conditions and reduced quality of life;
4. although the nature of the relationship is not entirely clear, race or ethnicity is linked to the accumulation of multiple chronic health conditions.

Further, CAD would suggest that accumulation of health conditions at an earlier point in time would predict accumulation at a later one. These conclusions along with the conceptual guidance from CAD motivate the following research questions and their accompanying hypotheses:

1. Are there discernible patterns of accumulation of chronic health conditions at two points during midlife (approximately 40 and 50 years of age)?

H_1: At 40 and 50 years of age, there will be discernible patterns of multimorbidity in which a small minority of individuals report a comparatively high number of chronic health conditions. In contrast, the vast majority of individuals at midlife will express morbidity pattern described by having none or one chronic health conditions.

2. How do patterns of accumulation at an earlier point in time (i.e., 40 years of age) relate to those at a later time (i.e., 50 years of age)?

H_2: Observed patterns of morbidity and multimorbidity at 40 years of age will predict patterns at 50. Specifically, individuals who report few health conditions at 40 will be likely to remain in good health. Conversely, for those individuals who have multiple chronic health conditions when 40 will likely experience more accumulation of chronic health conditions by the time they are 50.

3. Do life course individual and household socioeconomic characteristics predict midlife patterns of accumulation of chronic health conditions?

H_3: Individual and household indicators of socioeconomic position will predict (1) patterns of morbidity at 40, and (2) they will moderate the accumulation morbidities between 40 and 50. In particular, life course income, net worth, educational attainment, and home ownership will have a significant negative relationship with the accumulation of multiple chronic health conditions.

4. Does race or ethnicity relate to patterns of accumulation of chronic health conditions?

   H_4: Race or ethnicity will have a significant relationship with the accumulation of multiple chronic health conditions.

5. How do these patterns contribute to perceived functional health and well-being?

H_5: As health conditions accumulate, perceptions of functional health limitations and diminished well-being.

III. METHOD

The study described below examined data from a panel of respondents who were between 14 and 21 in 1979, the first year of the survey. The primary aim of the study was to examine whether individuals could be classified into distinct patterns of multimorbidity. An additional aim was to relate these patterns to social and economic factors.

A. Sample

Started in 1979 with primary sponsorship from the Bureau of Labor Statistics (BLS), the National Longitudinal Survey of Youth-1979 (NLSY79) consists of three independent multistage probability samples of individuals (N = 12,686) who were between 14 and 21 years old by the end of 1978. The primary sample (n = 6,111) was designed to represent non-institutionalized and non-military American youth. A second civilian sample (n = 5,295) was an oversample of Hispanic, African American, and economically disadvantaged White youth. Economic disadvantage was defined as a 1978 family income below the federal poverty line. For a family of four, this was $6,200. A final sample ($n$ = 1,280) focused on youth in the military with an oversample of females (Frankel, McWilliams, & Spencer, 1983). From inception through 1994, participants completed the survey annually. After 1994, interviews occurred biennially. Each interview lasted about one hour, was conducted in person or over the phone, and used either a paper and pencil form or a computer assisted application. Upon completion of each interview respondents received compensation of $10 from 1979 through 1994, $20 from 1996 through 2000, and $40 thereafter (Center for Human Resource Research, 2001).

Between 1979 and 2008, retention rates ranged between 96.3% in 1983 and 76.8% in 2006 (NLSY79a, n.d.). Calculation of these rates used all eligible respondents as the denominator and included individuals who refused the survey, could not be located, or had died.

At two time points, NLSY79 administrators permanently dropped respondents from the sample, thus reducing the overall sample size. Budgetary considerations motivated both actions. In 1985, 201 members of the military sample were randomly selected to continue in the sample. The remaining 1,079 were excluded and the total sample size was reduced to 11,607. Later, in 1991, all 1,643 economically disadvantaged White youth were eliminated and the sample size dropped once more to 9,986. Depending on the year, then, calculation of retention rates used one of three denominators (Center for Human Resource Research, 2001). The current study relied on data from a subset of respondents who had turned 50 years old prior to participation in the 2012 survey wave.

By design, the NLSY79 collects longitudinal data on respondents' socioeconomic characteristics, attitudes, life aspirations, and experiences with work. Starting in 1998, a health-at-40 questionnaire was included in the survey. The questionnaire, intended to be completed only once by each participant, asked respondents to indicate if they had any of about 40 health conditions. Respondents completed the questionnaire during their first interview after turning 40 years old. Later, in 2008, an abbreviated health survey was administered to respondents who had turned 50 years old by that wave. It was re-administered in 2010 and 2012 to collect health information on new 50 year olds. Twelve of the health conditions from the health-at-40 form were carried over to the health-at-50 questionnaire. Thus, when respondents were about 40 years old and again upon turning 50, they indicated if they had high blood pressure, diabetes or high blood sugar, chronic lung disease, arthritis, asthma, angina, coronary heart disease, and problems with emotional, nervous, or psychiatric conditions. At both time points, they further indicated if they had ever had a heart attack, congestive heart failure, a stroke, or a current malignant tumor that was not skin cancer. Both the health-at-40 and the health-at-50 questionnaires included the reduced version of the Short Form Health Survey (SF-12) (Ware, Kosinski & Keller, 1996). This is a widely used instrument intended to assess self-perceived general mental and physical health.

Given the combination of information on socioeconomic conditions over time and health at midlife, researchers have made extensive use of the data from the NLSY79 to relate life course social and economic factors to health outcomes (e.g., Baum & Ruhm, 2009; Der, Batty, & Deary, 2009; Quesnel-Vallée & Taylor, 2012). This study contains an analysis of multimorbidity at midlife and its relationship to life course individual and household socioeconomic factors. This entailed an analysis of NLSY79 data on reported health conditions and used data on life course individual and household socioeconomic factors from 1979 through 2012. The public use data set available from BLS contained all necessary individual level data for the proposed study, including participant demographics, lifetime socioeconomic characteristics, substance use behaviors, and mental and physical health outcomes at 40 and 50.

Of the 9,986 respondents retained in the study after the final administrative drop in 1991, 2,202 (22.05 percent) were under 50 years old during the 2012 survey wave and were excluded from the analysis, leaving 7,784 potential respondents. Of these, an additional 2,110 (27.11 percent) were omitted from the analysis because they had complete missingness on at least one of the health questionnaires. Data from another 478 (6.14 percent) of respondents were omitted from the analysis because of missing covariate data. The analytic sample, then, consisted of data from 5,196 (66.75%) respondents who completed at least one item on each of the health questionnaires and provided complete covariate data.

B. Human subjects protections

The University of Illinois at Chicago Institutional Review Board determined that research in this dissertation did not involve human subjects.

C. Measures

1. Morbidity and multimorbidity

As discussed in a previous section, a common challenge associated with measurement of multimorbidity is simultaneously assessing number and kinds of conditions and their impact on health. A potential solution to this problem, and the one used here, is to deploy two measurement strategies. The first of these entails the use of a list-based approach to determine the number of chronic health conditions individuals have. The second collects information on overall physical and mental health functioning and health related well-being. This is a common strategy. General measures of self-reported health are widely used in research and include instruments such as the Index of Activities of Daily Living (Katz, Ford, Moskowitz, Jackson, & Jaffee, 1963) and the Short Form Health Survey (SF-12) (Ware et al., 1996). Moreover, studies examining the accumulation of health conditions have collected both types of measures (e.g., Robert, 1998; Robert & Lee, 2002). After these two pieces of information are in hand, they may be interrogated to ascertain prevalence and patterns of multimorbidity in the sample.

During the respondents' first interview after turning 40 years old, a health questionnaire was administered. In one part of the questionnaire, respondents provide information about twelve types of chronic health conditions: high blood pressure, diabetes, malignant tumors of any kind except for skin cancer, chronic obstructive pulmonary disease, stroke, heart attack, coronary heart disease, congestive heart failure, angina, arthritis, asthma, and problems with emotional, nervous, or psychiatric conditions. The questions asked respondents if a doctor had ever told them that they had each of these conditions. At the first interview after turning 50, respondents provided information on the same list of conditions. The survey was structured so that respondents could report the onset of new conditions, confirm that previously reported ones were still present, or indicate those there were present at 40 were no longer there. The questionnaire, thus, provided a means of capturing changes as a result, for instance, of remitting cancers or psychiatric problems.

Information on chronic health conditions was used in two ways. First, to describe the sample, two count variables representing the number of chronic health conditions respondents had when they were 40 and again when 50 years old was calculated. Additionally, dichotomous variables were calculated. These variables described whether respondents reported the presence of each of the health conditions at two points, when they were 40 and again when they were 50 years old. These variables were used in the latent variable (i.e, latent class and latent transition) analyses described below.

2. Functional health and well-being: Short Form Health Survey (SF-12)

The Short Form Health Survey (SF-12) is contained in both the health 40 and health 50 questionnaires. Initially developed with 36 questions (SF-36) (Ware & Sherbourne, 1992) and later reduced to 12 questions, the SF-12 assesses self-reported physical and mental health functioning and health related well-being (Ware et al., 1996). The instrument produces two summary measures, one for physical health and one for mental health. Together these summary scores provide an overall picture of individuals' perception of their functional health and well-being. Questions about 12 health dimensions located in eight subscales comprise the summary measures. The physical health dimensions contain questions about limitations in physical function (2 questions), physical health related role limitations (2 questions), physical pain (1 question), and general health perceptions (1 question). Similarly, mental health dimensions contain questions about vitality (1 question), social functioning (1 question), mental health related role limitations (2 questions), and perceptions of mental health (2 questions) (Ware et al., 1996). Possible scores range between 0 and 100 (Trevisol, Moreira, Fuchs, & Fuchs, 2012). Higher scores suggest better health related quality of life (Chanfreau et al., 2011). The SF-12 has demonstrated high test-retest reliability ($r = 0.89$). It has also shown high construct and predictive validity (Ware et al., 1996).

3. Life course individual and household

As discussed above, income, education, and other markers of socioeconomic position (SEP) correlate with multimorbidity. SEP is a notoriously complex construct to define and measure (Krieger, Williams, & Moss, 1997). In a frequently cited discussion of its use in sociology and health research, Krieger et al. (1997) define it as:

> An aggregate concept that includes both resource-based and prestige-based measures, as linked to both childhood and adult social class position. Resource-based measures refer to material and social resources and assets, including income, wealth, educational credentials; terms used to describe inadequate resources include "poverty" and "deprivation." Prestige-based measures refer to individual's rank or status in a social hierarchy, typically evaluated with reference to people's access to and consumption of goods, services, and knowledge, as linked to their occupational prestige, income, and education level (p. 345).

Several implications follow from this definition. SEP is a multidimensional and dynamic construct requiring several indicators to describe it. Aspects of these dimensions may be observed at various levels of social organization such as the individual, the household, and the community. Moreover, SEP has a temporal component (Krieger et al. 1997). As such, individuals may occupy different SEPs during their life (Rigg & Sefton, 2006). And, the consequences of SEP for health may unfold over a life time (Glass & McAtee, 2006). Another complication of SEP is its alternate conception as a product of social policies and processes or as an essential causal factor or a marker of other complex multi-level factors used to explain the establishment and maintenance of between group disparities along a number of dimensions, not the least of which is health (Higgs, Rees Jones, & Scrambler, 2004).

A goal of the study was to develop a set of indicators that, consistent with literature in health research, tapped various facets of SEP with the intent of estimating their combined effect on onset and progression of multimorbidity at midlife. For current purposes, therefore, SEP was conceived as a precursor to the health outcome. This position aligned with current versions of CAD and other life course and social determinant frameworks that view SEP as a central component in explaining differential health outcomes (Dannefer, 2003; House, Lantz, & Herd, 2005; Phelan et al., 2010). To accomplish the main goal, I developed covariates to represent major constructs of SEP at the individual and household level. These were parental and respondent educational attainment, adult life course household income, adult household net worth, and home ownership (Galobardes, Lynch, & Davey-Smith, 2007; Krieger, Chen, Waterman, Rehkopf, & Subramanian, 2003).

These measures assessed individual and household socioeconomic position over time. Parental educational attainment was viewed as a proxy for early life SEP while respondent education was viewed as one for SEP in adulthood (Bradley & Corwyn, 2002). Three additional sets of covariates described SEP during the adult years. Covariates representing respondents' household income trajectories during two intervals (when respondents were between about 26 and 40 years old and again when they were between 41 and 50) were created. There were covariates to represent respondents' household net worth, excluding home value, during the two survey waves in which respondents completed their first and second health questionnaires. Finally, two covariates indicated if respondents' owned or made mortgage payment their primary residence during the survey waves in which respondents completed their first and second health questionnaires.

4. Individual educational attainment

Like income, educational attainment is a common measure to assess SEP (Galobardes, Shaw, Lawlor, Lynch, & Davey-Smith, 2006). Two educational attainment variables were calculated. The first, respondent educational attainment, was the highest level of education in years that respondents reported by the time they were 40 years old. For use in the descriptive statistics and in the multivariate models, educational attainment was centered at 12 years such that negative values represented educational attainment less than a high school diploma and positive values greater than one.

5. Parental educational attainment

The second education variable, parental educational attainment, had the same structure as respondents' education variable. Parental educational attainment is a common measure of childhood socioeconomic position (Galobardes et al., 2006). In 1979, the first wave of the survey, respondents reported the highest grade that their parents completed. Parental educational attainment was calculated using the report for the parent with the most education.

6. Adult household income trajectory

Starting with the first interview in which respondents were 20 years or older, enrolled in college, married, had a child, or moved out of their parents' home, and continuing at each subsequent interview, survey administrators collected detailed information on respondents' sources of family or household income in U.S. dollars. Total family income for each survey year was the sum of 16 potential sources. These were military income, wages or salary, net business income, net farm income, unemployment compensation, child support, Aid to Families with

Dependent Children payments, food stamps, other welfare or Supplemental Security Income, education benefits, veterans benefits, inheritance, gifts, parental or relative support, income of other household members, rental subsidies, and other income such as interest, dividends, or rent (NLSY79b, n.d.). During the course of the survey, NLSY administrators used four different methods to top code income amounts (NLSY79b, n.d.). All of these methods were used to protect anonymity of high earning individuals.

From 1979 to 1984, all annual reported incomes were top-coded at $75,000. Between 1985 and 1988, the top coding threshold was lifted to $100,000. These strategies lead to pronounced right truncation of the distribution (NLSY79b, n.d.). In 1989, all annual incomes over $100,000 were averaged. The mean value of these incomes was then imputed to all of these high income households. Finally, in 1996, a final top coding algorithm was introduced in which the annual incomes for the top two percent of earners were averaged. These average values were then imputed to the top earners. Given the right truncation of the data during the first years of the survey, I elected to use income data starting in 1989, when respondents were about 26 years old.

Two steps were used to create a household income measure that was standardized across years and adjusts for household size. First, for each respondent at each year, all sources of income were tallied and converted to 2010 inflation adjusted dollars. Next, to adjust for household size, the quotient of the income in 2010 dollars and the square root of total household members at each year was calculated (Burniaux et al., 1998). The rational for this adjustment rests on the idea that the addition of household members is associated with proportionally smaller increases on household income demand (OECD, 2011). Additionally, as the distribution of income within this sample was skewed, income values were transformed into their natural log to help linearize the distribution (Denavas-Walt, Proctor, & Smith, 2011).

Income information was used in two ways. To describe the sample, mean household income in 2010 inflation adjusted dollars was reported for multiple survey years. Further, a set of variables was constructed to estimate income trajectories during two intervals. The first of these intervals was bracketed by age 26 and the year when respondents completed their health-40-questionnaire. The second bracket started at the first wave after completion of the health-at-40 questionnaire and ended during the year in which respondents completed their health-at-50 questions. Creation of these covariates required the use of mixed regression models to calculate empirical Bayes estimates (Hedeker & Gibbons, 2006) for each respondent's intercept and slope during the two time intervals. In turn, these estimates were used to calculate estimated income when respondents were 26 years old, when they were around 40 and completed the health-at-40 questionnaire, and when they were 50 and completed the health-at-questionnaire.

Representation of time in mixed models is often a crucial consideration (Hedeker & Gibbons, 2006). In the current study, I chose to use the wave at which individuals completed their health-at-50 questionnaire as the starting point for the first time interval. In this case, then, the intercept was estimated income when individuals were around 50 years old and the slope modeled a trajectory that moved backwards in time until respondents were around 26 years old. The modeling procedure itself considered linear trends and polynomials up to cubic. Model selection was guided by standard statistical tools such as the Log Likelihood tests and Akaike and Bayesian Information Criteria.

In the proposal for this study, use of the linear slope was proposed to model change in income over time. The mixed model results, however, supported the inclusion of quadratic fixed and random terms to model the relationship between time and income. This would have required the use of linear and quadratic slope terms to describe change over time. A linear slope presents a clearly interpretable description of income growth. For each additional year, the estimated income changes by the value of the estimated linear slope. The interpretation of linear, quadratic, and cubic terms in combination, on the other hand, is much less intuitive. To avoid the difficulty associated with this interpretation, I opted to develop empirical Bayes estimates for income when respondents were 26, when they completed their first questionnaire at around 40, and when they completed their second questionnaire at around 50 years old. Together, these values were used to calculate a covariate representing income at 40 years of age, one for percent change in income between 26 and 40 years of age, one for income at 50 years of age, and one for percent change in income between 40 and 50 years of age. Interaction terms were also tested to see, for instance, if level of income at 40 by percent change between 26 and 40 had an effect on latent class membership.

7. Household net worth

Assessment of net worth relied on two point-in-time measures. These were net worth excluding home value when respondents were about 40 years old and again when they were about 50. These values were calculated by summing the value of respondents' household assets and debts. Total assets were derived from the total accumulation of material wealth in U.S. dollars of commercial properties, respondents' businesses, and other assets such as cash, stock, certificates of deposit, and retirement accounts. Debt was measured as the total in U.S. dollars of respondents' businesses, mortgages, and any other amounts over $1,000 (NLSY79b, n.d.). Like household income these values were converted in to 2010 inflation adjusted dollars and adjusted for household size. Finally, they were log transformed to adjust for skewness in the distributions.

8. Home ownership

Home ownership was determined based on the response to a question asked when respondents were around 40 and again when they were around 50 in which respondents indicated if they owned or made mortgage payments on their primary residence. Delaying assessment of household net worth and home ownership allowed time for respondents to accumulate assets such as homes, stocks and bonds, and businesses that make up material worth.

9. Race or ethnicity

During the first wave of the survey, respondents self-identified their racial or ethnic group. Survey administrators collapsed these reports into three categories: African American, Hispanic, Non-Hispanic and Non-African American which was labeled White.

10. Demographic variables

Demographic variables included respondent age in years when they completed the health questionnaires and gender.

11. Additional control variables

A number of variables adjusted for the effects of factors known to relate to health outcomes. These were obesity, alcohol use, and smoking tobacco (National Heart, Lung, and Blood Institute, n.d.; Centers for Disease Control, 2013).

a. Chronic obesity

Between 1979 and the year when the health questionnaire was administered, respondents were asked to report current weight in pounds during at least ten intervening interview waves. In combination with respondents' self-reported adult height in inches, a body mass index (BMI) at each interview was calculated with the formula: BMI = (weight in kilograms/height in meters x height in meters) (Ogden, Carroll, Kit, & Flegal, 2012). A mean BMI value was calculated for two intervals, when respondents were between 26 years old and completion of their first health survey and the period between the completion of the health-at-40 questionnaire and health-at-50 questionnaire. These mean values were then centered at 30 such that values greater than zero were indicative of individuals who on average had obese BMIs during the respective intervals (Ogden et al., 2012). Conversely, values less than zero reflected non-obese BMI values.

b. Problematic alcohol use

During the survey waves in 2002, 2006, 2008, 2010, and 2012, respondents indicated the number of times in the previous 30 days that they had had six or more drinks during a single sitting: (1) never, (2) between one and three times, (3) between four and nine times, (4) or ten or more times. For each wave, these variables were recoded to describe whether respondents reported that in the past 30 days they had had six or more drinks during a single sitting during four or more days. In turn, the wave that was on or most closely preceded each health questionnaire wave was selected to indicate if respondents had indicated whether they had drunk six or more drinks in a single sitting at least four days in the past month. The variables resulting from these calculations approximated unhealthy drinking behavior during a wave on or immediately preceding their health surveys.

c. Smoking

In 1994, 1998, 2008, 2010, and 2012, respondents were asked if they smoked (1) less than a cigarette per day, (2) between one and five cigarettes per day, (3) about a half a pack per day (6-15 cigarettes), (4) about one pack per day (16-25 cigarettes), (5) about one and half packs per day (26-35 cigarettes), or (6) two or more packs per day (over 35 cigarettes). From these questions, two variables were constructed to calculate whether individuals had been a daily smoker during a wave on or immediately preceding their health surveys.

d. Early health limitations

During each wave until respondents were about 26 years old, they were asked if they had had any health conditions in the previous year that limited the type or amount of work they could perform. Reponses were used to create an early adult health limitation variable in which individuals were categorized as having health conditions that limited the kind or amount of work that they could perform during zero or one wave or during two or more waves.

D. Analysis plan

The analysis proceeded in several steps. First, the results for the descriptive statistics are presented, including chronic health conditions used as indicator variables in the latent variable models as well as covariates representing socioeconomic position and other control variables. I then present results for the mixed regression models used to estimate life course income. The mixed model analysis produced estimates of life course income for use as covariates in the latent variable analyses. Because these models are an intermediate step of the study and not its central aim, their results are presented in less detail in the main body of the text. Appendix A contains a detailed discussion of the mixed modeling process. Finally, the results for the latent class and latent transition analyses are presented. Using indicator variables representing chronic health conditions from the health-at-40 questionnaire, a latent class analysis examined whether clusters of multimorbidity occurred when respondents were around 40 years old. A second LCA performed the same analysis on data from the health-at-50 questionnaire. These two analyses provided initial evidence useful for evaluating the assertion of the first research hypothesis, that discernible patterns of multimorbidity are present during midlife. A latent transition analysis

(LTA) provided additional evidence relevant to hypothesis 1 and initial evidence for hypothesis 2 that accumulation of morbidities when respondents were 40 years old would predict accumulation at 50. Like the LCA, The LTA modeled morbidity patterns at 40 and again at 50. Unlike the two LCAs, however, which treated morbidity patterns at 50 as independent from those at 40, the LTA adjusted for any dependency in the data resulting from repeated measurements of individuals. That is, it modeled individuals' morbidity classification at 50 after adjusting for their classification at 40. This relationship is represented by transition probability parameters which estimate the probability that individuals classified in a particular latent status when 40 will remain in that same status when 50 years old or will have transitioned to a new status. After the development of the basic LTA model and examination of transition probabilities, covariates were incorporated into the LTA model to assess the association of life course SEP with latent status membership at 40 and the probability of transitioning to new statuses at 50. In this stage, the latent status at 40 acted as an outcome in a multinomial regression and was regressed on socioeconomic position and control variables. In addition to assessing covariate effects on latent status membership at 40, I also conducted an analysis to assess covariate associations with the probability of transitioning. This analysis essentially interacted latent status at 40 with selected covariates. As such, it shed light on change in transition probabilities associated with covariate effects at particular levels of the latent status at 40 (Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). As discussed below, this step deployed a three-step technique to preserve latent status structure during the introduction of covariates. A final step related morbidity statuses in the LTA to functional health and well-being, thus addressing hypothesis 5. All statistical analyses used SPSS 22 and MPLUS 7.1.

1. Latent variable mixture models

Latent class and latent transition analyses are types of latent variable mixture models (Muthén & Muthén, 2000). Both statistical techniques presume that a population is composed of a mixture of sub-populations, each of which is associated with specific response patterns to a set of observed indicator variables (Muthén & Muthén, 2000). In both LCA and LTA models, respondents receive a posterior probability for membership to a level or class/status of a postulated latent variable or variables based on responses to indicators (McCutcheon, 2002). For interpretation, individuals are frequently assigned to the modal class, that is, the class for which they had the largest posterior probability. By convention, levels of the latent variable are referred to as classes in the LCA context and statuses in the LTA context. This is done to differentiate clearly between the static quality of latent class membership in the LCA and potential dynamic quality associated with movement from a particular status at an earlier time point into a different one at a later time (Collins & Lanza, 2010).

A frequent use of mixture models, then, is to ascertain the presence in a population of particular sub-groups which display relatively high levels of within group homogeneity and between group heterogeneity in the multivariate distribution of the indicator variables (Collins & Lanza, 2010). One practical application of this technique is the identification of small, high risk sub-groups. A recent study, for instance, decomposed a sample of college freshman into five classes described by differences in types of reported drinking behavior: a normative class (42%) whose members rarely or never drank, a weekend non-binging class (20%) whose members reported weekend drinking without intoxication, a weekend binging class (30%) whose members drank to intoxication on weekends, and a small heavy drinking class (8%) whose members reported drinking to intoxication on weekends and weekday drinking (Cleveland, Lanza, Ray, Turrisi, & Mallet, 2012).

Both LCA and LTA use full information maximum likelihood estimation to estimate model parameters which classify respondents in probabilistic typologies. A property of full information estimation procedures is that missing data are allowed under the assumption of missing at random. As such, the model includes respondents who have either complete data or partial missingness on the latent class indicator variables. Two sets of estimated parameters, class prevalence or size and estimated conditional probabilities of endorsing each of the indicator variables, describe the LCA model (Collins & Lanza, 2010; McCutcheon, 2002). For the current study, the first set of parameters estimated the prevalence of each morbidity class based on responses to questions about chronic health conditions. The second, a set of conditional probabilities, estimated the probability that members reported having each of the health conditions given their class membership. Figure 2 is conceptual depiction of this relationship in which the latent morbidity pattern variable predicts the estimated probability that members of a particular class report having each health condition.

As the longitudinal extension of LCA, LTA models have estimates of latent status prevalence and conditional probabilities (Collins & Lanza, 2010). To model change over time, the LTA contains one more estimated parameter set, transition probabilities (Collins & Lanza, 2010). These probabilities estimate the likelihood that individuals, given their status at time one (e.g., when they 40 years old), will transition to a different status at time two (e.g., when they are 50 years old), as seen in Figure 3, Arrow 1.

Figure 2. Conceptual relationship of indicator variables to latent class variable

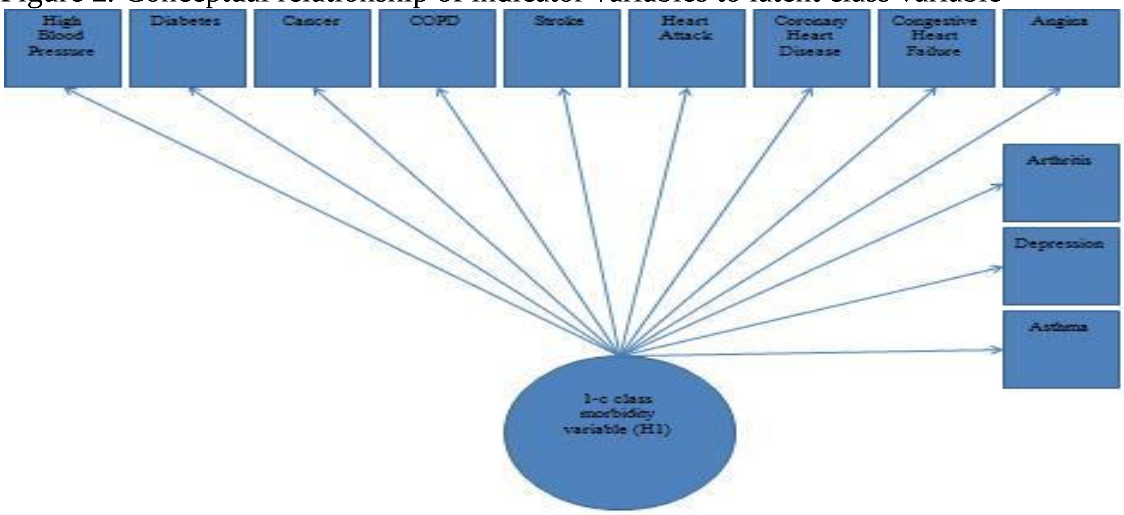
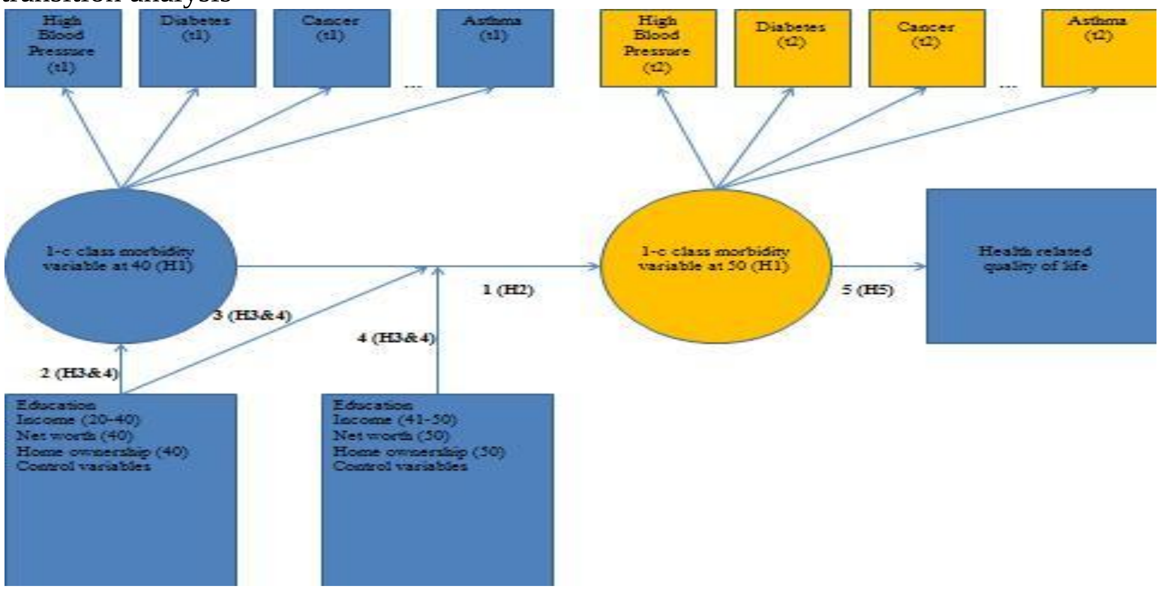


Figure 3. Conceptual relationship of indicator variables, covariates, and transition in the transition analysis



LCAs and LTAs accommodate covariate effects. For the LTA, these effects may be tested at two points. The latent variable at time one becomes the outcome in a multi-nomial regression. Covariates representing, say, SEP are then related to this outcome to determine how they affect the relative odds that individuals will be assigned to a particular level of the latent variable representing a particular morbidity pattern (Muthén & Asparouhov, 2011) (Figure 3, Arrow 2). In the LTA, covariates may also be introduced to condition the relationship between status membership at a prior time on status membership at a later time (Figure 3, Arrow 3). Conceptually, this is analogous to an interaction effect in which the main effect of time one status membership on time two membership is moderated by different levels of the covariates (Muthén & Asparouhov, 2011). As seen in Figure 3, the current research introduced covariates representing individual and household SEP and race when individuals were between 26 and 40 as well as other control variables to predict respondents' likelihood of membership in a particular pattern of morbidity when they were 40 years old (Arrow 2). A subset of these covariates was Then related to respondents' transition probabilities between morbidity patterns at 40 and 50 years (Arrow 3). I then introduced covariates representing individual SEP when individuals were between 41 and 50 years old as well as other control variables to predict respondents' transition probabilities between 40 and 50 years old (Arrow 4). Finally, it brought in a variable representing functional health as a distal or predicted outcomes of the LTA (Arrow 5) (Lanza, Tan, & Bray, 2013).

a. Model selection

Determination of appropriate number of morbidity classes the latent class analyses followed Nylund, Asparouhov and Muthén (2007) and employed an iterative process to generate a set of models with one- through five-class latent variables. Models used the dichotomized responses to chronic health conditions as indicator variables. The maximum likelihood algorithm used to estimate LCA and LTA models provided a log likelihood for use in calculation of three fit indices: the Akaike, Bayesian, and sample size adjusted Bayesian information criteria (AIC, BIC, BICadj) (Collins & Lanza, 2010). Values from these sources guided identification of models with the most statistically appropriate number of morbidity-classes. When coupled with conceptual knowledge of the modeled construct and ease of interpretation, this empirical information supported the selection of a model that was conceptually and statistically appropriate (McCutcheon, 2002). The latent class models at 40 and 50 were used to guide selection of the number statuses for use in the latent transition analysis.

b. Assumption of local independence

A primary assumption of mixture modes is local independence of the observed indicator variables within each level of the latent variable (Collins & Lanza, 2010). Under this assumption indicator variables are independent conditional on the latent variable. One technique to discern the presence of existing residual correlations among indicator variables (i.e., non-independence) is to test each of the bivariate associations among the indicator variables. To adjust for the effect of any existing residual correlations, parameters modeling these associations may be introduced (Asparouhov & Muthen, 2014b). Degrees of freedom for these tests are calculated with the formula $l_i l_j - l_i - l_j + 1$ where l_i and l_j are, respectively, the one through *i*th and *j*th number of levels in the categorical indicator variables. Residual associations were performed during initial modeling of the latent class analyses to assess the plausibility of local independence. Violations of local independence may be addressed by introduction of parameters to model residual dependency in the indicator variables. Alternatively, if fit indices support it, the addition of another level of the latent class analysis may also result in the local independence.

c. Measurement invariance

An important consideration for an LTA is the plausibility that the estimated probabilities associated with particular latent classes of endorsing each indicator variable do not change across time points (Collins & Lanza, 2010). Termed measurement invariance, imposing this modeling restraint to a set of response probabilities is desirable for at least two reasons. It reduces the number of parameters. Additionally, it makes direct comparisons between latent statuses at two points in time straight forward (Collins & Lanze, 2010). In the current context, however, it is possible, perhaps likely, that measurement invariance in item response estimated probabilities of corresponding morbidity statuses at 40 years and 50 is not tenable. One might imagine, for instance, a number of healthy individuals probabilistically assigned to a latent transition status at time one who report with exceeding infrequency any chronic health conditions. Ten years later these same individuals may have remained in this low morbidity latent status. However, at time two, the estimated probabilities of reporting chronic health conditions may have increased significantly if not substantially. In this scenario, the estimated probabilities at two points for this low morbidity status may be noticeably different while still clearly meriting the description of low morbidity.

To investigate the plausibility of measurement invariance, I used cross-sectional models developed in the latent class analyses as tentative models for the latent transition models. These models were then introduced twice into the latent transition context. The first latent transition model was unrestricted and allowed paired estimated conditional probabilities (e.g., asthma at 40 and asthma at 50 years old) at each status to vary between the two time points. A second latent transition model held probabilities invariant between the two time points. As above, AIC, BIC, and adjusted BIC model fit statistic values were produced for each model to guide decisions. To restate model selection strategy from above, statistical evidence, though important, may be considered next to conceptual and interpretative issues which often prove crucial to decisions (Collins & Lanza, 2010).

d. Covariate effects

For latent variable models, a frequent difficulty confronting researchers is related to the introduction of covariates after the selection of the appropriate number of classes for the measurement model. Traditionally, decisions about the number of and descriptive labels for classes or statuses for latent class or latent transition models are based on models without the inclusion of covariates or distal variables. Once these decisions are made, the model is re-estimated with the addition of covariates in a single step. Depending on the strength of relationship between the added covariates and indicator variables, the latent class and latent transition model parameters (i.e., estimated conditional probabilities, class prevalence, or transition probabilities) may change, at times, dramatically enough to render the original labels inappropriate (Asparouhov & Muthén, 2014a; Vermunt, 2010). One technique to deal with this challenge, is to treat modal class as if it were a manifest variable (Clark & Muthen, 2009). This prevents any shift in model parameters when covariates are incorporated to the model. Unfortunately, it ignores the uncertainty associated with class or status assignment which, especially in situations where there are relatively high levels of classification uncertainly, can lead to bias in the model (Asparouhov & Muthen, 2014a). Recent research proposes and describes the implementation in MPLUS software of a three-step approach to address undesirable shift in model parameters and bias in the model (Asparouhov & Muthen, 2014a; Vermunt, 2010). In this approach, a latent variable is estimated in step one. Step two assigns individuals to their modal class. In a final step, the latent variable is re-estimated with parameters calculated in step two that adjust for the uncertainty in modal assignment (Asparouhov & Muthen, 2014a). Research has found that this technique is robust to bias when with moderate classification uncertainty (i.e., entropy levels not less than 0.60) (Asparouhov & Muthen, 2014a). With uncertainty around the latent variables accommodated, covariates and distal outcomes may be introduced without shifting class or status prevalence or estimated conditional probabilities.

2. Mixed regression models

The development of covariates for income over time relied on mixed regression models. Mixed models estimated the trend for the overall sample's income when respondents were between around 26 and 50 years old. Estimation of mixed models used two methods. Maximum likelihood methods estimated the variance, covariance, and fixed effect parameters. Empirical Bayes methods generated individual random effects (Hedeker & Gibbons, 2006). The empirical Bayes estimates (EBE) generated from these methods described an individual respondent's intercept and temporal trend and was used to calculate estimates of individual income over time.

The empirical Bayes estimates were of primary importance for this study, as they contained the information used to construct covariates representing patterns of individual income across time. Like classical Bayes and unlike classical frequentists approaches, empirical Bayes methods assume that covariate parameters are random variables drawn from a population (Casella, 1992). Under this assumption, covariate parameters may be described by a population mean and variance. Bayes theorem is then applied to a postulated fixed prior distribution and observed data to estimate the variability. The results of these estimates are characterized in the posterior distribution. Empirical Bayes methods use the same approach. However, the prior distribution is constructed from the observed data and does not use a fixed distribution. In MRM context, the prior distribution is the marginal parameter estimates (Casella, 1992). In cases where an individual has little data (i.e., few repeated observations) or observations that are uncorrelated, the EBE estimate depends more on the value of the marginal estimates. Conversely, in those cases where an individual has numerous repeated observations or where these observations are highly correlated, EBE attaches more weight to individuals' observed data. Once estimated, the EBEs were used to calculate estimates of individuals' income when they were 26 years old, when they completed the health-at-40-questionnaire, and when they completed the health-at-50-questionnaire. These values were used to calculate percent change in income for two intervals of time.

There are a number of benefits of this technique. It provides a convenient means by which longitudinal data may be used to predict a cross sectional outcome variable. The EBEs, as they are estimated in the mixed models context, account for the missing income data in the sample. Finally, unlike techniques that arbitrarily categorize income levels into high or low, this technique allows for more precise estimates of individuals over time.

3. Evaluation of research questions and hypothesis tests

Hypothesis testing relied on identification of an appropriate LCA and LTA models in which covariates and distal outcomes were introduced. The sub-sections a through e are descriptive labels based on the research questions enumerated in Chapter 1, Section D.

a. Patterns of accumulation of chronic health conditions at midlife

The latent class models provide preliminary evidence to answer the first research question about whether there are discernible patterns of morbidity at two points during midlife. The latent transition analysis provides additional evidence to evaluate this hypothesis. As discussed above, latent class and latent transition models produce parameters for class prevalence or size and estimated conditional probabilities of endorsing each of the indicator variables. The prevalence parameter allows for the determination of the size of each class or status. Further, the estimated conditional probabilities provide a means to estimate how likely members of each class are to report each of the chronic health conditions. Inspection of these parameters produce evidence to support or undermine the assertions in hypothesis 1 that there are discernible patterns of multimorbidity at 40 and 50 years of age in which a small minority of individuals report a comparatively high number of chronic health conditions and a large majority of individuals report few chronic health conditions.

b. Relationship between accumulation at 40 and 50 years of age

The latent transition model produced information about whether patterns of accumulation of chronic health conditions at 40 were related to those at 50. The hypothesis associated with this question was that patterns of morbidity and multimorbidity at 40 years of age predict patterns at 50. In particular, it asserts that individuals who report few health conditions at 40 are likely to remain in good health and report few health conditions at 50. Conversely, those individuals with multiple chronic health conditions when 40 are likely to experience more accumulation of chronic health conditions by the time they are 50. Assuming confirmation of Hypothesis 1, the estimated transition probabilities in the latent transition models may be used to evaluate Hypothesis 2. Inspection of these probabilities, for instance, would allow one to determine if individuals in a low morbidity status when 40 years old would be likely to remain in that status or transition into a status whose members reported multiple chronic health conditions.

c. Life course socioeconomic characteristics and midlife patterns of accumulation of chronic health conditions

With the introduction of covariates, the latent transition model produced information about whether life socioeconomic characteristics were related to patterns of accumulation of chronic health conditions at 40 were related to those at 50. The associated hypothesis stated that individual and household indicators of socioeconomic position predict patterns of morbidity at 40 and that they moderate the accumulation morbidities between 40 and 50. In particular, life course income, net worth, educational attainment, and home ownership have a significant negative relationship with the accumulation of multiple chronic health conditions. To test this hypothesis, the latent status at 40 was treated as the multinomial outcome variable in which the predicator variables were income, net worth, educational attainment and home ownership. Additionally, these same predictors were tested to see if they were associated with differential probability of transitioning to a new status when respondents were 50 years old.

d. Race/ethnicity and patterns of accumulation of chronic health conditions

The latent transition analysis with covariates provided information relevant to the research question about race or ethnicity was related to patterns of accumulation of multiple chronic health conditions at midlife. As discussed in subsection c above, the latent transition status when individuals were 40 years old became multinomial outcome variable that was regressed onto to a variable representing race and ethnicity. The effect of race of race on transitions in latent statuses from 40 to 50 was also modeled.

e. Patterns of morbidity and perceived functional health and well-being

Finally, to test hypothesis 5, I introduced distal variables into the model to determine if there were differences in the functional health outcomes of individuals who were placed in different model statuses at 40 and again at 50 years old.

CHAPTER IV. RESULTS

A. Chronic Health Conditions

Table I presents information on proportion of the analytic sample that reported a diagnosis for each of seven chronic health conditions when completing the health-at-40 and health-50-questionairre. The health questionnaires asked about 12 specific conditions. Initial review of prevalence of conditions revealed that cancer and stroke were exceedingly rare in the sample and were dropped from the analysis. Further, for similar reasons, angina, coronary heart disease, heart attack, and congestive heart failure were collapsed into a single category labeled heart disease.

When respondents were about 40 years old, all conditions were relatively uncommon. Only arthritis was reported by more than ten percent of the sample (*n* = 614, 11.8%). The next two most frequently reported conditions were high blood pressure (*n* = 513, 9.9%) and asthma (*n* = 379, 7.3%). Diabetes was reported by 263 (5.1%) respondents. Less than five percent of respondents reported a diagnosis for each of the three remaining conditions, psychological problems, heart disease, and chronic lung disease. By the time respondents were around 50 years old the prevalence of reported conditions increased markedly. The prevalence of high blood pressure, for instance, jumped 227 percent from 9.9 percent (*n* = 513) when respondents were 40 years old to 32.3 percent (*n* = 1,677) when they were 50. The prevalence of all conditions except for asthma more than doubled during the ten year interval between survey waves. At 40 years old, 5.1 percent of respondents reported diabetes. By the time respondents were 50 years old, 32.3 (n = 735) indicated a diagnosis of the condition. Similarly, the prevalence of psychological problems increased from 4.4 percent to 10.7 percent (n = 558), a 145 percent increase. Arthritis

Table I. Chronic health conditions

		40 years old n=5,196		50 years old n=5,196	
Chronic Health Conditions		n	%	n	%
Arthritis	yes	614	11.8	1,366	26.3
	No	4,578	88.2	3,825	73.7
	missing	4		5	
High Blood Pressure	yes	513	9.9	1,677	32.3
	no	4,658	90.1	3,509	67.7
	missing	25		10	
Asthma	yes	379	7.3	571	11.0
	no	4,808	92.7	4,625	89.0
	missing	9		0	
Diabetes	yes	263	5.1	735	14.2
	no	4,932	94.9	4,456	85.8
	missing	1		5	
Psychological Problems	yes	228	4.4	558	10.8
	no	4,963	95.6	4,632	89.2
	missing	5		6	
Heart Disease	yes	214	4.1	472	9.1
	no	4,981	95.9	4,719	90.9
	missing	1		5	
Chronic Lung Disease	yes	151	2.9	313	6.0
	no	5,044	97.1	4,875	94.0
	missing	1		8	
# chronic health conditions		n	%	n	%
	0 CHCs	3,636	69.7	2,615	50.1
	1 CHC	1,060	20.3	1,408	27.0
	2 CHCs	500	9.6	1,173	22.5
		M	sd	M	Sd
# chronic health conditions		0.45	0.85	0.89	1.19

and heart disease increased by about 120 percent, climbing from 11.8 percent to 26.3 percent (*n* = 1,366) and from 4.1 percent to 9.1 percent (*n* = 472), respectively. The prevalence of chronic lung disease doubled, moving from 2.9 percent to 6.0 percent. As mentioned, asthma was the only condition in which the increase in reported prevalence did not double, increasing 51 percent from 7.3 percent to 11.0 percent (*n* = 571). These substantial increases were reflected in the number of respondents at each wave who reported multiple chronic health conditions. When respondents were 40 years old, 500 (9.6 percent) reported that they had been diagnosed with two or more chronic health conditions, and a large majority (69.8 percent, *n* = 3,636) reported none of the seven chronic health conditions on the questionnaire. By 50 years of age, just over half (*n* = 2,617) of respondents in the sample reported having no chronic health conditions, and the number of those reporting multiple chronic health conditions more than doubled (22.5 percent, *n* = 1,173). Inspection of mean number of chronic health conditions at each time point reveals a similar pattern. At 40, individuals reported less than on chronic health condition on average (*M* = 0.45, *sd* = 0.85). Mean number of reported conditions increased to 0.89 (*sd* = 1.19) by the time respondents were 50 years old. Finally, the increase in spread of the standard deviation between the two questionnaires waves implied more pronounced heterogeneity in the overall sample when respondents were around 50 years. Nevertheless, despite the substantial growth in the prevalence of chronic health conditions and heterogeneity between 40 and 50 years of age, they remained relatively uncommon.

B. Covariates and control variables

Table II contains information on the primary variables of interest, life course income, individual net worth, home ownership, participant and parental educational attainment, and race as well the control variables.

1. Participant educational attainment

Participant and parental educational attainment was centered at 12 years. This was done to approximate the effect of education by the extent to which it fell short of or exceeded a high school diploma, a major educational mile stone. By the time they were 40 years old, survey participants reported on average completing about 13.72 (*sd* = 2.66) years of education, that is, about 1.72 years beyond a high school diploma.

2. Parental educational attainment

In contrast, respondents reported that the maximum level of educational attainment for either parent was on average less than the number of years required to receive a high school diploma (*M* = 11.63 (-0.37 years less than high school diploma) years, *sd* = 3.47).

3. Household size adjusted net worth at 40 and 50 years old in $1,000 increments

Upon completion of the health at 40 questions, respondents reported a total household size adjusted net worth of just over $80,000 in 2010 inflation adjusted dollars (*M* = 84.51, *sd* = 182.54). By the time respondents completed their health at 50 questions, their reported net worth had grown to around $160,000 (*M* = 163.82, *sd* = 307.69). Again, to deal with natural skew in income and wealth data (Denavas-Walt et al., 2011), the log transformed values were selected for use as covariates in the latent variable models. These values are also presented in the Table II.

4. Adult household size adjusted annual income

Household size and inflation adjusted observed income in dollars, observed log transformed dollars, and estimated log transformed dollars is reported for four time points, when respondents were 26 years old, when they were 30, the wave during which they completed the health at 40 questions, and the wave when they completed the health at 50 questions. All income was converted to $1,000 increments and to 2010 inflation adjusted dollars. Observed income was for descriptive purposes only. The log transformed income estimates were for use as covariates in the latent variable models. These estimates were the product of the mixed regression models described above. Over time, there is a consistent growth in average annual income, increasing from 32.76 (*sd* = 25.88) thousand dollars when respondents were 26 to 48.02 (*sd* = 47.35) thousand dollars when they were 50 years old. As observed in wealth and chronic health conditions, there is also a corresponding increase in the amount of heterogeneity in income amounts across time.

5. Home ownership

By the time they completed their health-at-40 questions, 70.6 percent (*n* = 3,682) of respondent reported that they owned or were making mortgage payments on their primary residence. The rate of ownership increased slightly to 73.1 percent (*n* = 3,809) by the time that the health-at-50 questionnaire was administered.

6. Race and/or ethnicity

Just over one half (n = 2,697, 51.7%) of respondents reported that they were White. About a third reported that they were Black (*n* = 1,526, 29.3%). The remainder (n = 973, 18.7%) reported that they were Hispanic.

7. Gender

Just over half of the respondents were female (n = 2,724, 52.2%).

8. Age

Respondents were about 18.56 years old (sd = 1.76) during the first survey wave in 1979.

9. Body mass index

Body mass index (BMI) was centered at 30. Traditionally, this is the threshold above which individuals are deemed to have an obese body mass. Centering the variables in this manner allowed for an assessment of the effect BMI as it exceeded or fell short of this threshold. At 40, respondents reported a BMI that was on average 4.51 (*sd* = 4.55) points below the threshold for obesity. By the time they reach 50, respondents' average BMI had increased such that they are only about 1.39 (*sd* = 5.82) points below the obese threshold.

10. Heath insurance

At both time points, just over eighty percent of respondents reported having employer-based health insurance either through themselves or their spouse or a government managed insurance such as Medicaid (*n* = 4,270, 82.14 percent at 40 years old) and (*n* = 4,329, 83.28 percent at 50 years old).

11. Binge drinking

About 37.6 percent (*n* = 1,956) respondents reported binge drinking in the past 30 days during the survey wave when they were 40 years old. By the time they were 50 years old, only 12.68 percent (*n* = 350) respondents reported binge drinking in the past 30 days.

12. Current smoking

Like binge drinking, the number of respondents who reported being a current smoker decreased over time. At 40, 22.4 percent (*n* = 1,165) reported daily smoking. In contrast, by the time respondents were 50 years old, 17.3 percent (*n* = 899) reported smoking.

13. Early adult health conditions

Until respondents were about 26 years old, they were asked if they had had any health conditions in the previous year that limited the type or amount of work they could perform.

Table II. Covariate and control variables		26 Years Old		30 Years Old	
		M	*sd*	*M*	*sd*
Education attainment by 40 years old centered at 12 years					
Parental education attainment					
Networth in $1,000					
Net worth in $1,000 (ln transformed)					
Average income in $1,000		32.76	25.88	35.76	29.03
Average income in $1,000 (ln transformed) geometric mean		3.14	1.12	3.19	1.24
Estimated average income in ln transformed dollars		3.14	0.79	3.15	0.85
Home ownership	yes				
	no				
Race					
	Hispanic				
	Black				
	White				
Control Variables					
Gender					
	Female				
	Male				

Table II. Covariate and control variables		26 Years Old		30 Years Old
Age in years				
Average BMI (centered at 30)				
Has insurance				
Binge drinking	yes			
	no			
Current smoker				
	yes			
	no			
Early Adult Health Limitations		n	%	
	2 or more limitations	825	15.9	
	0 or 1 limitation	4,371	84.1	
SFPCS				
SFMCS				

Table II. Covariate and control variables		40 years old		50 years old	
		M	sd	M	sd
Education attainment by 40 years old centered at 12 years		1.72	2.66		
Parental education attainment		-0.37	3.47		
Networth in $1,000		84.51	182.54	163.82	307.69
Net worth in $1,000 (ln transformed)		1.91	4.30	2.54	4.60
Average income in $1,000		42.38	39.53	48.02	47.35
Average income in $1,000 (ln transformed) geometric mean		3.22	1.58	3.31	1.59
Estimated average income in ln transformed dollars		3.21	1.03	3.33	1.16
		N	%	n	%
Home ownership	yes	3,682	70.9	3,809	73.3
	no	1,514	29.1	1,387	26.7
Race		n	%		
	Hispanic	973	18.7		
	Black	1,526	29.4		
	White	2,697	51.9		
Control Variables					
Gender		n	%		
	Female	2,724	52.4		
	Male	2,472	47.6		

Table II. Covariate and control variables		40 years old		50 years old	
		M	*sd*	*M*	*sd*
Age in years		18.56	1.76		
Average BMI (centered at 30)		-4.51	4.55	-1.39	5.82
Has insurance		82.14	26.32	83.29	28.93
Binge drinking	yes	1,956	37.64	659	12.68
	no	3,240	62.36	4,537	87.32
Current smoker					
	yes	1,165	22.4	899	17.3
	no	4,031	77.6	4,297	82.7
Early Adult Health Limitations					
	2 or more limitations				
	0 or 1 limitation				
		M	sd	M	sd
SFPCS		52.22	7.74	49.41	10.03
SFMCS		53.10	8.24	52.90	8.85

Of the 5,198 respondents, 825 (15.8 percent) reported two or more waves during which they had health conditions that limited the amount or type of work that they could perform.

14. Functional health and well-being: Short Form Health Survey (SF-12)

The Short Form Health Survey (SF-12) sub-scale scores are reported for physical well-being (SFPCS) and mental health (SFMCS) to describe perceived functional health for members of each latent class status at each time point. As discussed, scores ranged between 0 (worst quality of life) to 100 (best quality of life).

C. Mixed regression models

On average, the 5,196 participants reported their incomes at 11.61 interview waves (*sd* = 2.75). A large majority of participants reported income during at least five waves (97.40%). Table III depicts average reported income in 2010 inflation adjusted dollars in $1,000 increments during four time points, when participants were 26 years old, 30 years old, and upon completion of their health-at-40 (*M* = 40.35 years, *sd* = 0.95) and health-at-50 questions (*M* = 49.71 years, *sd* = 0.66). As discussed, the mixed models, while necessary, were not the central analysis of this project. As such, the presentation of results in the main body of the dissertations provides less detail than Appendix A where there is a full discussion of the mixed models.Table III also contains log transformed incomes for these time points. As seen in Table III, average income increased as participants aged. Between the ages of 26 and 30 years old, average annual income grew from $32,760 to $35,760. By the time respondents completed their health-at-40 questionnaire, average income had grown an additional $6,620 to $42,380. During the subsequent decade, average annual income increased once more to $48,020. As previously indicated, the mixed regression models used log transformed dollars as outcomes to deal with the skewed distribution of income (Denavas-Walt, Proctor, & Smith, 2011).

To determine the most statistically viable description of income growth, six mixed regression models were fit to reported income. Starting with a random intercept model, each subsequent model introduced an additional fixed or random effect to assess whether mean and individual income growth best conformed to a simple linear pattern or would be better described with the inclusion of quadratic and cubic trends. The specific models are listed in Table IV below.

Table III. Age in years at four time points by income in dollars ($1,000 increments) and log transformed dollars ($1,000 increments)

		Dollars		log dollars	
	N	M	Sd	M	sd
Age 26	636	32.76	25.88	3.14	1.12
Age 30	3,522	35.76	29.03	3.19	1.24
Health-at-40-questions (M = 40.35 years)	4,379	42.38	39.53	3.22	1.58
Health-at-50-questions (M = 49.71 years)	4,461	48.02	47.35	3.31	1.59

Table V contains information for use in selecting the most appropriate model. Specifically, the total parameters estimated for each model and Akaike and Bayesian Information Criteria (AIC and BIC) to guide model selection. Additionally, because these are nested models, that is, they contain an identical number of observations and each simpler model is fully contained in its subsequent more complex model, the deviance values (-2 Log Likelihood) could be used to construct χ^2 test statistics to detect significant differences between models (Hedeker and Gibbons, 2006). As seen in Table IV, there is strong evidence for a more complex model than the random intercept only scenario. First, the intra-class correlation ($\sigma^2/\ \sigma^2 + \sigma_\upsilon$), a ratio of

Table IV. Six mixed regression models

Model	Between Subjects	Within Subjects
(1) Random intercept model, Fixed linear effect (RI)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+e_{ij}$	$b_{0i} = B_0 + u_{0i}$
(2) Random intercept model, Fixed and random linear effects (RLE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+ e_{ij}$	$b_{0i} = B_0 + u_{0i;}$ $b_{1i} = B_1 + u_{1i}$
(3) Random intercept model, Fixed and random linear effects, Fixed quadratic effect (FQE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+b_{2i}T^2_{ij}+ e_{ij}$	$b_{0i} = B_0 + u_{0i}$ $b_{1i} = B_1 + u_{1i}$ $b_{2i} = B_2$
(4) Random intercept model, Fixed and random linear effects, Fixed and random quadratic effects (RQE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+b_{2i}T^2_{ij}+ e_{ij}$	$b_{0i} = B_0 + u_{0i}$ $b_{1i} = B_1 + u_{1i}$ $b_{2i} = B_2 + u_{2i}$
(5) Random intercept model, Fixed and random linear effects, Fixed and random quadratic effects, Fixed cubic effect (FCE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+b_{2i}T^2_{ij} +b_{3i}T^3_{ij} + e_{ij}$	$b_{0i} = B_0 + u_{0i}$ $b_{1i} = B_1 + u_{1i}$ $b_{2i} = B_2 + u_{2i}$ $b_{3i}= B_3$
(6) Random intercept model, Fixed and random linear effects, Fixed and random quadratic effects, Fixed and random cubic effects (RCE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+b_{2i}T^2_{ij} +b_{3i}T^3_{ij} + e_{ij}$	$b_{0i} = B_0 + u_{0i}$ $b_{1i} = B_1 + u_{1i}$ $b_{2i} = B_2 + u_{2i}$ $b_{3i}= B_3 + u_{3i}$

within individual variance to the overall variance, is 0.47, indicating that nearly half of the variation is a function of the dependency of repeated measurements nested within individuals.

Further, the inclusion of random linear effect produced substantial improvement in model fit. AIC and BIC values decreased by over 2,000 points. The difference in deviance scores was highly significant ($\chi^2 = 2{,}419$, $df = 2$, $p/2 < 0.001$). The inclusion of a fixed quadratic term achieved only moderate improvement. AIC values dropped by four points when moving from the RLE to the FQE model. BIC values increased. The Likelihood Ratio test was still significant ($\chi^2 = 6$, $df = 1$, $p/2 < 0.01$). The addition of a random effects term to represent individual quadratic trends (RQE) was associated with substantial improvement in model fit over the FQE. AIC and BIC values decreased by about 800 points each. On three degrees of freedom, the Likelihood Ratio test was highly significant ($\chi^2 = 812$, $df = 3$, $p/2 < 0.001$). The final model contained an additional fixed effect to capture the cubic effect of time. There was some model improvement. The AIC and BIC scores decreased by 25 and 16 points, respectively, and the Likelihood Ratio test was significant ($\chi^2 = 27$, $df = 1$, $p/2 < 0.001$). Interestingly, much of the improvement across models was realized with the addition of random effect terms, suggesting that individual effects made a substantial contribution to variation in the models.

For the calculation of covariates, I selected the empirical Bayes estimates from the RQE. This was done for two reasons. Model improvement between the RQE and FCE was modest. Moreover, as seen in Table VI, the RQE marginal estimates comport better with observed marginal incomes at three points of interest. At the beginning of the survey when respondents were about 26 years old and when individuals were around 50 years old, the marginal estimates of the RQE models were nearly identical to observed values.

Table V. Fit statistics for selection of the best fitting mixed regression model

	RI	RLE	FQE	RQE	FCE
-2 Log Likelihood	186,855	184,436	184,430	183,618	183,591
Fixed effect parameters	2	2	3	3	4
Random effects parameters	1	3	3	6	6
Residual	1	1	1	1	1
Total parameters	4	6	7	10	11
χ^2		2,419	6	812	27
Df		2	1	3	1
p/2		<0.001	<.01	<0.001	<0.001
BIC	186,899	184,502	184,507	183,728	183,712
AIC	186,863	184,448	184,444	183,638	183,613
BIC difference		-2,397	5	-779	-16
AIC difference		-2,415	-4	-806	-25

RI=Random intercept model, RLE=Random intercept with random and fixed linear effects model, FQE=Random intercept with random and fixed linear effects and a fixed quadratic effect, RQE=Random intercept model with random and fixed linear and quadratic effects, FCE= Random intercept model with random and fixed linear and quadratic effects and a fixed cubic effect

RQE estimates were lower than observed reported mean income when respondents were 30 years old (Observed M = 3.19 vs. Estimate RQE = 3.15). Further, accepting the FCE estimate would not have provided any improvement at this particular point in time (Estimate FCE = 3.15). Table VII depicts the model weights for the RQE.

D. Patterns of accumulation of chronic health conditions at midlife

1. Latent class analysis results

The latent class models provided initial evidence to answer research question one. When respondents were 40 years old, AIC, BIC, and sample size adjusted BIC values on balance favored a three-class solution. Specifically, as seen in the top half of Table VII, values for all of these metrics decreased between the two- (AIC = 15,457, BIC = 15,555, BICadj = 15,507, Entropy = 0.99) and three- class solution (AIC = 15,280, BIC = 15,431, BICadj = 15,357, Entropy = 0.79). AIC values dropped slightly between a three- and four-class solution (three-class AIC = 15,280 vs. four-class AIC = 15,260). The BIC and sample size adjusted BIC values reversed their decline, indicating deteriorating model fit for the four-class compared to the three-class solution.

Also noted in Table VII is entropy, a measure of average certainty with which individuals were assigned to classes. Possible values are between 0 and 1 where higher values reflect greater certainty. A substantial strength of latent class and latent status data reduction techniques is that they assign individuals to classes or statuses probabilistically. As such, the model provides information about certainty with which individuals are being classified. This uncertainty is taken into account when introducing covariates.

Table VI. Observed and estimated income at four ages

		Dollars		log dollars	
	N	M	Sd	M	Sd
Age 26	636	32.76	25.88	3.14	1.12
Age 30	3,522	35.76	29.03	3.19	1.24
Health-at-40-questions (M = 40.35 years)	4,379	42.38	39.53	3.22	1.58
Health-at-50-questions (M = 49.71 years)	4,461	48.02	47.35	3.31	1.59

Table VI. Observed and estimated income at four ages

		EBE (RQE)		EBE (FCE)	
	N	M	Sd	M	Sd
Age 26	636	3.14	0.79	3.14	0.79
Age 30	3,522	3.15	0.85	3.15	0.85
Health-at-40-questions (M = 40.35 years)	4,379	3.21	1.03	3.21	1.03
Health-at-50-questions (M = 49.71 years)	4,461	3.33	1.16	3.33	1.16

Table VII. Fit statistics for cross-sectional latent class models

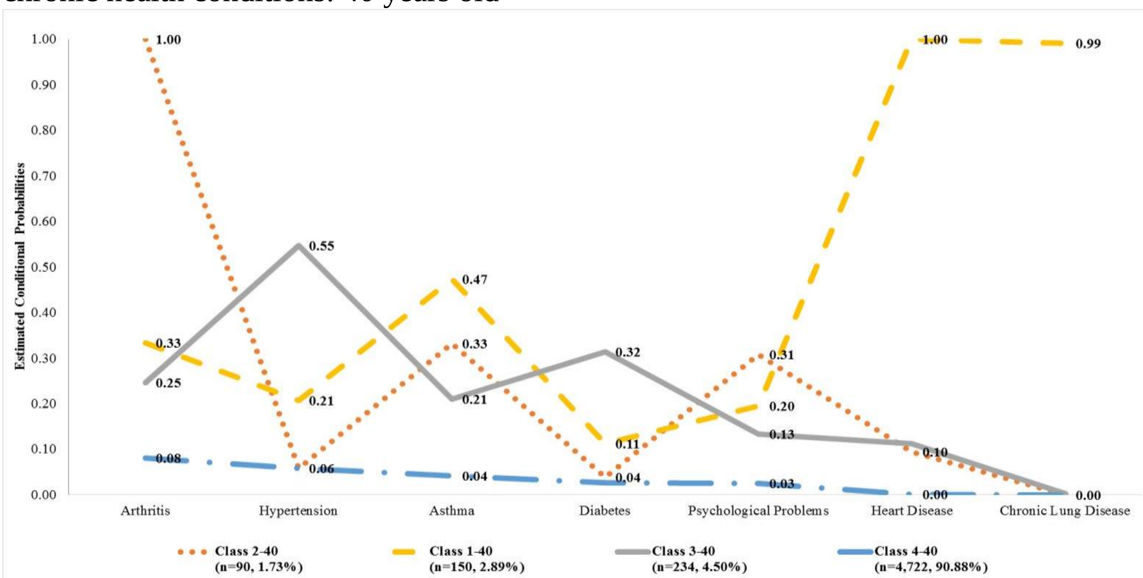
	1-Class	2-Class	3-Class	4-Class	5class
40 years old					
AIC	16,948	15,457	15,280	15,260	15,265
BIC	16,994	15,555	15,431	15,464	15,520
BICadj	16,971	15,507	15,357	15,365	15,397
Entropy	1.00	0.99	0.79	0.86	0.82
50 years old					
AIC	29,433	27,754	27,512	27,434	27,394
BIC	29,479	27,852	27,663	27,638	27,650
BICadj	29,457	27,805	27,590	27,539	27,526
Entropy	1.00	0.71	0.69	0.73	0.73

When respondents were 50 years old, a four-class model solution garnered the majority of support. All fit statistic values decreased steadily through the four-class solution. For instance, compared to the three-class model solution (AIC = 27,512, BIC = 27,663, BICadj = 27,590, Entropy = 0.69), the four-class solution produced superior values across all fit indices (AIC = 27,434, BIC = 27,638, BICadj = 27,539, Entropy = 0.73). In the five-class solution, BIC values started to increase (four-class BIC = 27,638 vs. five-class BIC 27,650). Values for the AIC and sample size adjusted BIC values, however, lent some support to a five class solution (four-class AIC = 27,434 vs. five-class AIC 27,394; four-class BICadj = 27,539 vs. five-class BICadj 27,526). Tentatively, then, preliminary analyses of morbidity patterns in the cross-section, supported a 3-class model at 40 and a 4-class model at 50. Although not empirically necessary, Collins and Lanza (2010) recommend use of identical number of classes at each time point to ease interpretative burden. With this in mind, I opted to use the four-class solutions at 40 and 50. In this scenario, the four-class latent class model at 50 years of age had the preponderance of statistical support. Additionally, although the three-class model at 40 years of age was the best fitting, it was not an unambiguously favored. In fact, the AIC fit statistic preferred this solution. As such, using the four-class solution to represent the latent statuses in the latent transition analysis seemed a reasonable compromise among the competing cross-sectional models from the latent class analyses. Pearson bivariate single degree freedom tests of residual associations among indicator variables within each class revealed an absence of statistically significant residual correlations in indicator variables within each class for the four-class model, suggesting that the assumption of conditional independence was warranted in both models (Asparouhov & Muthen, 2014b). See Appendix B for detail. Finally, as seen below, the four-class solution in both the 40 and 50 year old waves presented the opportunity to examine three distinct and relatively well differentiated morbidity patterns (i.e., a class dominated by heart and lung problems, one characterized by arthritis, and one in which hypertension was the primary condition) in comparison to a low morbidity class. The three-class solution produced the heart and lung class and the low morbidity class. Its third class appeared to collapse the two relatively well differentiated classes of arthritis and hypertension into a moderate morbidity class whose members expressed no specific pattern of conditions.

2. Latent Class Descriptions

Figures 4 and 5 depict the four-class models when respondents were 40 and 50 years old, respectively. At 40, there was a relatively small class (Class 1-40) whose members reported over three health conditions on average (n = 150, 2.89%; M = 3.31 health conditions, SE = 0.08). Members of Class 1-40 reported heart disease (ECP = 1.00) and chronic lung disease (ECP = 0.99). They also had somewhat elevated likelihood of reporting asthma (ECP = 0.47), arthritis (ECP = 0.33), hypertension (ECP = 0.21), and psychological problems (ECP = 0.20). Class 1-40 was the only class in which members were on average multi-morbid. Members of a second small class (Class 2-40) (n = 90, 1.73%; M = 1.83 health conditions, SE = 0.10) were characterized by high a probability of reporting arthritis (ECP = 1.00). Members of Class 2-40 also had some tendency to report diagnoses of asthma (ECP = 0.33) and psychological problems (ECP = 0.31). Although not multi-morbid on average, members of this class reliably reported more than one chronic health condition. A third class (Class 3-40) (n = 234, 4.50%; M = 1.57 health conditions, SE = 0.07) had elevated estimated conditional probabilities of reporting several chronic health conditions, including hypertension (EP = 0.55), diabetes (EP = 0.32), arthritis (EP = 0.25), and asthma (EP = 0.21). During the health-at-40 survey wave, a large majority (n = 4,722, 90.88%; M = 0.23 health conditions, SE = 0.01) of respondents were grouped into a fourth class (Class 4-40) whose members had estimated conditional probabilities (*ECP*) of less than 0.10 of reporting any of the seven chronic health conditions and reported on average less than one chronic health condition.

Figure 4. Latent class membership by estimated conditional probabilities of reporting chronic health conditions: 40 years old



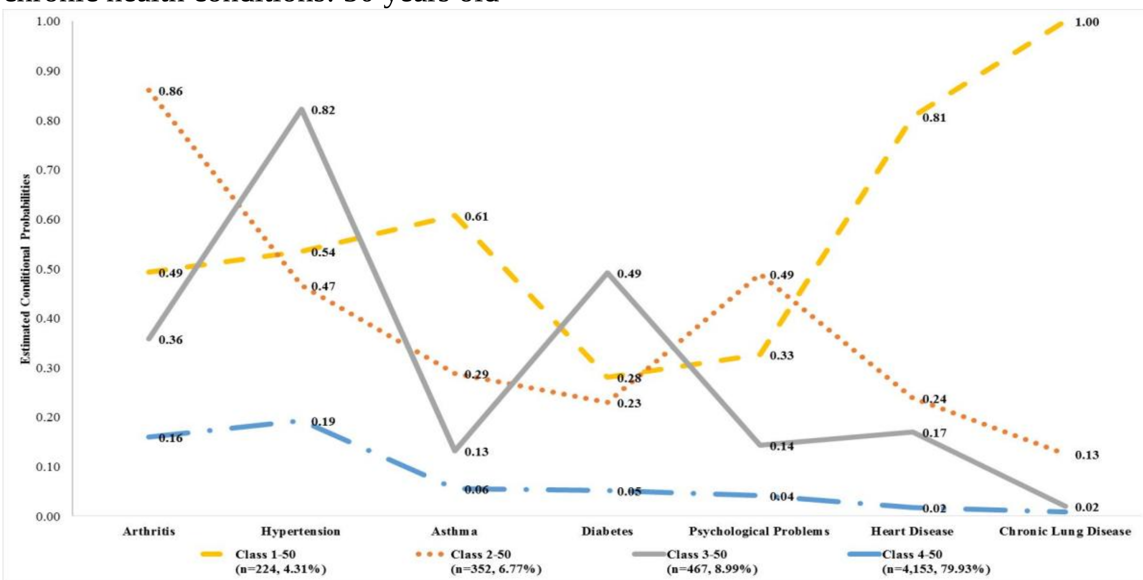
At 50 years of age, the four class model was largely consistent with the one produced when respondents were 40 years old. As seen in Figure 5, Class 1-50 had similar patterns of estimated conditional probabilities for reporting chronic health conditions as the Class 1-40 model. The small Class 1-50 model was (*n* = 224, 4.31%; *M* = 3.75 health conditions, *SE* = 0.10) characterized by large ECPs of reporting heart disease (*ECP* = 0.81) and chronic lung disease (*ECP* = 1.00). It was also characterized by elevated likelihood of reporting asthma (*ECP* = 0.61), hypertension (*ECP* = 0.54), arthritis (*ECP* = 0.49), psychological problems (*ECP* =

0.33), and diabetes (*ECP* = 0.28). Compared to the Class 2-40 generated from the health-at-40 data, Class 2-50 generated from data when respondents were 50 years old was larger (n = 352, 6.77%; M = 2.43 health conditions, SE = 0.07). Members of this multimorbid class were likely to report arthritis (*ECP* = 0.86) and were as equally likely as not to report the hypertension (*ECP* = 0.47) and psychological problems (*ECP* = 0.49). They also experienced somewhat elevated ECPs of reporting asthma (*ECP* = 0.29), heart disease (*ECP* = 0.24), and diabetes (*ECP* = 0.23). As in the 40 year old models, the four-class models at 50 produced a class (Class 3-50) whose members (n = 467, 8.99%; M = 1.64 health conditions, SE = 0.05) tended to report a diagnosis of hypertension (*ECP* = 0.82) and also had somewhat elevated likelihoods of reporting diabetes (*ECP* = 0.49) and arthritis (*ECP* = 0.36). Finally, there was a large class (Class 4-50) (n = 4,155, 79.93%; M = 0.40 health conditions, SE = 0.01) whose members tended to have no chronic health conditions. Like the low morbidity class at 40, members of Class 4-50 had few if any of the queried health conditions. Inspection of Figures 4 and 5 reveal that for two conditions, arthritis and hypertension, ECPs increased from 0.08 to 0.16 and 0.06 to 0.19, respectively.

a. Hypothesis 1

As a whole, the results of the two four-class latent class models support Hypothesis 1. By 40 years of age, there were four distinct patterns of morbidity. Members of Class 1-40, a multi-morbid group, had high likelihoods of reporting heart conditions and chronic lung problems and tended to have one other condition, including asthma, arthritis, hypertension, or psychological problems. Perhaps not unexpectedly, Class 2-40, generally characterized by a high prevalence of arthritis, and Class 3-40, generally characterized by hypertension and some diabetes, increased in prevalence between 40 and 50 at the expense of a Class 4-40, the class whose members tended to have no chronic health conditions. Between 40 and 50 years of age, this low morbidity class decreased in prevalence from 90.88 percent to 79.93 percent. Additionally, on balance, the chronic health conditions that characterize each class became more

Figure 5. Latent class membership by estimated conditional probabilities of reporting chronic health conditions: 50 years old



prevalent for members of these classes. At 40, for instance, members of the Class 3 were more likely than not to report hypertension (*ECP* = 0.55). By 50, members of this class are very likely to report hypertension (*ECP* = 0.82).

E. Relationship between accumulation at 40 and 50 years of age

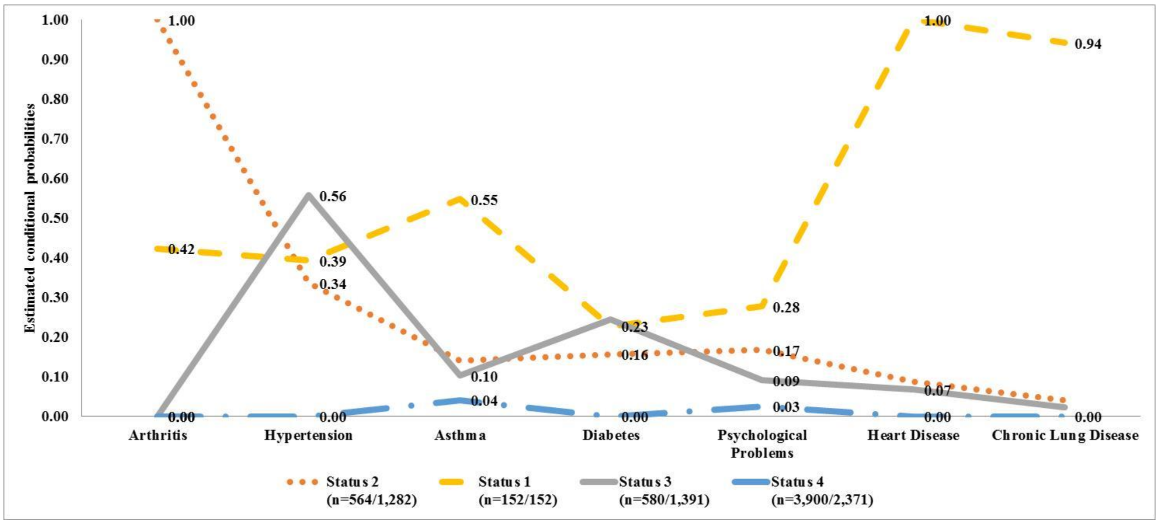
1. Latent transition analyses

a. Model selection and measurement invariance

Tests of measurement invariance provided conflicting evidence in support of holding estimated conditional probabilities of reporting the same conditions (i.e., the probability within a particular status of reporting hypertension at 40 equal to the probability of reporting hypertension at 50) constant across the two time points. Specifically, the four-status latent transition model in which estimated conditional probabilities were held invariant produced two fit index values (AIC = 42,833.36 and BICadj = 42,948.21) larger than a four-class latent transition model in which estimated conditional probabilities were allowed to vary (AIC = 42,691.34 and BICadj = 42,900.77). BIC values, however, were lower (BIC = 43,056.25) in the fully restricted model than in the unrestricted model (BIC = 43,097.79). As discussed, imposing invariance on the estimated probabilities of endorsing repeated instances of the same variable brings substantial interpretative and conceptual advantages (Collins & Lanza, 2010). Most importantly, it allows equivalence when comparing statuses between two or more time points. In addition to easing comparison between time points, this like-to-like set up also clarifies the meaning of transitions for individuals (Collins & Lanza, 2010). Despite these advantages, measurement invariance is not an empirically necessity. Lifting these constraints may be warranted in the absence of supporting statistical evidence or if their imposition does not muddy too severely interpretation. Given the ambiguity produced by the three fit indices above, it is prudent to rely on interpretative and conceptual considerations. As seen in Figure 6, the latent transition model shares notable similarities with the cross sectional latent class models. The four classes or statuses, the one characterized predominantly by heart and lung conditions, the one characterized by arthritis, the one characterized predominantly by hypertension, and the one whose members had few if any health conditions are clearly discernible in the cross sectional and latent transition models.

As in the cross-sectional models, Status 1 was clearly characterized by high likelihood of reporting heart disease (*ECP* = 1.00) and chronic lung disease (*ECP* = 0.94) and moderate

Figure 6. Latent status membership by estimated conditional probabilities of chronic health conditions



likelihood of asthma (*ECP* = 0.55). In the two latent class models and the latent transition model members of Class 2 and Status 2 were distinguished by high probabilities of reporting arthritis. Like the cross-sectional models, those in Status 3 tended to report hypertension (*ECP* = 0.56) and had some probability of reporting diabetes (*ECP* = 0.23). Finally, members of the largest status (Status 4) were unlikely to report any health conditions. In the latent transition context, Status 4 was considerably smaller (n = 3,900, 75.06%, M = 0.73 health conditions, SE = 0.05 at 40 and n = 2,371, 45.63%, M = 0.10 health conditions, SE = 0.01 at 50) than Classes 4-40 and 4-

50 in the cross-sectional models. The decrease in prevalence in Status 4 was to the benefit of Status 2 (n = 564, 10.85%, M = 1.48 health conditions, SE = 0.03 at 40 and n = 1,282, 24.67%, M = 1.93 health conditions, SE = 0.03 at 50) and Status 3 (n = 580, 11.16%, M = 0.94 health conditions, SE = 0.03 at 40 and n = 1,391, 26.77%, M = 0.81 health conditions, SE = 0.03 at 50) statuses whose prevalence at each time point increased considerably compared to their LCA versions. Status 1 in which heart and lung conditions were predominant demonstrated almost complete stability between the two time points (n = 152, 2.93%, M = 3.30 health conditions, SE = 0.09 at 40 and n = 152, 2.93%, M = 3.89 health conditions, SE = 0.15 at 50). These differences not-withstanding, the reproduction of these four morbidity typologies in the longitudinal setting makes desirable the acceptance of measurement invariance.

b. Transition Probabilities

As seen Table VIII, depending on individuals' original classification at 40, transition dynamics varied substantially. Individuals initially classified in Status 1 ($\tau_{2,2}$ = 1.00 of remaining in the same status) status or Status 2 ($\tau_{1,1}$ = 0.98 of remaining in the same status) did not transition. Conversely, it was estimated that about one quarter ($\tau_{3,1}$ = 0.24) of members of the Status 3 at 40 transitioned to the Status 2 when 50, perhaps developing arthritis in addition to hypertension. Estimates suggested that about 14 percent ($\tau_{4,1}$ = 0.14) of members of the Status 4 at 40 moved to the Status 2. Further, about 28 percent of members Status 4 at 40 transitioned to Status 3 at 50 ($\tau_{4,3}$ = 0.28). Depending on individuals' initial latent status membership, then, they expressed considerable stability or some proclivity for movement. Members of Status 1 statuses remained positioned in the same status. Just over one half of individuals in Status 4 at 40 had moved to either Status 2 or Status 3 by the time that they were 50 years old. To a lesser extent, members of Status 3 at 40 displayed some tendency to move to Status 2 status.

Table VIII. Estimated probability of transitioning (τ) between morbidity statuses from 40 to 50 years[a]

	Status 1	Status 2	Status 3	Status 4
Status 1	0.98	0.02	0.00	0.00
Status 2	0.00	1.00	0.00	0.00
Status 3	0.00	0.24	0.76	0.00
Status 4	0.00	0.14	0.28	0.58

[a]There are small discrepancies between transition probabilities and the class numbers reported in Figure 4. Figure 4 reports prevalence based on the modal status. Transition probabilities are calculated based on the estimated model.

To summarize, classification in the Status 1, predominantly a heart and lung status at 40, and Status 2, predominantly an arthritis status, was associated with notable stability. At 50 years of age, members of these statuses occupied the same status at 40 years old. This stability contrasted sharply with the dynamic process observed for those individuals who were originally classified in Status 3 or Status 4. About 42 percent of occupants of the Low Morbidity status at 40 transitioned to either the Arthritis or Hypertension Class by the time they were 50 years old. Although less pronounced, nearly one quarter of the individuals from the hypertension status at 40 years of age moved to the Arthritis status at 50.

c. Hypothesis 2

Research hypothesis 2 stated that morbidity patterns at 40 would be related to those at 50 and that accumulation of chronic health conditions at 50 would be concentrated in those individuals who had already begun accumulating chronic health conditions at 40. Morbidity status at 40 was related to status at 50, clearly supporting the first position of hypothesis 2. In particular, individuals in Status 1 at 40 had essentially no probability of changing status, that is, membership in these statuses at 40 determined status at 50. About 14 percent of respondents in Status 4 at 40 transitioned to the Status 2 by the time they were 50 years old. Another 28 percent of respondents had moved to Status 3. Of the respondents originally classified in Status 3 at 40, 28 percent moved to Status 2 by the time they were 50 years old. No respondents in Statuses 3 or 4 were promoted to Status 1 at 50. Evidence for the second part of hypothesis 2 that accumulation of health conditions at 40 would be positively related to accumulation at 50 is less apparent. Members of Statuses1 and 2, for instance, did not transition to any other higher morbidity status. These were individuals who had demonstrated early accumulation, and hypothesis 2 could reasonably have created the expectation that at 50 these individuals should have experienced movement into a morbidity status where chronic health conditions were even more prevalent.

F. Life course socioeconomic characteristics and race and midlife patterns of accumulation of chronic health conditions

1. A three step latent transition analysis with covariates

Initial modeling included covariates for wealth when respondents were 40 years old and 50 years old as well as annual income at 40, percent change in income between 26 and 40 years of age, and an interaction term of these two variables. It also included annual income at 50, percent change between 41 and 50 years of age, and an interaction term of these two. Inclusion of all these covariates created model identification problems. Exploration revealed that inclusion of either of these sets of variables (i.e., from the 40 interval or from the 50 interval) to predict transition produced essentially equivalent results. For that reason, I chose to use income and wealth data from the 26 to 40 year interval to model covariate effects on status membership at 40 years and transition probabilities. The same estimation difficulties emerged when two sets of corresponding control variables were introduced (e.g., Average BMI from 26 to 40 and average BMI from 40 to 50). For this reason, I limited control variables to only those assessed at or prior to 40 years of age. As discussed above, I used a three-step approach to introduce covariates to preserve the status structure developed in the unconditional latent transition model.

Table IX contains a final latent transition model with covariates to predict latent status at 40. After adjusting for the control variables, factors representing social and economic status were related to morbidity status when respondents were 40 years old. In particular, examination of the Status 2 revealed that for each log transformed $1,000 dollar increase in wealth at 40, individuals had three percent lower odds (OR = 0.97, 95% CI [0.95,1.00]) of membership in

Status 2 relative to Status 4. Similarly, estimated income at 40 was negatively associated with classification in Status 2 compared to Status 4 (OR = 0.86, 95% CI [0.74,1.00]). Neither percent change in income between 26 and 40 (OR = 1.35, 95% CI [0.42,4.37]) nor the interaction term of income at 40 and percent change (OR = 0.94, 95% CI [0.64,1.39]) were statistically significant. Compared to White respondents, Hispanic (OR = 0.65, 95% CI [0.48,0.87]) and Black (OR = 0.63, 95% CI [0.49,0.80]) respondents were less likely to be in Status 2 than in Status 4. Although the results are not shown, initial modeling of race without inclusion of other covariates revealed that African American respondents were more likely to be classified in Status 2 than Status 4. After conditioning on all covariates, the direction of this relationship reversed. Covariate effects on classification in Status 1 at 40 displayed a similar pattern of results. Each log transformed $1,000 increase in net worth was associated with 5 percent lower odds of classification in the Status 1 at 40 than in Status 4 (OR = 0.95, 95% CI [0.91,0.99]). Likewise, increased income at 40 years old was associated with lower odds of membership in Status 1 than in Status 4 (OR = 0.75, 95% CI [0.60,0.94]). As above, percent change in income and the interaction of income at 40 and percent change were not significant. After conditioning on covariates, African American respondents had 49 percent lower odds of being in Status 1 relative to Status 4 (OR = 0.51, 95% CI [0.33,0.78]). None of the socioeconomic covariates were significantly associated with classification in Status 3 at 40 compared to Status 4.

With respect to the control variables, female respondents were more likely than their male counterparts to be classified at 40 in Status 2 (OR = 1.60, 95% CI [1.32,1.95]) or Status 1 (OR = 2.38, 95% CI [1.60,3.55]) classes than the Status 4. Higher body mass indices and early adult health limitations were similarly associated with higher odds of membership in Statuses 1, 2, and 3 than in Status 4.

Table IX. Multinomial logistic regression relating socio economic class to morbidity status at 40 (Reference = Status 1)

	Status 1				Status 2			
	OR	(95% CI)	*p*		OR[a]	(95% CI)	*p*	
Parental education (Centered at 12 years)	1.02	(0.96,1.09)	0.523		1.01	(0.98,1.04)	0.674	
Respondent education (Centered at 12 years)	0.96	(0.88,1.05)	0.330		0.98	(0.94,1.02)	0.310	
Net worth in log transformed dollars (40 years old)	0.95	(0.91,0.99)	0.008	**	0.97	(0.95,1.00)	0.042	*
Individual annual income log transformed dollars (40 years old)	0.75	(0.60,0.94)	0.012	***	0.86	(0.74,1.00)	0.043	*
Percent increase in income (26 - 40 years old)	1.30	(0.54,3.13)	0.564		1.48	(0.81,2.73)	0.205	
Interaction of income at 40 and percent change	0.93	(0.70,1.23)	0.597		0.91	(0.75,1.10)	0.315	
Respondent owns home (Reference = does not own home)	0.96	(0.63,1.47)	0.852		0.93	(0.73,1.19)	0.570	
Hispanic (Reference = White)	0.78	(0.47,1.30)	0.343		0.65	(0.48,0.87)	0.003	**
Black (Reference = White)	0.51	(0.33,0.78)	0.002	**	0.63	(0.49,0.80)	0.000	***
Female (Reference =Male)	2.38	(1.60,3.55)	0.000	***	1.60	(1.32,1.95)	0.000	***
Average Body Mass Index 30 to 40 years (Centered at 30)	1.11	(1.07,1.15)	0.000	***	1.11	(1.08,1.13)	0.000	***
Health Insurance at 40 years (Reference = no insurance)	2.48	(1.19,5.16)	0.016	*	1.69	(1.11,2.58)	0.015	
Respondent binged drank in last 30 days (Reference = did not binge drink)	0.79	(0.46,1.33)	0.371		1.13	(0.87,1.48)	0.356	
Respondent reports current smoker (Reference = Does not smoke)	3.02	(2.12,4.32)	0.000	***	1.23	(0.98,1.55)	0.077	
Two or more health limitations before 26 (Reference = 0 or 1 limitations)	1.91	(1.29,2.83)	0.001	***	2.26	(1.81,2.83)	0.000	***

[a] OR = adjusted odds ratios, * $p < .05$, ** $p < .01$, *** $p < .001$

Table IX. Multinomial logistic regression relating socio economic class to morbidity status at 40 (Reference = Status 1)

	Status 3			
	OR	(95% CI)	*p*	
Parental education (Centered at 12 years)	0.97	(0.94,1.01)	0.133	
Respondent education (Centered at 12 years)	1.04	(0.99,1.09)	0.109	
Net worth in log transformed dollars (40 years old)	0.97	(0.95,1.00)	0.057	
Individual annual income log transformed dollars (40 years old)	0.90	(0.76,1.07)	0.245	
Percent increase in income (26 - 40 years old)	1.66	(0.79,3.48)	0.177	
Interaction of income at 40 and percent change	0.88	(0.70,1.10)	0.254	
Respondent owns home (Reference = does not own home)	0.93	(0.72,1.21)	0.596	
Hispanic (Reference = White)	0.88	(0.65,1.20)	0.431	
Black (Reference = White)	1.30	(1.01,1.67)	0.044	*
Female (Reference =Male)	1.15	(0.93,1.42)	0.191	
Average Body Mass Index 30 to 40 years (Centered at 30)	1.15	(1.12,1.17)	0.000	***
Health Insurance at 40 years (Reference = no insurance)	2.09	(1.31,3.34)	0.002	**
Respondent binged drank in last 30 days (Reference = did not binge drink)	0.93	(0.69,1.25)	0.630	
Respondent reports current smoker (Reference = Does not smoke)	1.00	(0.77,1.31)	0.996	
Two or more health limitations before 26 (Reference = 0 or 1 limitations)	1.75	(1.35,2.28)	0.000	***

* $p < .05$, ** $p < .01$, *** $p < .001$, [a] OR = adjusted odds ratios

To assess covariate effects on transition probabilities, three sets of interaction terms were modeled. These terms were intended to model covariate associations with transition probabilities for only transitions from the Status 3 to Status 2, the Status 4 to Status 2, and Status 4 to the Status 3. These were the only statuses where members had estimated probabilities of greater than 0.05 of movement to a different status. As seen in Table X, none of the covariate proxies for socioeconomic position were related to transition from Status 3 at 40 to Status 2 at 50. However, after conditioning on all other covariates, female respondents in Status 3 at 40 had 168 percent higher odds compared to males of transitioning to the Status 2 (OR = 2.68, 95% CI [1.72,4.16]). Further, for every point increase in body mass index values, respondents in Status 3 at 40 years old had eight percent increased odds of transitioning from Status 3 to Status 2 (OR = 1.08, 95% CI [1.04,1.12]). Movement out of Status 4 was, depending on the destination status, associated with different sets of covariates. Parental and respondent educational attainment were negatively associated with transitions from Status 4 to Status 2. In particular, for each increasing year of parental and respondent educational attainment, individuals had respectively four percent (OR = 0.96, 95% CI [0.92,1.00]) and five percent (OR = 0.95, 95% CI [0.90,1.00]) lower odds of movement into Status 2. Additionally, as net worth increased, there were lower odds of transitions out of Status 4 and into Status 2 (OR = 0.96, 95% CI [0.93,0.99]). Finally, after controlling for other covariates, Hispanic respondents were compared to their White counterparts less likely to move from Status 4 into Status 2 (OR = 0.54, 95% CI [0.38,0.77]).

Table X. Covariate effects on transition probabilities

	Status 3 to Status 4				Status 4 to Status 2			
	OR[a]	(95% CI)	*p*		OR	(95% CI)	*p*	
Parental education (Centered at 12 years)	0.98	(0.91,1.05)	0.483		0.96	(0.92,1.00)	0.046	*
Respondent education (Centered at 12 years)	1.07	(0.97,1.17)	0.180		0.95	(0.90,1.00)	0.030	*
Net worth in log transformed dollars (40 years old)	0.99	(0.94,1.05)	0.786		0.96	(0.93,0.99)	0.003	**
Individual annual income log transformed dollars (40 years old)	0.89	(0.66,1.21)	0.460		0.93	(0.77,1.11)	0.419	
Percent increase in income (26 - 40 years old)	1.35	(0.42,4.37)	0.621		0.82	(0.38,1.76)	0.613	
Interaction of income at 40 and percent change	0.94	(0.64,1.39)	0.751		1.07	(0.84,1.35)	0.595	
Respondent owns home (Reference = does not own home)	0.78	(0.48,1.26)	0.311		1.14	(0.86,1.53)	0.363	
Hispanic (Reference = White)	0.76	(0.38,1.51)	0.433		0.54	(0.38,0.77)	0.001	***
Black (Reference = White)	0.88	(0.55,1.42)	0.605		0.83	(0.62,1.11)	0.205	
Female (Reference =Male)	2.68	(1.72,4.16)	0.000	***	1.56	(1.24,1.95)	0.000	***
Average Body Mass Index 30 to 40 years (Centered at 30)	1.08	(1.04,1.12)	0.000	***	1.11	(1.07,1.14)	0.000	***
Health Insurance at 40 years (Reference = no insurance)	1.17	(0.42,3.25)	0.760		1.30	(0.81,2.08)	0.271	
Respondent binged drank in last 30 days (Reference = did not binge drink)	1.35	(0.72,2.52)	0.344		1.38	(1.02,1.88)	0.039	*
Respondent reports current smoker (Reference = Does not smoke)	1.14	(0.66,1.95)	0.640		1.36	(1.04,1.77)	0.024	*
Two or more health limitations before 26 (Reference = 0 or 1 limitations)	1.66	(1.02,2.68)	0.040	*	2.00	(1.50,2.66)	0.000	***

* *p* < .05, ** *p* < .01, *** *p* < .001, [a] OR = adjusted odds ratios

Table X. Covariate effects on transition probabilities

	Status 4 to Status 3			
	OR	(95% CI)	*p*	
Parental education (Centered at 12 years)	0.99	(0.96,1.03)	0.697	
Respondent education (Centered at 12 years)	0.97	(0.92,1.02)	0.213	
Net worth in log transformed dollars (40 years old)	1.01	(0.98,1.04)	0.657	
Individual annual income log transformed dollars (40 years old)	0.94	(0.77,1.14)	0.509	
Percent increase in income (26 - 40 years old)	0.97	(0.39,2.41)	0.948	
Interaction of income at 40 and percent change	1.03	(0.79,1.35)	0.810	
Respondent owns home (Reference = does not own home)	1.17	(0.89,1.55)	0.263	
Hispanic (Reference = White)	0.97	(0.72,1.31)	0.834	
Black (Reference = White)	1.86	(1.44,2.42)	0.000	***
Female (Reference =Male)	0.99	(0.80,1.24)	0.960	
Average Body Mass Index 30 to 40 years (Centered at 30)	1.13	(1.10,1.17)	0.000	***
Health Insurance at 40 years (Reference = no insurance)	1.04	(0.66,1.63)	0.871	
Respondent binged drank in last 30 days (Reference = did not binge drink)	1.54	(1.15,2.07)	0.004	**
Respondent reports current smoker (Reference = Does not smoke)	1.24	(0.95,1.60)	0.111	
Two or more health limitations before 26 (Reference = 0 or 1 limitations)	1.41	(1.02,1.94)	0.036	**

* $p < .05$, ** $p < .01$, *** $p < .001$, [a] OR = adjusted odds ratios

After conditioning on other covariates Black respondents were more likely than their White counterparts to transition from Status 4 to Status 3 (OR = 1.86, 95% CI [1.44,2.42]). As with the other status transitions, BMI and reported early adult health related limitations on work were positively associated with transition from Status 4 to Status 3.

a. Hypothesis 3

Hypothesis 3 posited that individual and household indicators of socioeconomic position would predict patterns of morbidity at 40 and moderate the accumulation morbidities between 40 and 50. In particular, it asserted that decreasing income would be associated with the development of multiple chronic health conditions. The results offer mixed support of this hypothesis. There was a negative relationship between wealth at 40 and the classification in Statuses 1 and 2, the higher morbidity statuses, compared to Status 4, the lower morbidity status. However, change in income between 26 and 40 and parental education, variables representing earlier life socioeconomic status, were not differentially related to classification in statuses when respondents were 40 years old. With respect to transitions between statuses, higher levels of parental education, respondent education, and net worth at 40 were associated with lower odds of transitioning from Status 4, a low morbidity status, at 40 to the Status 2 at 50, the status dominated by arthritis. These results supported hypothesis 3. There were no other significant covariate relationships in support of hypothesis 3. Additionally, there were no transitions from the lower morbidity Status 4 to Status 1. This absence of transitions is also inconsistent with hypothesis 3.

b. Hypothesis 4

Hypothesis 4 stated that Race or ethnicity would have a significant relationship with the accumulation of multiple chronic health conditions. It did not specify a direction. There were significant relationships between race and ethnicity and classification into morbidity patterns at 40 and transitions between 40 and 50. In particular, after conditioning on other covariates, African American and Hispanic respondents were more likely than their White counterparts to be classified in Status 2 than Status 4 at 40. Further, African Americans but not Hispanics were less likely than Whites to be classified in Status 1 than Status 4 at 40. With respect to transitions, Hispanics respondents in the Status 4 at 40 were less likely to move to Status 2 at 50 than White respondents. Finally, though Status 3 was not strictly a high morbidity status, African American respondents in Status 4 were more likely to move to this status than White respondents. Together, these results suggest some support for hypothesis 4 that race and ethnicity was associated with morbidity patters during midlife.

G. Patterns of morbidity and perceived functional health and well-being Overall physical and mental health

1. Distal Outcomes

Table XI depicts mean scores for the SF12 sub-scales scores of mental (SFMCS), physical well-being (SFPCS), and average number of chronic health conditions reported for each latent status. At 40, members of Status 4 uniformly reported significantly higher physical well-being and mental health quality of life scores and fewer chronic health conditions than their counterparts in Statuses 1 through 3. At 50, an identical pattern was observed for comparisons between the Status and all other morbidity statuses.

a. Hypothesis 5

Hypothesis 5 asserted that as health conditions accumulated, perceptions of functional health limitations and well-being would decrease. The evidence supported this hypothesis. In

Table XI. Mean SFPCS and SFMCS scores by latent class assignment

	SFPCS40[a]				SFMCS40				Chronic Health Conditions			
	M	SE	*p*		M	SE	*p*		M	SE	*p*[a]	
Status 1	44.79	1.04	0.00	***	47.71	1.03	0.00	***	3.3	0.09	0.00	***
Status 2	45.52	0.47	0.00	***	50.85	0.41	0.00	***	1.48	0.03	0.00	***
Status 3	51.4	0.31	0.00	***	52.59	0.33	0.00	***	0.94	0.03	0.00	***
Status 4	53.74	0.1			53.78	0.13			0.07	0.01		

	SFPCS50				SFMCS50				Chronic Health Conditions			
	M	SE	*p*		M	SE	*p*		M	SE	*p*[a]	
Status 1	39.69	1.23	0.00	***	46.79	1.15	0.00	***	3.89	0.15	0.00	***
Status 2	43.1	0.35	0.00	***	50.99	0.3	0.00	***	1.93	0.03	0.00	***
Status 3	50.22	0.23	0.00	***	52.98	0.22	0.00	***	0.81	0.03	0.00	***
Status 4	53.63	0.14			54.45	0.17			0.1	0.01		

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

[a] pairwise single *df* tests between Low Morbidity Class and each of the three remaining morbidity classes.

fact, there appeared to be a graded relationship between increasing numbers of health conditions in each morbidity status and lower self-reported physical and mental health.

H. Summary

As a whole, the findings suggest aspects of social and economic position including race or ethnicity, net worth, and annual income are associated with different patterns of morbidity at 40. After adjusting for other covariates, the net effect of wealth and income were associated with increased likelihood in membership in Statuses 1 and 2, essentially multimorbid and moderate morbidity statuses. On average members of these two statuses reported higher numbers of chronic health conditions the Statuses 3 and 4. The effect of race and ethnicity had a more complicated association with morbidity status. On balance minority respondents were less likely than Whites to be classified in these high morbidity statuses. African Americans, however, were more likely than Whites to be located in Status 3, the status dominated by hypertension.

The relationship between socioeconomic factors and transitions to elevated morbidity statuses was less pronounced. For individuals classified in Status 4 at 40, parental education, respondent education, and net worth were all negatively associated with transitioning to Status 2 at 50. As above the relationship between race and ethnicity and transition was more complicated than the other socioeconomic factors. Hispanic respondents in Status 4 at 40 were less likely to transition to Status 2 at 50 than White respondents. African Americans, on the other hand, were more likely than Whites to move from Status 4 to Status 3.

CHAPTER V. DISCUSSION

A. General summary and hypotheses

The research findings of this study lend themselves to several tentative conclusions and generally support the study's research hypotheses. In support of research hypothesis 1, there were discernible patterns of morbidity observed in this sample, one of which was associated with multiple chronic health conditions. These patterns included two statuses in which respondents had fewer than one health condition on average. The first of these statuses, Status 4, was associated with few if any chronic health conditions at 40 and 50. The second of these, Status 3, was also associated with less than one chronic health condition on average. Member of this status, however, had elevated probability (> 0.50) of reporting hypertension. Members of Status 2 reported on average between one and two health conditions. They almost always reported arthritis and tended to favor reporting hypertension when reporting a second condition. Finally, Status 1 was a truly multi-morbid group of individuals, reporting an average of more than three conditions. Members of this status almost always reported a heart and lung conditions. When reporting a third condition, they tended to select asthma, hypertension, or arthritis.

As mentioned earlier, the evidence in support of research hypothesis 2 is, at least on its face, mixed. There was evidence that morbidity status at 40 was related to status at 50 and was interpreted as relatively strong support of the first assertion of hypothesis 2. Evidence, however, for the second assertion of hypothesis 2, essentially that early accumulation begets later accumulation, was less apparent. Members of Status 1 and 3, the high and moderate morbidity status, for instance, did not transition to any other higher morbidity status. These individuals demonstrated early accumulation. Hypothesis 2 could have created the reasonable expectation that at 50 these individuals should have moved into a morbidity status where chronic health conditions were even more prevalent. Confirmation of this expectation would have been movement of those in Status 2 at 40 into Status 1 at 50 or those in Status 1 at 40 into a latent status in which chronic health conditions were even more prevalent. Finally, one might have anticipated infrequent movement of individuals in Status 4, the low morbidity status, at 40 to any other status at 50. Because this type of evidence was absent, it is less clear how to construe the results as support for hypothesis 2. This absence of evidence for the second part of hypothesis 2, however, may be an artifact of the latent status classification strategy used. This strategy did not specifically consider directly the number of chronic health conditions when generating latent statuses. Rather, it described patterns of accumulation without direct consideration of number of chronic health conditions. Members of these statuses could have continued to accrue health conditions without altering the general pattern of chronic health conditions for which the status was labeled. In this scenario, during the interval between 40 and 50 years of age, each individual could have accumulated a new health condition, say, hypertension for one and depression for the other, that would not have altered the classification scheme.

A comparison of average number of chronic health conditions within each status at each time point revealed that this may have been the case. Viewing these statuses as located on continuum of accumulation is useful to understand accumulation within each status. If this were done, Statuses 4 and 3 would occupy the no or low morbidity areas at one end of the continuum. Because members of Status 2 reported on average more than one health condition but less than two, this status would fit in a moderate morbidity area toward the middle of the continuum. Status 1, the only truly multi-morbid status, would occupy the high morbidity area at the other end of the continuum. At the low or no chronic health conditions end of the continuum, Statuses 3 and 4 demonstrated no accumulation over time. At 40, those in the Status 4 reported about 0.07

and at 50 about 0.10 health conditions. Similarly, those in Status 3 at 40 reported 0.94 health conditions. By 50, they reported only 0.81 conditions. For those individuals in Statuses 1 and 2, the average number of reported chronic health conditions increased from 3.30 at 40 to 3.89 at 50 and 1.48 at 40 to 1.93 at 50, respectively. Viewed in this way, it appears that members of the two statuses with accumulation of health conditions at 40 tended to accrue additional conditions over time. This was not the case members of Statuses 3 or 4. Considered in this way, it is possible to adopt, albeit with caution, some confidence that the second component of hypothesis 2 is plausible.

With respect to hypothesis 3, there was mixed evidence that life course socioeconomic variables were related to morbidity status at 40. The evidence was similarly inconsistent when examining the relationship between socioeconomic variables and the probability of transitioning from low morbidity statuses to higher ones. Higher income and wealth at 40 were associated with lower likelihood of membership in the higher morbidity Statuses 1 and 2. Net worth at 40 was also negatively related to the probability of transitioning from Status 4 at 40 to the Status 2 at 50. There was no evidence that other socioeconomic factors had any significant associations with morbidity status at 40. Home ownership and respondent education were unrelated to morbidity status 40. Interestingly, change in income and parental education were also unrelated. These two variables were the only two that explicitly represented earlier life course effects from childhood and early adult life.

The evidence was also mixed with regard to transitions across statuses. There was, for instance, evidence that early life course factors such as parental educational moderated the odds of transitioning from the Status 4 to Status 2. Further level of respondent education and wealth at 40 were also negatively associated with transitions from the Status 4 to the Status 2.

Although hypothesis 4 posited a relationship between Race and Ethnicity and morbidity patterns, it did not characterize the direction of this relationship. After covariate adjustment, African Americans and Hispanics were less likely than White respondents to be classified in the higher morbidity statuses than Status 4, the low morbidity status. The literature on this front is unclear. There is evidence, for example, that at about 65 years of age and after controlling for income African Americans report more chronic health conditions than Whites (Quiñones et al., 2011). Their ensuing accumulation, however, proceeds at a slower rate (Quiñones et al., 2011). Conversely, Hispanics at 65 years of age have fewer health conditions and also accumulate conditions more slowly than African Americans and Whites. This is consistent with the so called Hispanic Paradox used to explain the somewhat counterintuitive observation that Hispanics frequently have better health outcomes that Whites in spite of higher levels economic deprivation (Markides & Eschbach, 2005). Still other research has failed to find an association between race and multiple chronic health conditions after controlling for early and adult socioeconomic status (Tucker-Seeley et al., 2011). This research is consistent with the notion health disparities between African Americans and Whites are largely explained by economic differences (Beckett, 2000).

Self-reported physical and psychological function was lower for individuals in the higher morbidity statuses than for members of the lower morbidity statuses. Again, if morbidity status is viewed as a continuum in which the Status 4 and 1 anchored the ends, there appeared to be a graded relationship such that increasing number of chronic health conditions corresponded to diminished functional health. As discussed previously, these findings provide reasonably strong support for the research hypotheses.

B. Cumulative disadvantage, life course determinants of health, and morbidity at midlife

Several of this study's findings fit naturally within a Cumulative Advantage and Disadvantage framework. By 40 years of age, there is evidence that accumulation processes are already engaged in the formation of morbidity patterns. Respondents who were classified in Status 4 (75.06% of the sample) or Status 3 (11.16% of the sample) during this period reported less than one chronic health condition. A smaller proportion of respondents were in status 2 (10.85% of the sample) and reported more than one chronic health condition on average. Members of the smallest (2.93% of the sample) and only multi-morbid status at 40, status 1, reported over three chronic health conditions. Moreover, during the decade between 40 and 50 years of age, accumulation of additional chronic health conditions was isolated to those two statuses in which respondents reported a moderate to high number of morbidities at 40. At 40, for instance, members of Statuses 1 and 2 reported, respectively, 1.48 and 3.30 morbidities on average. By 50, average reported chronic health conditions for members of these two statuses jumped about 0.50 conditions. In contrast, the number of chronic health conditions reported in Status 3 and 4, the two lower morbidity groups, remained reliably less than one and did not increase over time. These four patterns and the differential accumulation of chronic health conditions within them are a clear articulation that one aspect of CAD principals that "gaps between the haves and have-nots" develop, maintain, and widen (Merton, 1988, p. 606). The previous quotation was directed toward academic careers and the uneven concentration of prestige, resources, and professional influence on a small minority scientists and institutions. Merton was aware of the applicability that general mechanisms of accumulation and concentration of advantage or, as is the case here, disadvantage, might have for any area in which social stratification processes are at play. Unsurprisingly, CAD principals have been adopted as a potential primary mechanism for conceptualizing and examining the development of health disparities (Cullati, Rousseaux, Gabadinho, Courvoisier, & Burton-Jeangros, 2014). Further, as described in the literature on CAD (e.g., DiPrete & Eirich, 2006; Merton, 1988), there appeared to be some countervailing processes that slowed accumulation. Increased wealth and income were associated with higher probabilities of classification in Status 4 at 40 compared to Statuses 1 and 2. During the subsequent decade, higher levels of respondent and parental education appeared to act as protection against movement from Status 4, the low morbidity status, into status 2, largely characterized by arthritis.

The findings in this study also align broadly with the literature on social determinants of health. Specifically, higher net worth and annual income at 40 years of age were associated with greater likelihood of diminished health, that is, of membership in Statuses 2 and 3. This is consistent with research on accumulation of chronic health conditions (Quiñones et al., 2011; Tucker-Seeley et al., 2011). Additionally, it appeared that parental education, respondent education, and net worth conferred protection from transitioning from a status of low morbidity to one of moderate morbidity (i.e the status characterized by arthritis). This is also consistent with research suggesting that education delays the onset of poor health and income slows its progress once present (Herd et al., 2007; Zimmer & House, 2003). Specifically, education cofactors were unrelated to morbidity status at 40. It appeared, however, that parental education and respondent education may have acted as a prophylactic against progression from Status 4 to Status 2. This could be understood as onset of chronic health conditions between 40 and 50, a similar finding to those of observed by Herd et al. (2007) and Zimmer and House (2003).

Although these findings fit broadly within life course social determinant of health framework, the details of these findings are at points inconsistent and at odds with a large body of research linking higher levels of education to better health (Mirowsky & Ross, 2003). For one, at 40 respondent level of education was not related to membership in any particular status. This absent relationship is surprising when contrasted numerous findings that observe an education gradient in which higher levels of attainment are associated with ever improving health and reduced mortality (e.g, Rogers, Everett, Zajacova, & Hummer, 2010; Ross & Wu, 1995; Smith, 2004). Two points are of interest. First, during initial modeling, I constructed unconditional models relating latent status membership at 40 and probability of transitions to education. Results of these models showed that years of respondent education was negatively related to membership in Statuses 1, 2, and 3 at 40 relative to Status 4. Introducing wealth and annual income to the model completely mediated this relationship. Moreover, closer inspection of the studies on multimorbidity and its cofactors reviewed for this study revealed a varied pattern between education level and accumulation of chronic health conditions. Two studies reported that education but not income was negatively associated with accumulation of health conditions (Andrade et al., 2010; Neeleman et al., 2001). Two other studies found a negative association (Nagel et al., 2008; van den Akker et al., 1998). Unfortunately, in these studies, education was the only indicator of social and economic position, eliminating the possibility estimating the net effects of income, wealth, and education in a combined model. Finally, Wang et al. (2015) observed a similar pattern as the one observed in the current study. In unconditioned logistic regression models, education and income were negatively associated with the odds of reporting two or more versus less than two chronic health conditions. When introduced simultaneously, only income maintained a significant relationship.

Recent research has, moreover, started to question whether the education gradient is universally applicable to all dimensions of health. A relevant critique for the current project is that the large preponderance of evidence for the education-health link was developed using global health measures as the proxy for health (Zajacova, Rogers, & Johnson-Lawrence, 2012). Although these measures provide useful summaries of self-reported overall health, they may mask relationships between education and underlying constituents of the health construct. To this point, when examining the relationship between a number of chronic conditions such as cardiovascular disease, respiratory problems, hypertension, diabetes, chronic pain, and functional limitations, the authors reported that dropping out of college posed the same risk of reporting these conditions as having completed a high school diploma without any college. Interestingly, they also observed that individuals who completed an academic associate's degree had decreased risk of reporting these conditions compared to individuals who quit college (Zajacova et al., 2012). In this scenario, individuals who potentially had the same number of years of education would have different educational accomplishments. A variable representing the educational accomplishment may have shed light on potential health differences across educational levels where a one representing years of education may not have.

Race and ethnicity were significantly associated with latent status membership at 40 and the probability of transition at 50. African American and Hispanic respondents were less likely than their White counterparts to be classified in the Arthritis status at 40. African Americans but not Hispanics were less likely to be classified in Status 1 than Whites and were more likely to be classified in Status 3. Further, African Americans in Status 4 at 40 were likely to transition to Status 3 at 50 than Whites. As above, these findings are in some way at odds with the general research on health and well being (Williams, 2012). It is not, however, completely inconsistent with research on multimorbidity. Quiñones et al. (2011), for instance, found that at a baseline African Americans had more chronic health conditions than Whites but accumulated conditions at slower rate. Moreover, Tucker-Seeley et al. (2011) did not observe a statistically significant association between race and number of chronic health conditions reported. In this dissertation, unconditional models did not reveal a different pattern of relationships between race and ethnicity and morbidity status or the probability of transitioning.

D. Limitations

Like other descriptive work, establishing a causal link is beyond the scope of this study and alternative hypotheses are available. The most obvious is that health determines social and economic status. In this scenario, poor health during youth and early adulthood undermine individuals' ability to obtain well-paying work and accumulate wealth. A variable capturing early health limitations was introduced as a statistical control for this possibility. After conditioning on this variable, income and wealth at 40, race and ethnicity, and education maintained statistical significance in parts of the model. This control reduced but cannot eliminate the possibility of this alternative explanation. In fact, depending on the particular context, it is more likely that health and income and other indicators of social and economic position alternate their roles as cause or recipient of that cause (e.g., Smith, 1999; Wu, 2003).

There are numerous factors that may have also contributed health at midlife that were impossible to model using the current data set. The proposal for this dissertation included an analysis of census level social and economic characteristics such as rates of poverty and single parent households. Grant funding for this part of the proposal did not become available. Research has produced evidence linking community social and economic conditions to individual health outcomes (Messer et al., 2006; Yao & Robert, 2008). This would have provided a means to model the effects of individual and household social and economic factors net those of community conditions. There is also research suggesting that epigenetic and fetal origins of disease has found that stresses or insults experience in utero may influence gene expression or HPA axis function to increase likelihood of disease and other chronic health conditions later in life (Miller, Chen, & Parker, 2011).

It is also possible that the types of conditions individuals report is in part an artifact of the types of health conditions queried. Detection requires inquiry. In the sample used for the current study, 9.6 percent of respondents at 40 and 22.6 percent at 50 reported two or more health conditions. I intended to use 12 conditions. One of them, stroke, was dropped because it appeared only four times. Heart conditions were collapsed into a single variable because of low occurrence of these individual conditions, leaving a total of seven conditions. In contrast, in the Portuguese study cited above, over half of individuals between 35 to 49 years old reported multiple chronic health conditions (Prazeres & Santiago, 2015). The Portuguese sample was developed from a primary care population. This could have increased the number of conditions reported. However, researchers also inspected data for the presence of 147 possible conditions. Severity of conditions is also an important component when examining multiple chronic health conditions. This was not assessed directly in this study. Including severity measure could have, for instance, allowed one to distinguish between individuals who had debilitating arthritis versus those for whom arthritis is a nuisance.

Measurement error is always a potential threat, as mistakes or inaccuracies in self-report inhere in the social survey method (Tourangeau, Rips, & Rasinski, 2000) and have been observed in the presence of self-reported health conditions (Molenaar, Van Ameijden, Grobbee, & Numans, 2007). Although impossible to have perfect confidence in self-reports, accuracy appears to increase when conditions have sudden and life threatening onset or are chronic and require regular management (Okura, Urban, Mahoney, Jacobsen, & Rodeheffer, 2004). These types of conditions (e.g., heart attack and diabetes) are the ones the research described in this research, thus partially ameliorating concerns of accuracy.

Measurement of social and economic position relied on self-reported information about home ownership, education, income, and wealth. Each of these was associated with a number of factors that could have produced measurement error and should be considered when accepting the results of this study. When dealing with self-report income and wealth data, there is always the risk that individuals will systematically over estimate earnings (Fukuoka, Rankin, & Carroll, 2007). The variable for home ownership was based on a single question about whether respondents made mortgage payments on their primary residence. No information was available on the amount of equity respondents had accumulated or the overall value of the home. The parental education variable was based on two questions about years of completed education for each of the respondents' parents. The maximum value was taken to create the parental education variable. Use of this variable assumes implicitly that respondents were residing with this parent and accruing the benefits of his or her education. It was impossible to ascertain the validity of this assumption.

Like the covariates of interest, measurement error could have vitiated or otherwise biased the observed effect of control variables. The alcohol consumption variable is perhaps the most problematic variable. The variable calculated the number of times that respondents reported binge drinking in the previous month. This is a narrow definition and does not directly tap heavy chronic use of alcohol that is such a determinate to health.

One possible limitation of this study derives from the nature of data reduction techniques such as latent class and transition analyses. The benefit of these techniques is that one may triage individuals of a population in particular groups based on a set of indicator variables. As such, these techniques allow for the creation of meaningful and convenient to mark sub-populations. This is especially important to a field such as social work in which a primary goal is the identification of small at times hidden populations who are in need of services or policy protections. There is, however, the risk that the uncertainty associated with classification will be ignored and the classes treated as observed variables rather than probabilistic entities.

Between the 40 and 50 year old survey, 1,108 respondents dropped out of the study or failed to complete a health at 50 survey. Slightly less than one quarter of these were due to mortality. A primary goal of this dissertation was to describe patterns of morbidity and examine their relationship to social and economic experiences. In this light, it was not crucial to understand the role of mortality. Nevertheless, it is possible that participants who did not respond because of mortality or some other systematic reason could have influenced the final results.

E. Questions for future research

The current research suggests and is consistent with several areas of research. Narrowly, additional work is required to untangle the inter-relationships between the accumulation of chronic health conditions and social and economic factors across the life course. There is still, for instance, a lack of consensus about the role of education in health (Zajacova et al., 2012). The evidence for a relationship with health outcomes and education and income is decidedly abundant (e.g., Herd et al., 2007; House et al., 2005). However, less is known about the multiple pathways by which education, income, and other social class markers might relate to accumulation processes. There is, for instance, a dearth of research investigating how income might moderate the effect of education on accumulation of multiple chronic health conditions. Laying out these factors in detail will provide guidance for policy and practice strategies around multiple chronic health conditions.

Future research could also examine interactions among different components of socioeconomic status. It is, for instance, possible that the protective effects afforded by higher levels of income and wealth are not uniform across all racial or ethnic groups. Interacting these variables with race would allow shed light on whether higher levels of, say, income are equally protective for African Americans, Hispanics, and Whites.

Recent work has emphasized the importance of how micro and macro policy relates to health outcomes (Labonte & Schrecker, 2007a; Labonte & Schrecker, 2007b). An intriguing component of this work is the varied methods researchers deploy to understand how macro policies interact to establish economic and social arrangements that increase or decrease risk of poor health. One study of sub-Saharan Africa, for instance, found that the combined effects of economic and trade policies such as currency devaluation and liberalization of trade and reforms to social policies that increase personal costs for education and health result in higher rates of HIV/AIDS and tuberculosis (De Vogli & Birbeck, 2005). Moving down a causal chain set in motion by governing institutions, these policies influence the shape the economic and social conditions in which individuals reside, including an increase in cost of basic necessities, shrinking employment opportunities, promotion of migration to high density urban centers, and added barriers to the use of health care and education. The authors argued that one consequence of reduced employment opportunities, urbanization, and lack of education was greater rates of commercial exchanges for sex and sexual assault (De Vogli & Birbeck, 2005). Similarly, significant increases in income, as, for instance, those experienced in former East Germany after reunification, have also been associated with improved self-reported health outcomes (Frijters, Haisken-DeNew, & Shields, 2005). These two examples suggest scenarios in which political and economic policies establish an environment which may protect or harm individual health.

The recession of 2008 and its recalcitrant damage to median income levels present social science researchers with the opportunity to examine potential effects of poorly designed economic policy (e.g., unfettered banking deregulation) and the ensuing economic shocks on health (Catalano et al., 2011). Research of the 2008 economic downturn has linked the wide spread and lingering damage to employment markets and earning power to increased rates of cardiovascular disease and respiratory problems (Astell-Burt & Feng, 2013). Because the health-50-questionnaire was administered at nearly the same time of the economic downturn, the research in this dissertation could be naturally extended to explore longer term effects of the downturn through use of data from upcoming health-at-60 inventory to on the respondents turning 60 years old. This could include investigation of, for instance, the role of income volatility on health outcomes.

In a recent analysis of the chronic health conditions, the U.S. Department of Health and Human Services proposed a number of research activities and policy interventions to avoid or delay the onset of chronic health conditions or ameliorate their negative effects. These activities and interventions are manifold and include research to better determine the epidemiology of multimorbidity and develop and test the effectiveness of evidence-based care strategies, reform of reimbursement structures so that they incentivize coordination of care, and policies to address economic and social disparities associated with accumulation of health conditions (USDHHS, 2010). Some of these interventions could also include basic health education, changes to the built environment such as parks and other facilities for exercise, provision of basic medical care, and programs to ameliorate the deleterious effects of poverty. Currently, many of these types of interventions are of unknown efficacy or effectiveness (USDHHS, 2010).

Several other areas of potential research could address limitations found in the current project. These could include a detailed analysis of non-respondents to understand how attrition from the study may have biased model results. One limitation discussed was risk of ignoring the uncertainty associated with classification. Again, a substantial strength of latent class and latent status data reduction techniques is that they assign individuals to classes or statuses probabilistically. As such, the model provides information about certainty with which individuals are being classified. This uncertainty is taken into account when introducing covariates. Future research could explicitly report and analyze the uncertainty to determine which statuses, for instance, change in classification certainty over time.

F. Implications for policy and practice

In the light of this USDHHS report and of potential funding from the Affordable Care Act to further develop and study strategies for improved coordination of care, there are practice and policy implications for social work. One implication is related to the challenges of providing comprehensive care to individuals with multiple health conditions in the context of current care guidelines and practices. As discussed, treatment of the single condition informs much of the clinical research and development of evidence based care guidelines (Lugtenberg et al, 2011). A review of current care guidelines for nine conditions - hypertension, chronic heart failure, stable angina, atrial fibrillation, hypercholesterolemia, diabetes mellitus, osteoarthritis, chronic obstructive pulmonary disease, and osteoporosis – found that guidelines for only two conditions -

diabetes and angina, included modified treatment recommendations for circumstances in which patients had multiple co-occurring chronic health conditions. Guidelines for another two conditions, chronic heart failure and hypercholesterolemia, provided additional guidance when patients had cardiovascular disease (Boyd, et al., 2005). Comprehensively addressing these care issues may prove impossible. Given the complexity introduced by multiple chronic health conditions, it is perhaps implausible to introduce exhaustive care guidelines, nevertheless, some modifications might improve coverage. These include relaxing the restrictions of randomized clinical trials when developing and assessing efficacy of treatment protocols (McMurdo, Witham, & Gillespie, 2005). In addition to increasing external validity of tested treatments, if done properly this would allow researchers to perform sub group comparisons to investigate how a co-occurring chronic health condition might influence the effects of their prescribed treatment. Additionally, harnessing electronic technology would allow for convenient cross referencing of guidelines to highlight areas of contradictory care such as contraindicated drugs (Hugheset al., 2012). Accompanying these activities are movements to use global psychosocial assessments to help care providers understand and address barriers to care for patients with multimorbidity (Banerjee, 2015; Graziano et al., 2015). Additionally, if information about economic strain could be incorporated into these assessments, direct service providers could work to link individuals up with related services.

Research has begun to explore the comprehensive care models such as “health homes” (Barr, 2008; Dickinson & Miller, 2010) or case management strategies (Smith, 2012). As a result of the passage of the Affordable Care Act, access to health insurance has increased markedly. Moreover, there are provisions in the law that allow greater emphasis on promising methods for delivering care. Expanded use of community health centers as primary care facilities, for instance, has the potential of reaching greater numbers of poor patients (Wolfe, 2011/2012). Although community health centers have existed in some form since the 1960's, the 2010 Patient Protection and Affordable Care Act, 42 U.S.C. § 18001 (ACA) has expanded them as a potential mechanism to provide preventive and primary care to historically underserved and under resourced communities (Mandsager, Lebrun-Harris, & Sripipatana, 2015). Also a provision of the ACA, medical homes have emerged as an attractive idea for treating individuals with Medicaid who have significant risk for or current diagnoses of multiple chronic health conditions (CMS, 2010). Eligible for additional Medicaid funds, medical homes intend to provide one-stop, coordinated care for individuals with high levels of medical complexity, including individuals who suffer from multiple psychological and somatic health conditions and social stressors such as homelessness and other factors associated with chronic economic deprivation (Monti & Rosner, 2015). These direct practice interventions, especially if scaled up by the ACA, could prove useful in treating individuals with chronic health conditions.

Finally, there is the opportunity for social workers to advocate for reforms that would indirectly affect health. One area potential area is the effort to increase income and for those living at the lower ends of the socioeconomic strata. One study, for instance, has linked increases in income for those in poverty to reduced mortality (Bhatia & Katz, 2001). Further, there is also the potential to tie in health outcomes with income redistribution policies (Adler & Newman, 2000). At a time when economic disparities are increasing, focusing on this area will only become more important.

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APPENDICES

Appendix A Mixed regression models

On average, the 5,196 participants reported their incomes at 11.61 interview waves (*sd* = 2.75). A large majority of participants reported income during at least five waves (97.40%). Table AI depicts average reported income in 2010 inflation adjusted dollars in $1,000 increments during four time points, when participants were 26 years old, 30 years old, and upon completion of their health-at-40 (*M* = 40.35 years, *sd* = 0.95) and health-at-50 questions (*M* = 49.71 years, *sd* = 0.66). Table AI also contains log transformed incomes for these time points. As seen in both Table AI, average income increased as participants aged. Between the ages of 26 and 30 years old, average annual income grew from $32,760 to $35,760. By the time respondents completed their health-at-40 questionnaire, average income had grown an additional $6,620 to $42,380. During the subsequent decade, average annual income increased once more to $48,020. Table AI reveals two interesting aspects of average income growth. First, it appears that the most rapid increase in income occurred between 26 and 30 when respondents' income grew on average about $748 per year. This pace decreased to about $639 per year during the subsequent decade and slowed again to about $602 per year during their fifth decade. Additionally, an informal comparison of the standard deviations of means at each time point suggests increased heterogeneity in individual income trajectories.

As previously indicated, the mixed regression models used log transformed dollars as outcomes to deal with the skewed distribution of income (Denavas-Walt, Proctor, & Smith, 2011). Like untransformed dollars, average income in log transformed dollars increased as did

Table AI. Age in years at four time points by income in dollars ($1,000 increments) and log transformed dollars ($1,000 increments)

		Dollars		*log dollars*	
	N	***M***	***sd***	***M***	***sd***
Age 26	636	32.76	25.88	3.14	1.12
Age 30	3,522	35.76	29.03	3.19	1.24
Health-at-40-questions (M = 40.35 years)	4,379	42.38	39.53	3.22	1.58
Health-at-50-questions (M = 49.71 years)	4,461	48.02	47.35	3.31	1.59

the spread in standard deviations, essentially reiterating the observation that overtime income levels expressed growing heterogeneity. Figure AI contains graphic representation of correlations of the repeated assessments of income in log transformed dollars. Specifically, the lines in Figure AI depict the generally diminishing strength of correlation between income at particular ages and each lagged age through 51. Each solid line represents income at a particular age. The horizontal axis represents the lagged age for which each correlation was calculated. Not unexpectedly, incomes from immediately adjacent ages are highly correlated, and the strength of correlations diminishes as temporal distance between observations grows. The correlation between income when respondents were 27 and 28 years old, for instance, was 0.57 ($p \leq 0.001$). The correlation between income when respondents are 27 and when they were 40, however, had dipped to 0.25 ($p \leq 0.001$).

To determine the most statistically viable description of income growth, six mixed regression models were fit to reported income. Starting with a random intercept model, each subsequent model introduced an additional fixed or random effect to assess whether mean and individual income growth best conformed to a simple linear pattern or would be better described with the inclusion of quadratic and cubic trends. The specific models are listed in Table AII below.

Figure AI. Observed correlation income in log transformed dollars between 27 and 51

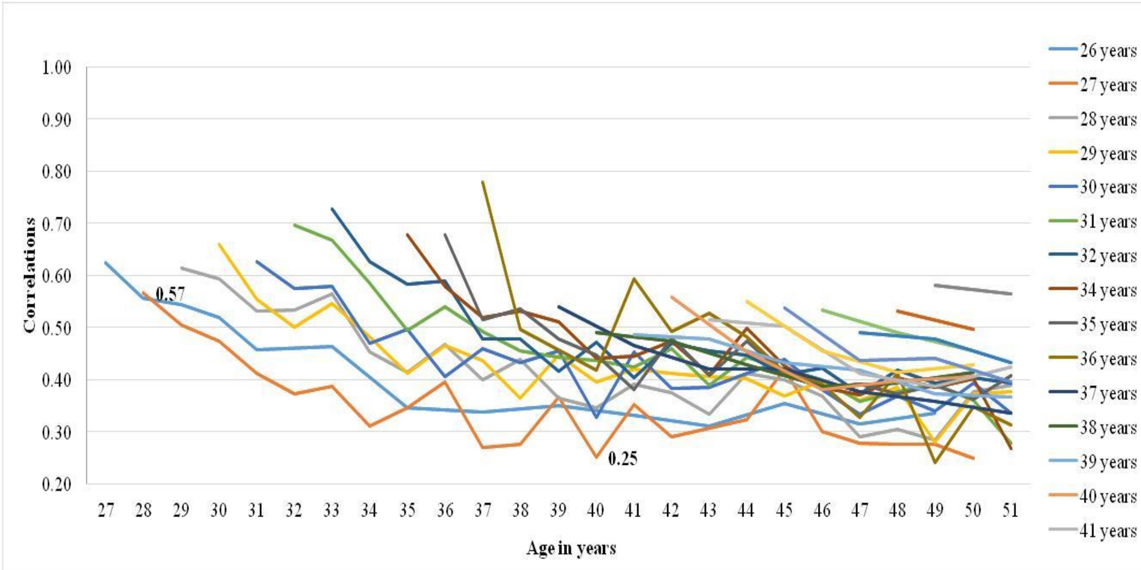

Table AII. Six mixed regression models

Model	Between Subjects	Within Subjects
(1) Random intercept model, Fixed linear effect (RI)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+e_{ij}$	$b_{0i} = B_0 + u_{0i}$
(2) Random intercept model, Fixed and random linear effects (RLE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+ e_{ij}$	$b_{0i} = B_0 + u_{0i;}$ $b_{1i} = B_1 + u_{1i}$
(3) Random intercept model, Fixed and random linear effects, Fixed quadratic effect (FQE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+b_{2i}T^2_{ij}+ e_{ij}$	$b_{0i} = B_0 + u_{0i}$ $b_{1i} = B_1 + u_{1i}$ $b_{2i} = B_2$
(4) Random intercept model, Fixed and random linear effects, Fixed and random quadratic effects (RQE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+b_{2i}T^2_{ij}+ e_{ij}$	$b_{0i} = B_0 + u_{0i}$ $b_{1i} = B_1 + u_{1i}$ $b_{2i} = B_2 + u_{2i}$
(5) Random intercept model, Fixed and random linear effects, Fixed and random quadratic effects, Fixed cubic effect (FCE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+b_{2i}T^2_{ij} +b_{3i}T^3_{ij} + e_{ij}$	$b_{0i} = B_0 + u_{0i}$ $b_{1i} = B_1 + u_{1i}$ $b_{2i} = B_2 + u_{2i}$ $b_{3i}= B_3$
(6) Random intercept model, Fixed and random linear effects, Fixed and random quadratic effects, Fixed and random cubic effects (RCE)	$y_{ij}=b_{0i}+b_{1i}T_{ij}+b_{2i}T^2_{ij} +b_{3i}T^3_{ij} + e_{ij}$	$b_{0i} = B_0 + u_{0i}$ $b_{1i} = B_1 + u_{1i}$ $b_{2i} = B_2 + u_{2i}$ $b_{3i}= B_3 + u_{3i}$

Table AIII contains information for use in selecting the most appropriate model. Specifically, the total parameters estimated for each model and Akaike and Bayesian Information Criteria (AIC and BIC) to guide model selection. Additionally, because these are nested models, that is, they contain an identical number of observations and each simpler model is fully contained in its subsequent more complex model, the deviance values (-2 Log Likelihood) could be used to construct χ^2 test statistics to detect significant differences between models (Hedeker and Gibbons, 2006). As seen in Table AIII, there is strong evidence for a more complex model than the random intercept only scenario. First, the intra-class correlation ($\sigma^2/\ \sigma^2 + \sigma_\upsilon$), a ratio of within individual variance to the overall variance, is 0.47, indicating that nearly half of the variation is a function of the dependency of repeated measurements nested within individuals. Further, the inclusion of random linear effect produced substantial improvement in model fit. AIC and BIC values decreased by over 2,000 points. The difference in deviance scores was highly significant (χ^2 = 2,419, *df* = 2, *p/2*< 0.001). The inclusion of a fixed quadratic term achieved only moderate improvement. AIC values dropped by four points when moving from the RLE to the FQE model. BIC values increased. The Likelihood Ratio test was still significant (χ^2 = 6, *df* = 1, *p/2*< 0.01). The addition of a random effects term to represent individual quadratic trends (RQE) was associated with substantial improvement in model fit over

the FQE. AIC and BIC values decreased by about 800 points each. On three degrees of freedom, the Likelihood Ratio test was highly significant (χ^2 = 812, *df* = 3, *p/2*< 0.001). The final model contained an additional fixed effect to capture the cubic effect of time. There was some model improvement. The AIC and BIC scores decreased by 25 and 16 points, respectively, and the Likelihood Ratio test was significant (χ^2= 27, *df* = 1, *p/2*< 0.001). Interestingly, much of the improvement across models was realized with the addition of random effect terms, suggesting that individual effects made a substantial contribution to variation in the models.

For the calculation of covariates, I selected the empirical Bayes estimates from the RQE. This was done for two reasons. Model improvement between the RQE and FCE was modest. Moreover, as seen in Table VI, the RQE marginal estimates comport better with observed marginal incomes at three points of interest. At the beginning of the survey when respondents were about 26 years old and when individuals were around 50 years old, the marginal estimates of the RQE models were nearly identical to observed values. RQE estimates were lower than observed reported mean income when respondents were 30 years old (Observed M = 3.19 vs. Estimate RQE = 3.15). Further, accepting the FCE estimate would not have provided any improvement at this particular point in time (Estimate FCE = 3.15). Table AV depicts the model weights for the RQE.

Table AIII. Fit statistics for selection of the best fitting mixed regression model

	RI	RLE	FQE	RQE	FCE
-2 Log Likelihood	186,855	184,436	184,430	183,618	183,591
Fixed effect parameters	2	2	3	3	4
Random effects parameters	1	3	3	6	6
Residual	1	1	1	1	1
Total parameters	4	6	7	10	11
χ^2		2,419	6	812	27
Df		2	1	3	1
p/2		<0.001	<.01	<0.001	<0.001
BIC	186,899	184,502	184,507	183,728	183,712
AIC	186,863	184,448	184,444	183,638	183,613
BIC difference		-2,397	5	-779	-16
AIC difference		-2,415	-4	-806	-25

Table AIV. Observed and estimated income at four ages

		Dollars		*log dollars*	
	N	***M***	***Sd***	***M***	***Sd***
Age 26	636	32.76	25.88	3.14	1.12
Age 30	3,522	35.76	29.03	3.19	1.24
Health-at-40-questions (M = 40.35 years)	4,379	42.38	39.53	3.22	1.58
Health-at-50-questions (M = 49.71 years)	4,461	48.02	47.35	3.31	1.59

Table AIV. Observed and estimated income at four ages

		EBE (RQE)		*EBE (FCE)*	
	N	***M***	***Sd***	***M***	***Sd***
Age 26	636	3.14	0.79	3.14	0.79
Age 30	3,522	3.15	0.85	3.15	0.85
Health-at-40-questions (M = 40.35 years)	4,379	3.21	1.03	3.21	1.03
Health-at-50-questions (M = 49.71 years)	4,461	3.33	1.16	3.33	1.16

Table AV. Estimated model of income in logged dollars with linear and quadratic fixed and random terms

	Estimate	**95% CI**	***t***	***p***
B_0	3.14	(3.10,3.18)	157.31	***
B_1	0.00	(-0.01,0.01)	0.05	ns
B_2	0.00	(0.00,0.00)	2.56	**
$\sigma^2_{\upsilon o}$	1.03			
$\sigma_{\upsilon o\ \upsilon 1}$	-0.06			
$\sigma^2_{\upsilon 1}$	0.02			
$\sigma_{\upsilon o\ \upsilon 2}$	0.00			
$\sigma_{\upsilon 1\ \upsilon 2}$	0.00			
$\sigma^2_{\upsilon 2}$	0.00			
σ^2	0.87			

** $p < .01$; ***$p < .001$

B_1 and B_2 are the linear and quadratic trends, respectively.

Appendix B Bivariate Perason tests of residual associations

Table B1. Bivariate Pearson χ^2 test of indicator variables residual associations*

		χ^2 40	χ^2 50
Arthritis	High Blood Pressure	0.48	0.66
Arthritis	Asthma	0.03	0.30
Arthritis	Diabetes	0.04	0.18
Arthritis	Psychological Problems	0.02	1.41
Arthritis	Heart Disease	0.01	0.44
Arthritis	Chronic Lung Disease	0.02	0.00
High Blood Pressure	Asthma	0.01	0.38
High Blood Pressure	Diabetes	0.04	1.09
High Blood Pressure	Psychological Problems	0.24	0.52
High Blood Pressure	Heart Disease	0.01	1.34
High Blood Pressure	Chronic Lung Disease	0.02	0.01
Asthma	Diabetes	0.15	0.92
Asthma	Psychological Problems	0.01	1.95
Asthma	Heart Disease	0.01	1.08
Asthma	Chronic Lung Disease	0.02	0.22
Diabetes	Psychological Problems	0.03	0.90
Diabetes	Heart Disease	0.12	0.23
Diabetes	Chronic Lung Disease	0.03	0.00
Psychological Problems	Heart Disease	0.11	0.73
Psychological Problems	Chronic Lung Disease	0.00	0.04
Heart Disease	Chronic Lung Disease	0.00	0.00

*df for each pairwsie correlation are $l_i l_j - l_i - l_j + 1$, where li-lj and are the number of levels in each indicator variable.

df = 2*2-2-2+1=1

Critcal value (.05) = 3.84

VITA

EDUCATION

Ph.D., University of Illinois at Chicago, Jane Addams College of Social Work, 2016.

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Master of Arts in Psychology, San Francisco State University, 2001
Thesis: The Causal "have" Construction

Bachelor of Arts in Psychology, University of Tennessee, Knoxville – 1994, Phi Beta Kappa

Visiting Student in Germanic Studies, Friedrich Wilhelms Universitaet, Bonn, Germany

RESEARCH EXPERIENCE

Senior Research Analyst *2014- Present*

Office of the Chief Judge of the Circuit Court of Cook County

- Implement case processing performance measures across the court
- Construct analytic data sets electronic docket
- Conduct multivariate data analysis
- Present findings to stakeholders

Graduate Research Assistant *2011- 2014*

Jane Addams College of Social Work, University of Illinois at Chicago

- Constructed analytic data sets from child welfare administrative data
- Conducted multivariate data analysis
- Authored research reports for The Department of Child and Family Services
- Presented to stakeholders and academic audiences
- Budget reconciliation
- Design and implementation of survey to assess factors related to disruption of foster care placements

Research Associate *May 2006 – May 2009*

Treatment Alternative for Safe Communities (TASC, Inc.) Chicago, Illinois

- Management of internal research and evaluation activities of TASC's Illinois Department of Corrections (IDOC) Transition Programs (TASC's Sheridan Correctional Center Drug Treatment and Reentry Program)
- Internal data monitoring and reporting to support development and improvement of Corrections Transition program services and outcomes

Project Manager *July 2005 – January 2006*

REALE Consulting, Chicago, Illinois

- Coordinated evaluation study of the Cook County Juvenile Court Clinic

Quality Control Specialist *February 2002 – August 2004*
Pacific Gas & Electric Company, San Francisco, California
Purchasing Department – Supplier Quality Improvement

- Developed trend reports to discover quality problems with energy distribution materials
- Coordinated quality improvement actions with manufacturers of energy distribution materials

TEACHING EXPERIENCE

Social Work Research I *Fall 2013*

- Co-taught course with Jane Addams faculty
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SCHOLARLY WORK

Refereed Journal Articles

Rolock, N., **Jantz, I**., & Abner, K. (2014). Community perceptions and foster care placement: A multi-level analysis. *Children and Youth Services Review*. doi:10.1016/j.childyouth.2014.12.011

Swartz, J., & **Jantz, I**. (2014). Association between nonspecific severe psychological distress as an indicator of serious mental illness and increasing levels of medical multimorbidity. *American Journal of Public Health. 104*(12), 2350 - 2358. doi 10.2105/AJPH.2014.302165

McCarty-Caplan, D., **Jantz, I.**, & Swartz, J. (2014). MSM and drug use: A Latent Class Analysis of Drug Use and Related Sexual Risk Behaviors. *AIDS and Behavior*. *18*, 1339 - 1351. doi 10.1007/s10461-013-0622-x

Jantz, I, Rolock, N., Leathers, S., Dettlaff, A. & Gleeson (2012). Substitute care entry: The relationship between race or ethnicity and levels of county organization. *Child Abuse and Neglect, 36*(11-12), 771 - 778.

Professional Reports

Swartz, J., & **Jantz, I**. (2014). An Assessment of the Treatment Need for Substance Use Disorders and Related Health Conditions by Chicago Community and Illinois County Areas. *Chicago, IL.*

Jantz, I, Rolock, N., Leathers, S. J., Dettlaff, A. J. & Gleeson, J. P. (2012). Substitute care entry: The relationship between county structure, individual characteristics, and the decision to place children in substitute care. *Chicago, IL: Child Welfare Research Collaborative at the Jane Addams College of Social Work, University of Illinois at Chicago.*

Rolock, N., Gleeson, J. P., Leathers, S. J., Dettlaff, A. J. & **Jantz, I.** (2011). The Evolution of Permanency in Illinois: 1985 to 2010. *Chicago, IL: Child Welfare Research Collaborative at the Jane Addams College of Social Work, University of Illinois at Chicago.*

Rolock, N., Dettlaff, A. J., Wilder, J. R., & **Jantz, I**. (2011). Disparities and disproportionality in child welfare: Trends in Illinois. *Chicago, IL: Child Welfare Research Collaborative at the Jane Addams College of Social Work, University of Illinois at Chicago.*

Rolock, N., Dettlaff, A. J., Wilder, J. R., & **Jantz, I.** (2011). The relationship between child victimization and child poverty rates in Illinois. *Chicago, IL: Child Welfare Research Collaborative at the Jane Addams College of Social Work, University of Illinois at Chicago.*

Refereed Presentations

Bowen, E., & **Jantz,** I. (2015, January). *Understanding patterns of HIV risk behavior in an under-researched, vulnerable population: A latent class analysis of single room occupancy building residents.* Paper presented at the 19th Annual Conference of the Society for Social Work Research. New Orleans, LA.

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Jantz, I., & Rolock, N. (2014, January*). Community context, race, and foster care placement: A multilevel analysis.* Paper presented at the 18th Annual Conference of the Society for Social Work Research. San Antonio, TX.

Jantz, I., & Walton, Q. (2014, January*). An analysis of experiences of discrimination and functional health over the life course among women.* Paper presented at the 18th Annual Conference of the Society for Social Work Research. San Antonio, TX.

McCarty-Caplan, D., & **Jantz, I**. (2014, January*). MSM and drug use: A latent class analysis of drug use and related and sexual risk behaviors* . Paper presented at the 18th Annual Conference of the Society for Social Work Research. San Antonio, TX.

Jantz, I., Huffman-Gottschling, K, & Rolock, N. (2013, January*). Multi-morbidity, poverty, and community context: An analysis of factors related to medical complexity at midlife*. Paper presented at the 17th Annual Conference of the Society for Social Work Research. San Diego, CA.

McCarty-Caplan, D., & **Jantz, I.** (2012, November). *MSM and drug use: A latent class analysis of drug use and related sexual risk behaviors*. Paper presented at the 2012 Chicago LGBTQ Health and Wellness Conference. Chicago, IL.

Jantz, I., Thomas, K., Baldwin, M., Caplan, D., Rolock, N., Huffman-Gottschling, K., & Swartz, J. A. (2011, January). *Multi-Morbidity, Serious Mental Illness, and Substance Use Disorders: An Analysis of Factors Related to Medical Complexity.* Paper presented at the 15th Annual Conference of the Society for Social Work Research. Tampa, FL.

Rolock, N., Leathers, S.J., Gleeson, J.P., Dettlaff, A.J., & **Jantz, I.** (2011, January). *AFSA revisited: Can Fostering Connections impact permanency outcomes among African American children.* Paper presented at the 16th Annual Conference of the Society for Social Work Research. Washington, DC.

Rolock, N., **Jantz, I**., Leathers, S.J., Gleeson, J.P., & Dettlaff, A.J. (2011, January). *Community context, race, and foster care placement: A multi-level analysis.* Paper presented at the 16th Annual Conference of the Society for Social Work Research. Washington, DC.

Jantz, I, & McDonnel, M. (2008, May). *The Cook County Mental Health Court***.** Paper presented at The Mental Health in Corrections Conference, Kansas City, Missouri.

Ruzich, D., Rohzon, J., Lyons, T., & **Jantz, I.** (2008) The Sheridan Correctional Center Therapeutic Community & Reentry Program: A System-wide Approach to Reentry. Presentation at Centerforce Inside/Out Summit, Rohnert Park, CaliforniaWashington, DC.

Jantz, I, Kim, J.J., & Grey, P. (1999, August). *The lexical representation of verbs: The case of the verb "have"*. Paper presented at the 21st Annual Conference of the Cognitive Science Society. Vancouver, British Columbia.

AWARDS

2012	2nd place award for best conference paper for presentation of *MSM and drug use: A latent class analysis of drug use and related sexual risk behaviors*. 2012 Chicago LGBTQ Health and Wellness Conference.
2009 – 2011	Jane Addams' College of Social Work Dean's Fellowship
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TECHNOLOGY AND SKILLS

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AFFILIATIONS

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