Depressive Symptoms in Late Life: The Role of Sociodemographic Factors, Retirement Timing, and Post-Acute Care

by

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Abstract

The mental well-being of older Americans is a pressing public health concern given the aging population and recent increases in midlife suicide and substance use. Depressive symptoms specifically are a common cause of poor quality of life in old age, and one of the leading causes of disability. This dissertation uses nationally-representative longitudinal data from the Health and Retirement Study to improve understandings of depressive symptoms in mid- and late life, their social patterning, and their intersection with post-hospital recoveries.

In Chapter 2, I used mixed-effect models to characterize population trends in how depressive symptoms change over ages 51-90 by gender, race/ethnicity, educational attainment, and birth cohort. This research highlighted large disparities in depressive symptoms in midlife by educational attainment, pointing to the importance of early life exposures for late life health. Results also reaffirmed mental health concerns about recent birth cohorts.

Looking at a key life event for this age group, I next focused on retirement timing. This research examined how expectations about full time work at age 62, reported between ages 51-61, align with realized labor force status to determine whether unmet expectations about retirement timing relate to depressive symptoms across sociodemographic groups. The results revealed that unmet retirement expectations are more common among Hispanic and Black Americans compared to White Americans. In addition, those of low educational attainment were at high risk of unexpectedly not working at age 62. Interestingly, unexpectedly working was not associated with depressive symptoms, pointing to the benefits of work for mental health at older ages and the resilience of those adapting to staying in the labor force. Unexpectedly not working

was associated with a small increase in depressive symptoms at age 62, which was explained by health declines between expectations and reaching age 62. Future research attention should be directed at mitigating health-related early labor force departures, which differentially occur among disadvantaged groups in America.

Finally, I linked survey data from the Health and Retirement Study to Medicare claims data to consider the role of depressive symptoms in recovering from acute hospitalizations. I tested whether different post-acute care settings might mitigate the association between depressive symptoms and poor health outcomes – hospital readmissions, falls, and mortality. Risk for 30-day hospital readmissions increased with increasing depressive symptoms for those recovering at home with or without home health, but not for patients in inpatient rehabilitation settings such as Skilled Nursing Facilities. Post-acute care settings did not modify the relationships between depressive symptoms and each of falls or mortality; therefore, referring depressed patients to inpatient rehabilitation settings could help hospitals avoid financial penalties for readmissions, but will not improve patients' risks for falls or mortality.

Together, this research provides a rich interdisciplinary look at social factors related to depressive symptoms in the aging population and gives insights into one aspect of health services that may address the harmful repercussions of depressive symptoms on other health outcomes.

Chapter 1 **Introduction**

Background

The aging population in the United States is rapidly growing. By 2030, there will be an estimated 71 million people over the age of 65 in the United States and 19.5 million people over age 80, compared to 35 million and 9 million respectively in 2000 (Centers for Disease Control and Prevention (CDC), 2003). The aging population poses many challenges to the field of public health, the health care system, and American society, as chronic disease prevalence, health care spending, and caregiving needs logically rise with an older population. Given that depression is the leading cause of disability worldwide (*Depression and Other Common Mental Disorders: Global Health Estimates*, 2017), focusing on the physical health and functioning of the aging population should not distract from the importance of affective functioning, the ability to process emotional experiences. Creative mental illness prevention efforts, interventions, and policies are critical because the aging population's growth is not matched by a growth in the supply of geriatricians, geriatric psychiatrists, or geriatric faculty to train the future work force (W.-C. Lee & Sumaya, 2013; Reuben, Bradley, et al., 1993; Reuben, Zwanziger, et al., 1993). It is therefore essential to understand population trends of depressive symptoms in late life, their socioeconomic predictors, and strategies to mitigate their negative effect on healthy aging.

This chapter serves as an introduction to this four-paper dissertation. I will start by demonstrating the importance of studying late-life depression by highlighting its consequences on overall health and mortality. Then, I will review evidence on population patterns and trends in

depression and depressive symptoms among middle-aged and older adults in the U.S., looking specifically at differences by age, gender, socioeconomic status (SES), race/ethnicity, birth cohort, and time period – key factors examined throughout this dissertation. Finally, I will evaluate the strengths and limitations of the Center for Epidemiologic Studies - Depression (CESD), a common measure of late-life depressive symptoms. A short version of the CESD is used for the empirical studies in this dissertation.

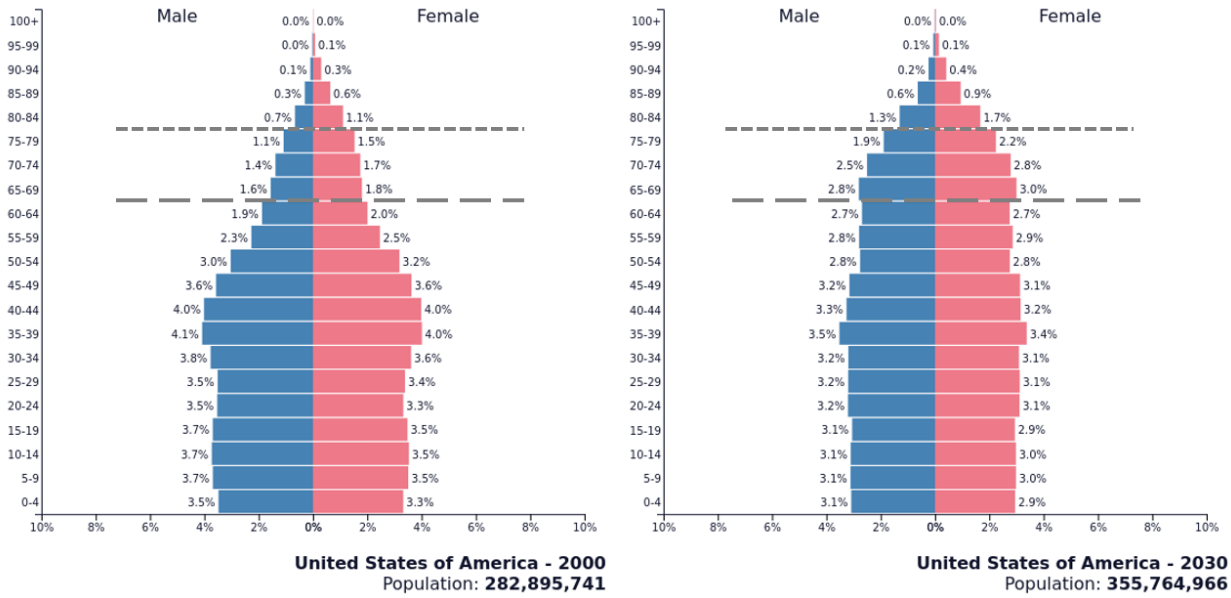

Figure 1-1 Comparing United States population pyramids in 2000 and 2030

Showing the "rectangularization" of the population and the shift to more adults over the age of 65 (large-dashed lines) and over the age of 80 (small-dashed lines) over time.

Consequences of late-life depression

Depression is one of the most common causes of emotional suffering and poor quality of life in the aging population (Volkert, Schulz, Härter, Wlodarczyk, & Andreas, 2013). Diagnosis with major depressive disorder requires experiencing either loss of interest in activities previously enjoyed or depressed mood, at least four other symptoms, symptoms lasting for at least two weeks, and symptoms interfering with usual functioning (*Diagnostic and Statistical*

Manual of Mental Disorders (DSM-5®), 2013). Therefore, baked into the diagnosis is a reduction in quality of life and functional ability. While depressive symptoms without reaching diagnostic criteria have similar implications for quality of life, they may or may not affect functioning depending on severity. Importantly, there is a close association between affective illness and suicide in older adults, and so effective diagnosis and treatment of depression can reduce mortality in this population (Conwell, Van Orden, & Caine, 2011). Recent increases in midlife mortality among non-Hispanic White Americans have been attributed to "diseases of despair" that include suicide, drug overdose, and alcohol-related liver disease, highlighting the link between mental well-being and mortality (Case & Deaton, 2017).

Major depression and depressive symptoms have other, less direct effects on morbidity and mortality. Both conditions are more prevalent among those with other medical conditions— such as myocardial infraction, dementia, Alzheimer's disease, and type-two diabetes— and can have detrimental effects on the progression of these conditions (Alexopoulos, 2005; Alexopoulos et al., 2002). For example, a meta-analysis revealed that depression as a co-morbidity is associated with three times higher odds of poor treatment adherence (DiMatteo, Lepper, & Croghan, 2000). One study focused on diabetics found that depression was associated with both worse self-reported adherence and lower percentage of days with adequate medication coverage based on pharmacy refill data (Kilbourne et al., 2005). A more recent paper using data from The Framingham Study found increases in CESD scores to be associated with poor treatment adherence among older patients with hypertension, dyslipidaemia, and diabetes (Hennein et al., 2018). Besides taking medications, depression is associated with other aspects of self-care and chronic disease management, such as following diet and exercise regimes and foot-checking for diabetics (Ciechanowski, Katon, Russo, & Hirsch, 2003; Gonzalez et al., 2008). Poor treatment

adherence, self-care, and disease management likely contribute to why depressed patients tend to experience worse disease specific outcomes (Alexopoulos, 2005; Sacco & Yanover, 2006) and higher mortality risk (Alexopoulos, 2005; Alexopoulos et al., 2002; Blazer, Hybels, & Pieper, 2001; Holwerda et al., 2007; Sacco & Yanover, 2006) than their non-depressed counterparts.

Depression can also influence the physical health of those without comorbid chronic illnesses. For example, among those with and without other chronic conditions, depressive symptoms are associated with increased likelihood of falling (Hoffman, Hays, Wallace, Shapiro, & Ettner, 2017) and incident or exacerbated disability (Bruce, 2001). Therefore, population rates of depressive symptoms may have implications for aging-in-place and for social security disability applications. Indeed, there is evidence showing that depressive symptoms relate to caregiving needs, as adjusted models revealed that older adults with four to eight depressive symptoms received on average six hours per week of informal caregiving, compared to 2.9 hours for those without depressive symptoms (Langa, Valenstein, Fendrick, Kabeto, & Vijan, 2004). Caregiving related to depressive symptoms for older adults in America are estimated to cost about nine billion dollars annually (Langa et al., 2004), a figure that has likely increased in the years since this study was conducted.

Population rates of depression in older adults also take a toll on formal caregiving and the entire health care system. While one might expect that older adults suffering from depression avoid medical encounters, in line with evidence of worse self-care, several studies have found the opposite – late-life depression leads to increased hospital visits and outpatient medical services utilization (Blazer, 2003; Luber et al., 2001; Luppa, Sikorski, Motzek, et al., 2012). One study found that depressed patients had a higher incidence of “nonspecific medical complaints,” which were associated with increased total ambulatory costs, tests, and consultations (Luber et

al., 2001). This suggests that somatic complaints or general pain could be contributing to increase service utilization in this population (Luber et al., 2001). A review of the increased costs of treating patients with depression concluded that only a small portion of those costs are due to treating the depression itself (Luppa, Sikorski, Motzek, et al., 2012). Clearly, depression and depressive symptoms influence the cost of the Medicare program. Increasing the policy relevance of these utilization patterns, high depressive symptoms increase risk for 30 day hospital readmission (Berges, Amr, Abraham, Cannon, & Ostir, 2015). However, this literature uses mostly site-specific clinical samples may not generalize to the national population.

Many of the discussed "consequences" of depression and depressive symptoms may also be precursors or exacerbators of depression, as these associations are complex, bi-directional, and sometimes cyclical (Alexopoulos et al., 2002). However, existing evidence makes it quite clear that depression in late life is an undesirable, consequential outcome for individuals and for American society.

Sociodemographic variation in depressive symptoms

Major depression disorder, as defined by the Diagnostic and Statistical Manual (DSM), occurs in 1-4% of the elderly population, but as much as 15% have clinically significant depressive symptoms without a diagnosis (Alexopoulos, 2005; Reynolds & Kamphaus, 2013). As discussed above, major depression and depressive symptoms are more prevalent among those with other medical conditions such as myocardial infraction, dementia, Alzheimer's disease, and type-two diabetes (Alexopoulos, 2005; Alexopoulos et al., 2002). Among those with and without comorbid conditions, depression is patterned by sociodemographic factors, partially due to the social patterning of stress exposures and coping resources (Thoits, 2010; Turner & Avison, 2003). In older adults, there is evidence that gender, education, and marital status relate to

depression due to the differential stress of social positions (Cairney & Krause, 2005). This section will review evidence on patterns of depression in middle aged and older adults in the U.S. by age, gender, SES, and race/ethnicity, as well as birth cohort and time period.

Many studies of how depressive symptoms change over age in adulthood show a U-shaped curve with a steep increase starting around the mid-sixties (Cairney & Krause, 2005; Mirowsky & Ross, 1992; Sutin et al., 2013; Tampubolon & Maharani, 2017; Wu, Schimmele, & Chappell, 2012). Evidence of this nonlinear pattern is strengthened by the fact that the U-shape has been identified in not only quadratic models, but also component curve models that do not force a specific shape onto the data (Mirowsky & Ross, 1992). Yang (2007) found that the positive association between age and depressive symptoms in late life reverses when accounting for age-related factors linked to depression such as disability, comorbid conditions, and changes in social support (Yang, 2007). Interestingly, the prevalence of major depressive disorder (rather than symptomology) declines with age (Kessler et al., 2010). This differing age pattern for depressive symptoms and major depressive disorder warrants further investigation.

Gender is one of the most powerful sociodemographic predictors of depression in the elderly population, as women are twice as likely to be affected than men (Alexopoulos, 2005). A review of 24 studies on depression in the elderly concluded that there is very little doubt that women are more at risk for depression than men in old age (Luppa, Sikorski, Luck, et al., 2012). Reasons for this gender disparity include differences in support, coping style, reporting, and help-seeking (Luppa, Sikorski, Luck, et al., 2012). A review examining depression trajectories over the full life course found that women were more likely than men to have increasing symptoms with age (Musliner, Munk-Olsen, Eaton, & Zandi, 2016). Indeed, Mirowsky's pivotal paper published in 1992 found that the depression disparity between men and women increased

with age (Mirowsky, 1996). A more recent evaluation of depression prevalence throughout the life course confirmed than women's higher odds of major depressive episodes is especially large in ages sixty-five and older (Kessler et al., 2010). Despite the consensus regarding women's higher depression, men in the U.S. are three to four times more likely to commit suicide than women, and men over age 70 are the demographic group at highest risk of suicide in most countries (*Preventing Preventing suicide suicide: A global imperative,* 2014). This perplexing contradiction between gender differences in depression and suicide suggests that preventing suicide involves considering other factors in addition to depression.

Socioeconomic status – which often refers to a combination of education level, income, and/or wealth – is another sociodemographic factor associated with depression in mid- and late life. For decades, there has been evidence that formal education is inversely related to depressive symptoms in late life (Mirowsky & Ross, 1992). Throughout the life course, having a low education level is associated with trajectories of greater depressive symptom burden (Musliner et al., 2016). A mediation analysis revealed that the relationship between education and late-life psychological distress is due almost entirely to stress exposure (chronic stress, recent life events, and childhood adversities) and psychosocial resources (mastery and self-esteem) (Cairney & Krause, 2005). Other factors that help explain the association between education and depression in late life include cognitive ability, economic resources, social status, social networks, and health behaviors (Lee, 2011). Taken together, there is strong evidence that education has a large effect on late-life depression because it is predictive of exposure to risks like stressors and promotes opportunities for coping like self-mastery, social support, and economic resources.

Depression is more common among people with low incomes due to mechanisms like financial stress, low social prestige, and poor working conditions (Musliner et al., 2016;

Zimmerman & Katon, 2005). While not looking specifically at older adults, an econometric paper showed that the inverse relationship between income and depression was no longer statistically significant when accounting for other economic factors such as employment status, debt-to-assets ratio, insurance status, home ownership, and occupational role (Zimmerman & Katon, 2005). This finding suggests that wealth is another important aspect of SES for mental health. In fact, education and wealth are more useful socioeconomic indicators for older adults than income, which is often misreported and fails to capture economic circumstances for those reaching retirement (Cairney & Krause, 2005). Interestingly, income and wealth are only weakly correlated, suggesting their use as independent measures at ages when both are relevant (Keister, 2014).

The Health and Retirement Study (HRS), one of the major data sources on middle aged and older adults in America, has a thorough evaluation of wealth that includes savings, assets, investments, and pensions (Sonnega et al., 2014). One study using HRS respondents ages 50-64 found that those with little wealth experienced greater increases in depressive symptoms following job loss compared to wealthy respondents (Riumallo-Herl, Basu, Stuckler, Courtin, & Avendano, 2014). Similarly, HRS has been used to show that changes in wealth due to the 2008 recession were associated with increased feelings of depression and antidepressant use, but not with significant changes in CESD depressive symptom scores (McInerney, Mellor, & Nicholas, 2013). Overall, wealth has a protective effect on mental health by suppling a safety net to make people less vulnerable to economic stressors (Oliffe et al., 2013).

There are also differences in depression in older adults by race and ethnicity because racial/ethnic minorities in the U.S. face increased exposure to psychosocial stressors correlated with depression (Thoits, 2010; Turner & Avison, 2003). One paper studying adults ages 54 to 65

in HRS found that Black and Hispanic respondents exhibited higher odds of depression than White respondents after adjusting for sociodemographic factors, health status, and economic profiles (Dunlop, Song, Lyons, Manheim, & Chang, 2003). Another study looking at HRS respondents ages 50 and older found Black and Hispanic respondents were more likely than White respondents to have elevated depressive symptom trajectories over age (Liang, Xu, Quiñones, Bennett, & Ye, 2011). This pattern is consistent with the racial/ethnic health disparities of other common conditions (Jackson, Knight, & Rafferty, 2010).

However, a more recent study using the National Comorbidity Survey-Replication data found Black adults to have lower rates of lifetime major depressive episodes than White adults (Mezuk et al., 2013). One paper reviewed years of evidence to find that Black adults consistently exhibit higher psychological distress but lower diagnosed major depression (Barnes & Bates, 2017). This discrepancy could be due to racial/ethnic differences in resilience (Keyes, 2009), such as using collective racial identity (Sellers & Shelton, 2003) or high religiosity (Mouzon, 2017) as successful coping strategies. Another potential explanation could be the validity of depressive symptom measures across racial/ethnic groups (Perreira & Harris, 2005) or systematic bias in the diagnostic algorithm (Barnes & Bates, 2017). Indeed, racial differences in aspects of the criteria for diagnosed depression – the prevalence of depressed mood and loss of interest, or the duration and severity of how symptoms are experienced or reported – could explain the pattern of high symptoms with low diagnoses. There is another hypothesis coming from evidence that engaging in unhealthy behaviors (i.e. smoking and overeating) may mitigate the effect of stressors to result in lower depression in Black Americans despite more disadvantaged circumstances (Jackson et al., 2010). However, there is not a solid reasoning for why the stress-mitigating effect of these behaviors would differ by race. A very recent finding suggests that

much of this "paradox" can be explained by the fact that White adults tend to take more prescription medications with depression as a side effect compared to Black adults (Schnittker & Do, 2020). Future research should explore the robustness of these many explanations, the effect of using different depression constructs (psychological distress, depressive symptoms, and depression diagnoses), and dynamics of this racial paradox specifically in older adults.

A similar "paradox" may exist in Hispanic adults. While the studies mentioned above found higher depression in older Hispanic Americans than White Americans, one study of adults ages 70 and older found no difference in depressive symptoms between White adults and English-speaking Hispanics adults (Mills & Henretta, 2001). However, there were higher depressive symptoms in Hispanics who opted to interview in Spanish, which was explained by differences in language acculturation, education, and years living in the U.S. (Mills & Henretta, 2001). In addition, major depression prevalence was higher among foreign born older adults (of many different countries and ethnicities) compared to US-born older adults (Angel & Angel, 1992). These disparities in ethnicity and nativity are important to understand given that the aging population is growing increasingly diverse (Liang et al., 2011).

Birth cohorts are the final source of sociodemographic variation discussed here. Some preliminary evidence suggests that newer cohorts of older adults in the U.S. have lower depression and more declining slopes of depressive symptoms with age compared to cohorts before them (Tampubolon & Maharani, 2017). However, the newer cohorts included in this analysis have not yet reached the age when depression typically increases, so this projection is not conclusive. Other evidence shows newer cohorts have a higher propensity for suicide (Conwell et al., 2011), which fits with Yang's 2007 finding that depression in adjusted models declines with age more slowly in newer cohorts of older adults than in prior groups (Yang,

2007). Much research and media attention has been placed on Case and Deaton's recent report of an increase in mental distress and related mortality in midlife between birth cohorts born from 1940 to 1988, specifically for non-Hispanic White adults without a bachelor's degree (Case & Deaton, 2017). One paper taking a period approach echoed concern about increasing population rates of distress, even across the age span, for those of low socioeconomic status (Goldman, Glei, & Weinstein, 2018).

However, Zivin and colleagues looked at depressive symptoms in HRS respondents from 1998 to 2008 and found lower late-life depression over time, mostly due to a rise in having zero depressive symptoms (Zivin, Pirraglia, McCammon, Langa, & Vijan, 2013). The negative association between education and depression might partially explain population level differences in depression over time, as earlier cohorts tend to have less education (Mirowsky & Ross, 1992). While the lowest education group is becoming a more select (Dowd & Hamoudi, 2014), evidence suggests that such compositional changes only account for part of the trend of worsening health for those without high school degrees (Hendi, 2015). Availability of depression treatment, awareness of mental health, and reduced stigma around depression might also play roles in population changes over time and between cohorts. There is a need for further research to better characterize depression differences between birth cohorts and over time, and to explore explanations for observed changes.

Measuring depressive symptoms in the elderly: The Center for Epidemiologic Studies Depression

When studying the relationship between age, sociodemographic characteristics, and depression, having valid measurements of the condition and its symptoms throughout the life course is important. Some evidence demonstrates that adults ages 65 and older are less likely

than young adults to endorse feelings of dysphoria (Gallo, Anthony, & Muthen, 1994). This finding suggests that a survey measure of depression should ask about a variety of symptoms rather than only depressed feelings. However, there is also concern that gauging bodily or somatic symptoms of depression in older adults might capture physical aspects of aging or disease, rather than specifically measuring affective functioning (Mirowsky, 1996). While depression is a pathology and not a normal part of the aging process, even clinicians have found it difficult to separate out the condition from inevitable changes that accompany aging (Anderson, 2001).

The eight item Center for Epidemiologic Studies Depression (CESD-8) is a common measure of depression in older adults for population surveys, where full psychiatric interviews are not feasible. It is important to interpret this measure in the context of its merits and limitations in terms of internal validity, external validity, and usability.

The CESD-8 asks respondents whether or not they have experienced the following symptoms much of the past week – felt depressed, everything was an effort, sleep was restless, was happy, felt lonely, felt sad, could not get going, and enjoyed life. High Cronbach alphas (ranging from 0.77-0.83) showed good reliability for the CESD-8 scale (Wallace et al., 2000). Principle components analysis revealed two main factors – depressed mood and somatic complaints (Wallace et al., 2000). In this short version of the CESD, which is used in all but the first wave of HRS, there is no information on the severity of each symptom, whether it impacted functioning, or whether the referenced week was similar or different from other weeks. In the case of HRS, this last omission limits the measure's external validity (Hulley et al., 2015), as it is unclear how the reported symptoms generalize to the two-year period between surveys. However, the short time-frame may mitigate recall bias, and the simplicity of the CESD-8 has

advantages for time-constrained survey administration (Wallace et al., 2000). In fact, the CESD-8 is a quite common choice for a survey measure of depression in older adults (Karim, Weisz, Bibi, & ur Rehman, 2015; Lewinsohn, Seeley, Roberts, & Allen, 1997; Turvey, Wallace, & Herzog, 1999). It has been used in hundreds of studies, translated into many different languages, and administered to specific subpopulations, like stroke survivors (Wallace et al., 2000).

To test internal validity – how well the CESD specifically and accurately captures the intended construct of depression (Hulley et al., 2015) – one study assessed the twenty-item CESD's congruences with depression diagnoses (Lewinsohn et al., 1997). The researchers found that the long-form CESD demonstrated acceptable and consistent internal validity among men and women ages 50 and older (Lewinsohn et al., 1997). They found no changes to psychometric properties due to age, gender, cognitive impairment, functional disability, or physical disease (Lewinsohn et al., 1997). Unfortunately, the multiple versions of the CESD might have different properties, creating challenges for measure validation and comparability of findings across different surveys. One study in Europe tested the 8-item CESD for psychometric properties in a large sample of older adults and found that higher CESD-8 scores were negatively associated with life satisfaction, happiness, social trust, self-esteem, optimism, subjective health, autonomy, and social relationships, as expected (Karim et al., 2015). A replication study in the U.S. context would be useful, given documented differences in depression reports in European versus American middle-aged and older adults (Mojtabai, 2016).

Some researchers have dichotomized CESD-8 scores at four symptoms to classify high depressive symptomology, which might approximate major depressive disorder (Han, 2002; Ní Mhaoláin et al., 2012; Stevens, Lang, Guralnik, & Melzer, 2008). However, studies weighing the tradeoff between specificity and sensitivity at different cut-points have only been conducted

using the twenty-item CESD and do not agree on a recommended threshold (Lewinsohn et al., 1997; Turvey et al., 1999). The CESD was designed to gauge symptomology not diagnose major depression, so it is not a useful measure for approximating depression prevalence (Karim et al., 2015). Illustrating this point, a study of diabetics showed that 70% of respondents who passed the 16-symptom cut-point for the twenty-item CESD were not clinically depressed and 34% who did not reach the CESD threshold *were* clinically depressed (Fisher et al., 2007). The authors concluded that dichotomizing the measure may result in poor internal validity (Fisher et al., 2007).

There are arguments for the importance of measuring symptomology, despite the fact that it cannot easily be translated to diagnosis or prevalence. One paper looking at depression scores from the revised Clinical Interview Schedule across the U.K. population concluded that overall population mean symptomology alone actually provided a good prediction of the number of cases above the conventional cut-off (Sellers & Shelton, 2003). This evidence supports the idea of examining depressive symptoms across the whole population, rather than focusing on identifying the sub-group with clinically significant symptoms. As the reviewed evidence has demonstrated, depressive symptoms, even without diagnosis, are an informative indicator of poor well-being and a risk factor for other poor health outcomes.

This Dissertation

Clearly, depression in late life is a pressing public health issue with far-reaching consequences. This introduction has reviewed the evidence of how depression varies across age, important sociodemographic factors, cohorts, and period, highlighting contradictions in pervious findings that warrant additional research. Reviewing the merits and limitations of the CESD has set up context for interpreting data on this measure throughout this dissertation.

The following four chapters are empirical studies using the Health and Retirement Study to learn about late-life depression in the United States. The first paper (chapter 2) examines longitudinal changes in depressive symptoms over age by gender, race, education, and birth cohort to highlight social inequalities and trends in depressive symptoms. The next paper (chapter 3) looks at the prevalence of unmet expectations about retirement timing, while the following (chapter 4) examines unmet expectations' association with depressive symptoms across these same sociodemographic subgroups. The final empirical paper (chapter 5) examines how the relationship between depressive symptoms and hospital readmission and health outcomes might vary in a range of post-acute care settings. Finally, the concluding chapter will discuss the implications of all three studies and future research directions.

Together, these chapters chart new territory in our understanding of how social and economic factors relate to affective functioning in the aging population and the role of health care in mitigating the consequences of depression on health. Furthering research on affective functioning in late life will help ensure that increases in longevity are adding healthy and happy years.

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Chapter 2 **Sociodemographic Differences in Trajectories of Depressive Symptoms Ages 51-90**

Introduction

In addition to changes in physical health, aging brings about profound changes in affective functioning (Alexopoulos 2005). While often preventable and treatable, depression is one of the most common causes of emotional suffering and poor quality of life in the aging population (Volkert et al. 2013). Depression in late life has important implications for the progression of chronic diseases (de Groot et al. 2001; Wassertheil-Smoller et al. 1996), informal care giving needs (Langa et al. 2004), health care utilization (Luber et al. 2001), and health care costs (Unützer et al. 1997). The rate at which depression changes during the aging process is an informative indicator of well-being, with increasing symptoms over time predictive of poor health outcomes like cognitive decline (Mirza et al. 2016) and cardiovascular disease mortality (Wassertheil-Smoller et al. 1996).

Depressive symptoms have long been understood to follow a U-shaped curve over age with a sharp increase beginning around age 65 (Mirowsky and Ross 1992; Tampubolon and Maharani 2017; Sutin et al. 2013). Age-related factors like disability, comorbidity, and changes in social support account for the positive association between age and depression in late life (Yang 2007). Recently, aging researchers have given much attention to alarming trends in physical functioning and mortality among middle- and older-aged American cohorts (Seeman et al. 2010; Martin et al. 2010; Bezruchka 2012). Especially concerning are the widening of disparities in life expectancy and disability-free life years by race, education level, and wealth

(Chetty et al. 2016; Freedman and Spillman 2016; Olshansky et al. 2012). Little is known, however, about the dynamics of depression among recent cohorts of U.S. older adults and particularly differences by gender, race/ethnicity, and educational attainment.

The objective of this analysis was to investigate differences in levels and age-related trajectories of depressive symptoms by gender, race/ethnicity, education level, and birth cohort among American adults ages 51-90 using recent nationally representative panel data. We sought to describe and visualize differences in changes in depressive symptoms in mid- and late life, given the importance of depression as a quality of life indicator and as a risk factor for other poor health outcomes.

Differences by gender

The higher prevalence of depressive symptoms among women compared to men at various stages of the life-course has been well documented in the United States (Alexopoulos 2005; Luppa et al. 2012; Kessler et al. 2010; Mirowsky 1996). Based on cross-sectional data from the 1980s and 1990s, Mirowsky conducted a component curve analysis to determine differences in men's and women's depression curves starting at age 18 (Mirowsky 1996). He found a U-shaped curve with men and women both starting at about 1.4 depressive symptoms; men's depression dropped faster and longer than did women's in ages 20-50, creating a large gender gap in ages 50-69. The gap's growth slowed in older ages, but the disparity remained. Mirowsky conducted mediation tests revealing that gender differences in depression were partially explained by marital status, employment, and other measures of social and economic status that differ by gender at specific ages (Mirowsky 1996). A more recent evaluation of depression prevalence over the life-course confirmed than women's higher odds of major depressive episodes was especially large at ages sixty-five and older (Kessler et al. 2010),

potentially resulting from a cumulative effect of differences in social status throughout the life course compounded by inequities specific to old age, such as women's higher morbidity burden (Cairney and Krause 2005; Luppa et al. 2012; Musliner et al. 2016). A meta-analysis using 24 studies on samples ages 75 and older found the depression prevalence ratio of men to women was 1:1.4-2.2, leaving very little doubt that women are more at risk for depression than men in old age (Luppa et al. 2012).

Differences by SES and race/ethnicity

For decades, there has been evidence that formal education is inversely related to depressive symptoms in late life (Mirowsky and Ross 1992). A recent systematic literature review found that low educational attainment was associated with higher depressive symptom burden in all seven of the studies that tested the association in older adults (Musliner et al., 2016). In late life, the relationship between education and psychological distress has been found to be mediated almost entirely by stress exposure (chronic stress, recent life events, and childhood adversities) and psychosocial resources (mastery and self-esteem) (Cairney and Krause 2005). Other factors that could link education to late-life depression include cognitive ability, economic resources, social status, social networks, and health behaviors (Lee 2011).

Similarly, social status and psychological stressors are unequally distributed between racial/ethnic groups in the United States, likely contributing to the higher rates of depression in Blacks and Hispanics compared to non-Hispanic Whites (Dunlop, Song, Lyons, Manheim, & Chang, 2003; Turner & William, 2003). While there is evidence that Black older adults have higher depressive symptoms than White adults (Assari et al. 2016), some studies find that Blacks have lower lifetime prevalence of major depressive episodes (Mezuk et al. 2013). Showing a similar paradox, Hispanics exhibit a pattern of high depressive symptoms despite lower rates of

major depression (Liang et al. 2011; Breslau et al. 2006). When considering racial/ethnic differences in how depressive symptoms change with age, Liang and colleagues found that, compared to White Americans, Black and Hispanic Americans were more likely to be in latent trajectories with elevated symptoms and less likely to be in stable (unchanging) trajectories (Liang et al. 2011). Little is known about the age-patterns of depression in older Native Americans, Asians, and other numerically small minority populations.

Current study

This study makes several contributions to our understanding of late-life depressive symptom trajectories across sociodemographic groups. First, we examined recent cohorts of Americans, updating prior analyses. Yang's 2007 paper, which used data from 1986 to 1996, found evidence of an age-by-cohort interaction, and called for future work with more waves of data, a broader age range, more birth cohorts, and larger datasets to examine non-linear age patterns in different groups (Yang 2007). Cohorts born after 1940 have worse disability compared to their predecessors (Seeman et al. 2010; Martin et al. 2010), potentially due in part to depression and other emotional problems (Martin 2014). Understanding the dynamics of depression in these recent cohorts compared to earlier cohorts is critical for understanding trends in affective functioning over time.

A second contribution of this paper is special attention to the measurement of depressive symptoms in old age. Some evidence demonstrates that adults ages 65 and older are less likely than young adults to endorse feelings of dysphoria (Gallo, Anthony, and Muthen 1994). There is also concern that gauging somatic symptoms of depression in older adults might capture physical aspects of aging or disease, rather than specifically measuring affective functioning (Mirowsky 1996). As sensitivity analyses, we separately examine two aspects of depressive symptoms based

on a factor analysis of this 8-item measure – depressed mood and somatic complaints (Wallace et al. 2000). In addition, we compare results of symptom count to those of a high-symptom cut-off. These measurement assessments improve the robustness and utility of our findings regarding the relationship between age, sociodemographic characteristics, and depressive symptoms.

Finally, prior analyses have often relied on latent class models (Musliner et al. 2016; Diegelmann, Schilling, and Wahl 2016; Kaup et al. 2016; Mirza et al. 2016; Liang et al. 2011). A review of these analyses concluded that female gender, minority race, and low socioeconomic status predict depression trajectories with high and increasing symptoms over the life course (Musliner et al. 2016). However, studies that identify latent trajectories and then associate factors with membership into a trajectory group cannot determine the shape of depression curves over age specifically within men versus women, different racial/ethnic groups, and different education levels. Our study visualizes changes in average depression symptoms within these key sociodemographic groups, which can inform policy by highlighting the dynamics of mental health needs in the growingly diverse elderly population.

Methods

Sample

Our data came from the Health and Retirement Study (HRS), an on-going nationally-representative longitudinal survey of U.S. men and women aged 51 and older who were not institutionalized at baseline (Sonnega et al. 2014). HRS data collection began in 1992 with individuals born between 1931 and 1941 and their spouses (Sonnega et al. 2014). Several other cohorts have since been added to the sample, and participants are interviewed every two years, even if they enter institutional settings (Sonnega et al. 2014). The study is conducted and distributed by the Institute for Social Research at the University of Michigan with funding from

the National Institute of Aging (grant number NIA U01AG009740) (Sonnega et al. 2014). We used the RAND dataset (Version P), which has been cleaned and compiled by Rand Corporation (RAND Center for the Study of Aging 2016).

Our observation window spanned from Wave 2 (1994)—the first wave with consistent depression questions—through Wave 12 (2014). We included 199,106 observations from 35,618 individuals who completed interviews between the ages of 51-90 at any time during the 1994-2004 period. After excluding 6,654 observations with zero weights and 14,449 observations missing data on depressive symptoms or sociodemographic variables, the analytic sample consisted of 178,003 observations from 33,280 individuals. Depressive symptoms were only asked of self-respondents, and so those too ill or cognitively impaired to respond without a proxy are not included (Wallace et al. 2000).

The six HRS birth cohorts included in our study were the Asset and Health Dynamics Among the Oldest Old (AHEAD) born 1890-1923, the Children of the Depression (CODA) born 1924-1930, the initial Health and Retirement Study (HRS) cohort born 1931-1941, the War Babies born 1942-1947, the Early Baby Boomers born 1948-1953, and the Mid Baby Boomers born 1954-1959.

Measures

Depressive symptoms were measured using the 8-item Center for Epidemiologic Studies Depression scale (CESD-8). Respondents were asked about whether they felt each of the following eight symptoms of depression "much of the week": felt depressed, everything was an effort, sleep was restless, was happy (reversed coded), felt lonely, felt sad, could not get going, and enjoyed life (reversed coded). The final depressive symptoms score was the number of symptoms that respondents reported feeling much of the week, ranging from zero to eight

symptoms. Respondents who did not answer three or more of the eight CESD items were considered missing on the total depressive symptoms score.

The CESD-8 is a commonly-used depression measure in older adults (Karim et al. 2015; Lewinsohn et al. 1997; Turvey, Wallace, and Herzog 1999). A longer form of the CESD has been validated against diagnostic interviews in adults ages 50 and older and showed internal consistency and test-retest reliability that was acceptable and consistent across gender and age groups (Lewinsohn et al. 1997). In 2015, the 8-item CESD was tested for psychometric properties in a large sample of older adults in Europe, and higher CESD-8 scores were significantly and inversely associated with life satisfaction, happiness, social trust, self-esteem, optimism, subjective health, autonomy, and social relationships (Karim et al. 2015). A psychometric evaluation of the CESD-8 in waves 2 and 3 of HRS identified two factors – depressed mood and somatic complains (Wallace et al. 2000).

To explore whether physical changes with age explain the rise in depressive symptoms, we grouped items into two subcategories based on prior psychometric work—"somatic complains" (everything was an effort, sleep was restless, and could not get going) and "depressed mood" (the remaining five feelings) (Mirowsky 1996; Wallace et al. 2000). Another measurement concern arises from the fact that the CESD was designed to gauge symptomology, rather than diagnose major depression (Karim et al. 2015). While some have dichotomized this measure at four symptoms to classify high depressive symptoms (Han 2002; Stevens et al. 2008), we examined mean symptom count using the full variability in symptoms to best understand changes in psychological well-being in late life. As a sensitivity analysis, we analyzed the probability of having four to eight symptoms compared to zero to three symptoms.

Our main independent variable was age, which was defined in years and ranged from 51 to 90. We created five-year wide age intervals—51-55, 56-60, 61-65, 66-70, 71-75, 76-80, 81-85, and 86-90. Using five-year groups allowed age to have a potentially non-linear relationship with depressive symptoms but did not force any certain shape onto the data or give differential influence to higher age values, as would occur with quadratic specifications. Another advantage of this strategy was that when examining potential differential effects of age by cohort, the age effect in each cohort was estimated using only those ages in which each cohort was observed. Mid Baby Boomers, for example, were only observed in their fifties.

Race and ethnicity were self-reported by respondents at baseline and grouped into four categories— non-Hispanic White, non-Hispanic Black, Hispanic, and non-Hispanic other. Education was operationalized as categories based on highest education level attained—less than high school degree, high school degree or GED, some college, and college or more. If a respondent has a high school degree or a GED and another degree less than a BA, such as an Associate's Degree, they were considered "some college". The final sociodemographic variable of interest in this analysis was birth cohort, with six groups defined as noted above.

Statistical analysis

We used mixed-effects negative binomial models to predict depressive symptoms based on age and sociodemographic covariates. This modeling strategy properly fit the count nature of the depressive symptoms outcome, which exhibited over-distribution in variation, while using a log link to adjust for the skewed distribution of depressive symptoms. Random intercepts accounted for the clustering of observations within respondents. To adjust for sampling, models were weighted at the observation and respondent level, sampling stratum were included in all

models, and standard errors were clustered by unique sampling error computing unit (Heeringa, West, and Berglund 2017). We exponentiated coefficients into incidence rate ratios.

Model 1 predicted depressive symptoms by age groups. In Model 2, we added all sociodemographic variables—gender, race/ethnicity, education, and birth cohort. We then implemented a series of models with age groups, all sociodemographic variables, and an interaction between age groups and one sociodemographic variable, leading to four interaction models (Models 3-6). Postestimation Wald tests evaluated the overall significance of interactions between age groups and sociodemographic variables. We plotted predicted depressive symptoms over age within each sociodemographic subgroup (i.e., men and women), holding other covariates at their mean.

For sensitivity analyses, we ran Model 2 separately predicting depressed mood and somatic complaints. We also ran the gender interaction model with these two outcomes to test whether gender differences in depression are due to ability or willingness to report certain types of symptoms. Models predicting somatic complaints could not converge and so this sensitivity analysis used unweighted population average models via generalized estimating equations with negative binomial families, log links, and exchangeable correlation structures. Finally, we ran all six models using mixed effect logistic regression predicting the binary outcome of four or more symptoms, then generating predicted probabilities of having high depressive symptoms. All analyses were conducted in Stata 15 (StataCorp 2017).

Results

Table 1 shows the unweighted distribution of sociodemographic characteristics and depressive symptoms at each respondent's first wave of observation. The mean age was 63.07 (SD=9.90) and 56% of the sample was female. Sixty-nine percent of the sample was non-

Hispanic White, 17% was non-Hispanic Black, 11% was Hispanic, and 3% was non-Hispanic other races/ethnicities. The majority of the sample had a high school degree or less education.

The distribution of depressive symptoms was right skewed, with many zeros and few people with high symptoms. Using unweighted baseline observations, 65% of respondents had at most one symptom and only 16% of the sample had four or more symptoms (high depressive symptoms). The mean depressive symptom count was 1.57 (SD=2.04) and the median was 1 symptom. Depressive symptoms over age formed a U-shaped curve; weighted mean symptoms decreased from 1.52 for those ages 51-55 to the low point of 1.29 at ages 66-70, and then increased through age 90 to a high point of 1.73 symptoms.

The incidence rate ratios from the unadjusted and adjusted models can be found in Table 2, with interaction results shown in Table 12 (Appendix). In Model 1, the rate of depressive symptoms was statistically significantly different in every age group compared to the reference group 51-55, with the exception of ages 71-75. There were decreasing depressive symptoms in ages 56-75 and increasing symptoms in ages 76-90. When adding the sociodemographic variables in Model 2, there was the same age pattern for rates of changing depressive symptoms, this time with significant decreases in ages 71-75. Women had higher rates of depressive symptoms compared to men, as did minority race/ethnicities compared to non-Hispanic whites, and low levels of education compared to those with at least college degrees. Compared to the AHEAD birth cohort, the HRS cohort had lower rates of depressive symptoms.

Variable	Ns or Means	Percentages or SDs
Age Groups		
51-55	12,545	37.70
56-60	6,648	19.98
61-65	2,940	8.83
66-70	2,555	7.68
71-75	4,650	13.97
76-80	2,044	6.14
81-85	1,346	4.04
86-90	552	1.66
Mean Age	63.07	9.90
Gender		
Male	14,544	43.70
Female	18,736	56.30
Race/Ethnicity		
NH White	22,987	69.07
NH Black	5,839	17.55
NH other	871	2.62
Hispanic	2,583	10.77
Education		
Less than HS degree	8,645	25.98
HS Grad/GED	11,167	33.55
Some college	7,253	21.79
College +	6,215	18.67
Birth Cohort		
AHEAD (1890-1923)	6,872	20.65
CODA (1924-1930)	3,764	11.31
HRS (1931-1941)	9,689	29.11
War Babies (1942-1947)	3,467	10.42
Early baby boomers (1948-1953)	4,616	13.87
Mid baby boomers (1954-1959)	4,872	14.64
Depressive Symptoms		
0	14,214	42.71
1	7,503	22.55
2	3,813	11.46
3	2,304	6.92
4	1,652	4.96
5	1,192	3.58
6	1,126	3.38
7	937	2.82
8	539	1.62
Dep. Symptoms 4+	5,446	16.36
Mean Dep. Symptoms	1.57	2.04

Table 1 Unweighted characteristics of sample at respondents' entry

Health and Retirement Study 1994-2014, N= 33,280. NH = Non-Hispanic; HS = High School; GED = General Education Development; AHEAD = Asset and Health Dynamics Among the Oldest Old; CODA= Children of the Depression; HRS = original Health and Retirement Study

Depressive Symptoms	Model 1	Model 2
Age Group		
51-55	1.00	1.00
56-60	0.971*	0.968*
61-65	0.911***	0.905***
66-70	0.904***	0.893***
71-75	0.964	0.934***
76-80	1.114***	1.066**
81-85	1.292***	1.220***
86-90	1.495***	1.396***
Gender		
Male		1.00
Female		1.272***
Race/Ethnicity		
NH White		1.00
NH Black		1.349***
NH Other		1.432***
Hispanic		1.267***
Education		
<HS		2.546***
GED/HS Grad		1.762***
Some College		1.428***
College+		1.00
Birth Cohort		
AHEAD (1890-1923)		1.00
CODA (1924-1930)		1.037
HRS (1931-1941)		0.929**
War Babies (1942-1947)		1.010
Early baby boomers (1948-1953)		1.068
Mid baby boomers (1954-1959)		1.077
var(cons[ID])	3.459***	2.984***

Table 2 Incidence rate ratios for increasing depressive symptoms

*Health and Retirement Study 1994-2014, N= 178,003 depressive symptom observations. NH = Non-Hispanic; HS = High School; GED = General Education Development; AHEAD = Asset and Health Dynamics Among the Oldest Old; CODA= Children of the Depression; HRS = original Health and Retirement Study; var(cons[ID])= Variance component corresponding to the random intercept; Interaction Models 3-6 in Table 12 (Appendix); *=p<0.05, **=p<0.01, ***=p<0.001*

The differences in age group effects by sociodemographic variables (Models 3-6) are depicted in Figure 2-1 as predicted depressive symptoms with all other covariates held at mean. Postestimation Wald tests revealed that interactions of age groups with each sociodemographic

characteristic were statistically significant at the p<.0001 level (Table 12 in Appendix). Starting with gender, women had consistently higher depressive symptoms, but men's faster increase at older ages led to a converging gender gap by ages 86-90.

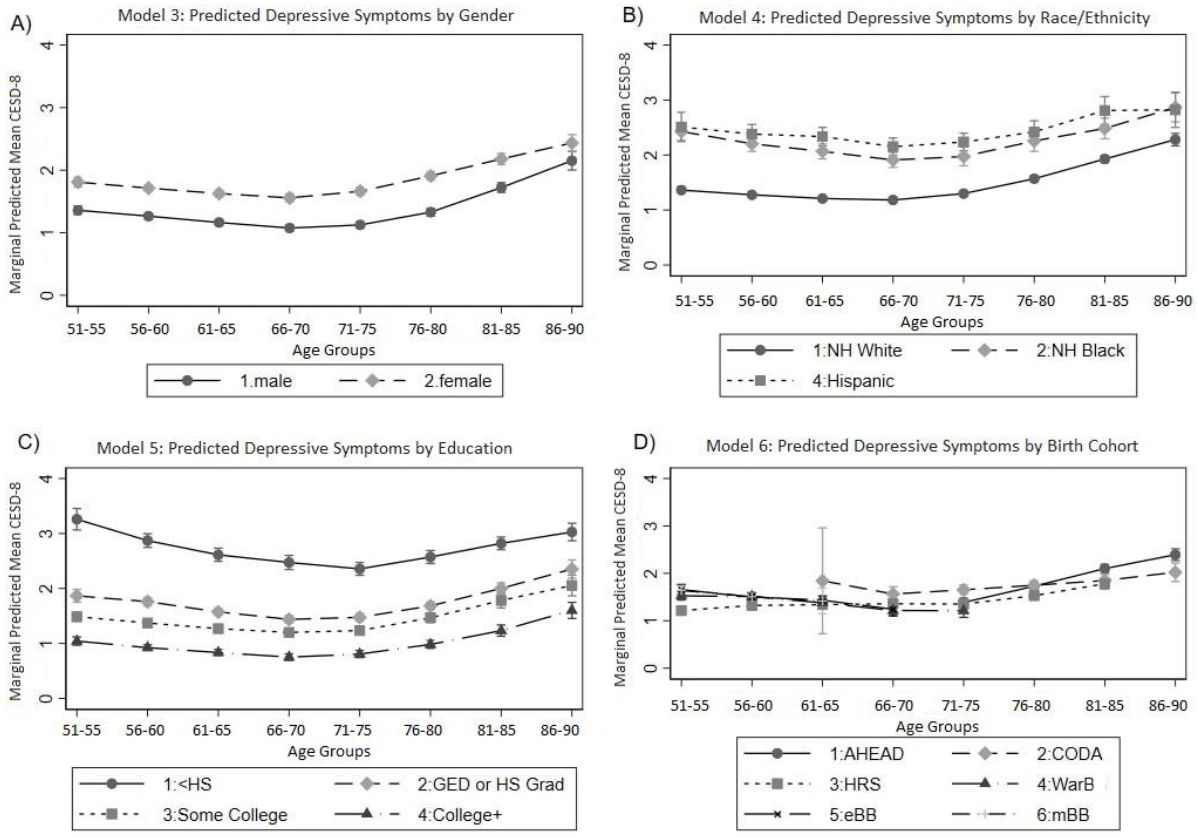

Figure 2-1 Adjusted predicted depressive symptoms and 95% confidence intervals from interactions between age groups and gender, race/ethnicity, education, and birth cohort

Health and Retirement Study 1994-2014, N= 178,003 depressive symptom observations. NH = Non-Hispanic; HS = High School; GED = General Education Development; AHEAD = Asset and Health Dynamics Among the Oldest Old; CODA= Children of the Depression; HRS = original Health and Retirement Study; WarB = War Babies; eBB = Early Baby Boomers; mBB= Mid Baby Boomers

Predicted symptoms by race/ethnicity show that Hispanic older adults had the highest depressive symptoms, followed by non-Hispanic Blacks, with White respondents having the lowest symptoms. Mean depressive symptoms for non-Hispanics of other races fell between non-Hispanic Blacks and non-Hispanic Whites, but with wide confidence intervals that made the

shape of the curve uninterpretable. Depressive symptoms increased significantly more quickly at higher ages for Whites than for Blacks or Hispanics, resulting in the smallest racial/ethnic disparity in the oldest age group, though White respondents remained significantly lower than the other two groups.

Education differences in depressive symptoms followed a clear inverse pattern, with the lowest education group showing the highest depressive symptoms throughout the age range and the highest education group showing the lowest symptoms throughout. Older adults with less than a high school degree had substantially higher depressive symptoms than those with a high school degree or GED, who hung more closely to the two higher education levels. In ages 51-55, the lowest education group had a mean predicted depressive score over two symptoms higher than the highest education group. This gap was reduced by about a third in ages 86-90, but groups remained significantly different. This converging trend was mostly due to a quicker drop in symptoms in ages 51-75 among those with the lowest educational attainment.

Age-by-cohort interactions included only those ages in which cohorts were observed. A color version of Figure 2-1D that more clearly differentiates cohort trajectories can be found in Figure A-1 (Appendix). AHEAD, the earliest cohort, was not sampled until their seventıes and showed monotonically increasing depressive symptoms over time. The next oldest cohort, CODA, was sampled starting in their sixties and showed an increase from ages 61 to 70, followed by a flat slope until another increase between ages 81 and 90. The original HRS cohort had the broadest age range and showed a slowly increasing slope ages 51-75, at which point depression symptoms increased faster to age 85. The more recent cohorts of War Babies, Early Baby Boomers, and Mid Baby Boomers showed decreasing depressive symptoms over age but have not yet reached ages at which depressive symptoms typically rise. A test of the age group

by cohort interactions in midlife (ages 51-65) showed significant differences in the age effect on depressive symptoms by cohort in this age range (chi-squared(7)=43.87, $p<0.001$), with more recent cohorts decreasing in symptoms when the HRS cohort trajectory was already rising. In addition, in ages 51-55, the original HRS cohort had significantly lower predicted depressive symptoms (1.24, 95% CI=1.16, 1.31) compared to more recent cohorts of War Babies (1.51, 95% CI=1.44, 1.59), Early Baby Boomers (1.59, 95% CI=1.50, 1.68) and Mid Baby Boomers (1.58, 95% CI=1.48, 1.66). Though substantively small, this difference remained significant through age 60.

Results from the sensitivity analyses are shown in Figure 2-2 and Figure A-2 (Appendix). The separate outcomes of depressed mood and somatic complaints showed similar U-shaped patterns, both rising at older ages to reach a mean around 1 by ages 86-90. Depressed mood fell a bit lower than somatic complaints at the minimum at ages 66-70. Interactions with gender showed that the gender gap is wider in symptoms of depressed mood compared to somatic complaints. Women's scores did not differ between the two outcomes, but men reported fewer symptoms of depressed mood than somatic complaints, especially in their sixties and seventies.

Looking at the probability of having 4-8 symptoms (Figure A-2 in Appendix), all four interactions look similar to the analysis of continuous symptom count. For example, those with less than high school educations had a 0.3 probability of high symptoms compared to 0.1 for those with college educations, rather than 3 and 1 predicted symptoms respectively. When looking at probability of high depressive symptoms, women's curves hit a low point at ages 66-70 and then started increasing, whereas men's lowest probability of high depressive symptoms was at ages 71-75. In addition, these models reveal statistically significant differences between Hispanics and non-Hispanic Blacks in ages 56-75.

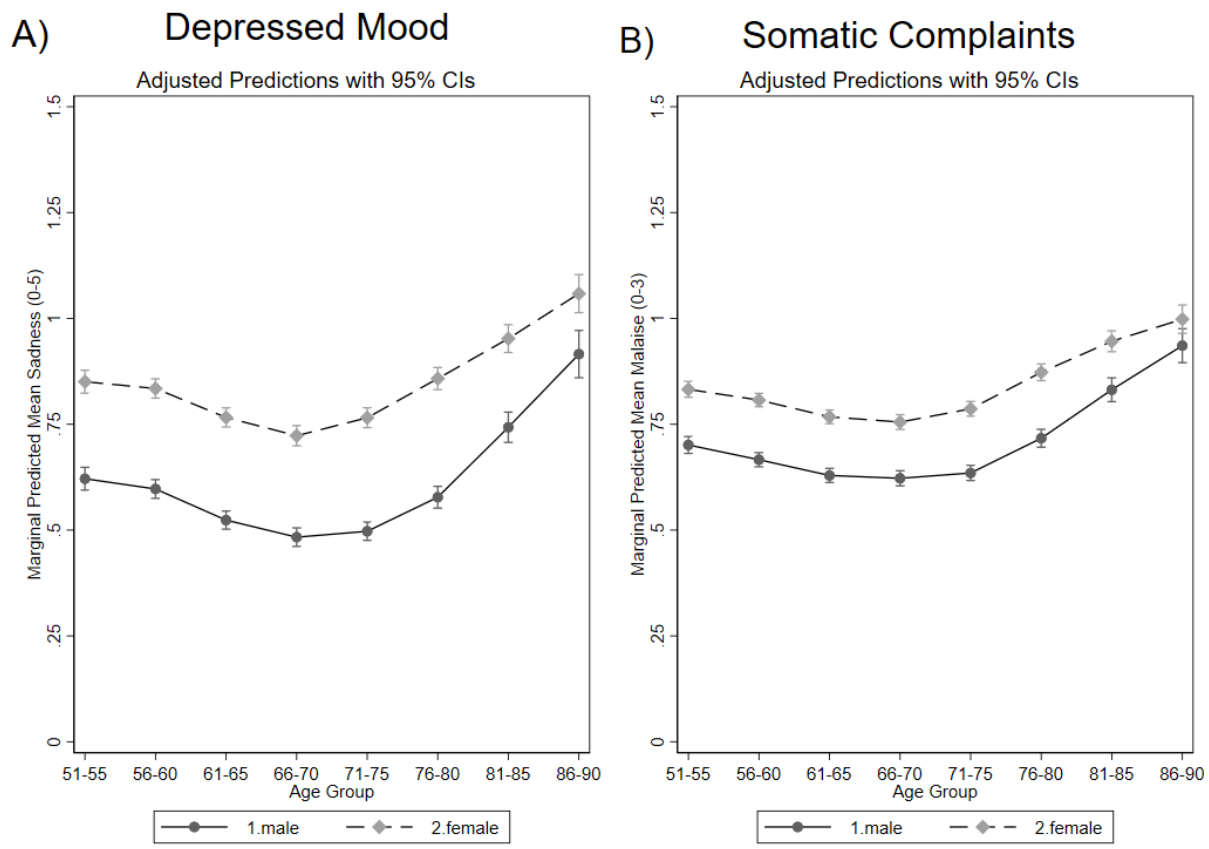

Figure 2-2 Adjusted predicted symptoms of depressed mood and somatic complaints from generalized estimating equations over age groups by gender

Health and Retirement Study 1994-2014. While the sadness models has all 178,003 observations, the malaise model has 177,444 observations due to item level missingness (295 missing on "could not get going", 187 missing on "everything was an effort", and 100 missing on "sleep was restless", with 23 missing on more than one of these items).

Discussion

Overall, our analysis revealed that gender, race/ethnicity, education, and birth cohort were associated with different levels of depressive symptoms in mid- and late life and different rates of change in symptoms during the aging process. Differences in depressive symptoms shrank in the oldest ages, in line with the "age as leveler" hypothesis that posits that group

differences converge in old age because universal health declines from aging overwhelm the disadvantage of low social status (Angel, Mudrazija, and Benson 2016).

Women had higher depressive symptoms, but men's symptoms rose faster in the oldest ages, shrinking the gender gap. Sensitivity analyses showed that the gender gap is larger when looking only at feelings of depressed mood rather than somatic complaints, revealing that gender differences may be partially due to men's ability or willingness to report feelings of depressed mood relative to somatic complaints. In both cases, the gender gap is smallest in the oldest age group. This result contrasts Mirowksy's finding that the gender gap increased with age (Mirowsky 1996).

Differences in depressive symptoms by race/ethnicity and by education level were also smallest in ages 86-90. Finding higher depressive symptoms in Black older adults than Whites is consistent with prior work (Assari et al. 2016), but contrasts findings that White adults have higher rates of diagnosable major depression disorder (Breslau et al. 2006; Mezuk et al. 2013). Hispanics also exhibit a pattern of high depressive symptoms, as seen in our results and some prior work (Liang et al. 2011), despite lower rates depression disorder (Breslau et al. 2006). High depressive symptoms in Hispanics supports the idea that lower mortality in this population is not necessarily accompanied by lower levels of disability or morbidity (Melvin et al. 2014). Given that Hispanic older adults are a rapidly growing population, it is important to understand patterns and causes of late-life depression in this group. Future work should collect data that enables testing differences by nativity and country of origin.

Of all sociodemographic comparisons, the most disadvantaged group in this study was those with less than a high school education, who averaged two depressive symptoms higher in ages 51-55 than those with a college degree or more. In addition, educational differences

remained into ages 86-90. Using the U.S. National Health Interview Survey, Case and Deaton (2017) reported an increase in mental distress in midlife between birth cohorts born from 1940 to 1988, specifically for non-Hispanic White adults without a bachelor's degree (Case and Deaton 2017). Our findings echo concerns about the health, and especially mental well-being, of the low educated adult population in the U.S.(Case and Deaton 2017). As educational attainment goes up over time, it is possible that not having a high school degree has worse implications for health than it has in the past (Olshansky et al. 2012).

Looking to cohorts, our results indicate that recent birth cohorts had slightly higher depressive symptoms in their fifties than did their predecessors, but with decreasing rather than increasing slopes. This finding suggests a small secular increase in depressive symptomology in midlife, with a shift in the low-point of the depressive symptom curve occurring at higher ages. Our findings show that Case and Deaton's trend in increasing midlife despair may hold in the overall population, not just for non-Hispanic Whites of low education. Future work can employ a life course perspective to test explanations of cohort differences in mid- and late-life depression, such as differential education quality in childhood, increased educational attainment over time, access to antidepressants, and experiences retiring in strong and weak economies.

Our findings of little-to-no cohort difference in symptom increases older ages contrast those reported by Tampubolon and Maharani (2017), who used HRS to find that post-war birth cohorts (born in 1946 or later) experienced inversed U-shaped curves over age (Tampubolon and Maharani 2017). As suggested by Blazer (2017), the trajectory reported by Tampubolon and Maharani may be an artifact of using a quadratic specification for age when cohorts have different observed age ranges (Blazer 2017). Our results, in contrast, were based on discrete age-categories that did not force any parametric shape on the age curves. In addition, while the

Tampubolon and Maharani study was restricted to White respondents, our analysis included all race/ethnic groups.

These results should be considered in light of the study's limitations. Our data cannot distinguish between the force of age leveling out sociodemographic differences versus the effects of selective mortality. Higher mortality at younger ages in disadvantaged groups may result in converging trajectories because respondents with high symptoms in these groups are not observed in older ages (Dupre 2007). In addition, as mentioned, the CESD does not measure diagnoses, and thus our results do not translate to depression prevalence. In addition, HRS data did not allow for comparisons of birth cohorts across the full age range, as the entry age differed between cohorts and some have not yet reached the highest ages of interest. The AHEAD cohort was recruited at age 70, and so HRS criteria of being non-institutionalized at baseline likely resulted in a more selective AHEAD sample than other cohorts that fulfilled this criteria at age 50 or 60. Further, our statistical approach modeled average depressive symptoms within subgroups and did not examine within-group heterogeneity. However, characterizing the shape of average depression trajectories in sociodemographic subgroups is important to understanding population dynamics in mental health, with implications for caregiving needs, health care utilization, disability, and disease outcomes.

A strength of this study was the sensitivity analyses, which considered the effect of how depressive symptoms are measured and operationalized. The first analysis demonstrated that increases in depressive symptoms at old ages is not primarily driven by somatic complaints. In addition, dropping individual CESD-8 items due to concern that they misrepresent depression in old age will affect the size of the gender gap in depression. While depressive symptomology is useful for characterizing the mental well-being of populations, diagnosis is important to

accessing mental health services. Our second sensitivity using a dichotomized variable for high depressive showed overall similar U-shaped patterns over age. However, important changes over age likely occur within the categories of low and high depressive symptoms, making symptom count a more informative outcome. It would be useful for future work to directly compare depressive symptomology and major depressive diagnosis over age in sociodemographic subgroups of older adults.

In conclusion, this study depicted growth curves of depressive symptoms in mid- and late life by major sociodemographic groups in the United States. Education level was the largest disparity and more recent birth cohorts revealed trends of higher depressive symptoms in midlife. As the population ages and the older population becomes increasingly diverse, understanding trends and disparities in depression is essential to ensuring the well-being of older adults now and in the future.

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Chapter 3 **Expectations and Realizations About Work at Age 62 Among Recent Cohorts of Americans**

Introduction

Retirement is a key life transition that is often planned and expected for decades before its arrival. The timing of retirement is important to individuals, families, employers, and government programs (Fisher, Chaffee, and Sonnega 2016). Some prior research suggests that wealth losses and unemployment resulting from the 2008 Great Recession impacted retirement timing for older Americans (McFall et al. 2011; Goda, Shoven, and Slavov 2011; Szinovacz, Martin, and Davey 2014). However, little is known about retirement expectations and their alignment with realized retirement timing across diverse sociodemographic groups of Americans in recent cohorts. The Health and Retirement Study presents a unique opportunity to examine retirement expectations and realities around the Great Recession, and to compare gender, race/ethnicity, education, and birth cohort differences in expected and realized retirement timing in the past two decades.

Trends in retirement timing

In 1910, the average age of retirement for men was 73 years old (Quinn, Cahill, and Giandrea 2011), as Americans spent most of their lives working to avoid poverty. Then, for several decades, retirement age gradually declined due to increased safety nets protecting against poverty in old age and more wealth for individual savings. The Social Security Act of 1935 provided insurance against poverty in old age, as did the rising number of private pensions

(Cahill, Giandrea, and Quinn 2015). Such policies and programs encouraged early retirement to make way for the influx of workers brought by the baby boomer cohort entering the labor force around the 1970s (Cahill, Giandrea, and Quinn 2015). When retirement age reached is lowest point in the 1990s, half of men retired by age 62 and many Americans could expect around two decades of life in retirement (Cahill, Giandrea, and Quinn 2015).

Then, starting in the 1990s, the pattern began to reverse, with retirement gradually occurring at later ages. This trend of prolonging work in late life was partially due to improved health at older ages while occupations became less physically strenuous (Quinn, Cahill, and Giandrea 2011). Public policies again played an important role. Anticipating baby boomers approaching retirement age and a shortage of younger cohorts to support pension and health insurance programs, policies began incentivizing later retirement (Fisher, Chaffee, and Sonnega 2016). Such policies included the elimination of mandatory retirement age and laws protecting workers from age discrimination (Fisher, Chaffee, and Sonnega 2016). Also incentivizing later retirement, Social Security gradually raised the normal age of retirement for full benefit eligibility from 65 to 67 years of age (Fisher, Chaffee, and Sonnega 2016). For people born before 1938, normal retirement age is 65. This eligibility age is pushed up two months for each birth year among those born between 1938 and 1942. The normal retirement age is 66 for Americans born between 1943 and 1954, with similar two month increases for each subsequent birth years from 1955 to 1959. For those born in or after 1960, the normal retirement age is 67 years old (Choi and Schoeni 2017). In addition to pushing back normal retirement age, the delayed retirement credit (increases in benefits from postponing receipt beyond the normal retirement age) gradually increased from 3% to 8% between 1983 and 2008 (Cahill, Giandrea, and Quinn 2015).

At the same time, employee benefit packages were changing in ways that incentivized longer work. Fewer employers offered retirement health insurance (Fronstin and Adams 2012), increasing the importance of Medicare eligibility (age 65) for retirement timing (Coe, Khan, and Rutledge 2013). Pensions switched from defined benefit, which de-incentivized work after reaching the earliest age of eligibility, to defined contribution, which used tax-deferred savings accounts that no longer incentivized earlier retirement (Munnell 2006). Finally, Americans began working longer because they had on average fewer savings than in the past and defined contribution pensions placed the financial market risks of those savings on individuals rather than employers (Cahill, Giandrea, and Quinn 2015; Wolff 2004). Indeed, baby boomers plan to work longer than previous cohorts given differences in policies, pensions, educational attainment, health, and wealth over time (Mermin, Johnson, & Murphy, 2007).

Impact of the Great Recession

The financial risks of retirement savings became highly relevant during the Great Recession. Several studies that examined the effects of the Recession on retirement timing found that wealth losses were associated with modestly higher expected retirement age (Hurd and Rohwedder 2010; McFall et al. 2011), lower probabilities of retirement (Ondrich and Falevich 2016), and increased reported probabilities of working at age 62 (Goda, Shoven, and Slavov 2011). At the same time, the Recession also resulted in increased and prolonged unemployment, which pushed some into earlier retirement (Gorodnichenko, Song, and Stolyarov 2013). One study showed that the Recession first increased labor force participation in 2007-2009 for men ages 62 to 64 in response to wealth loss and then decreased labor force participation for these men in 2009-2011 because of unemployment induced early retirement (Johnson 2012).

It is worth noting that effects of the Great Recession on wealth loss, delayed retirement, and unemployment were modest (Goda, Shoven, and Slavov 2011; McFall et al. 2011; Szinovacz, Martin, and Davey 2014). McCall et al. (2011) found that wealth losses were associated with an average of 2.5 months of longer work, and Szinovacz et al. (2014) observed that the largest differences in work probabilities due to unemployment were less than 13%. In addition to changes in retirement timing, Americans who were retirement age during the Recession adjusted other economic behaviors like reducing consumption and giving smaller inheritance gifts (Hurd and Rohwedder 2010).

Importantly, the Recession was experienced differently depending on socioeconomic status (Szinovacz, Martin, and Davey 2014). When considering a change in planned retirement timing, Americans of high socioeconomic status were responding to changes in wealth, while those of low and middle socioeconomic status were responding to employment insecurity (Szinovacz, Martin, and Davey 2014). One study found that, while married men experienced 14-17% lower probability of retiring when they lost housing wealth during the Great Recession, this effect was offset in households that had pensions (Ondrich and Falevich 2016) – typically households with high socioeconomic status. However, much remains unknown regarding how the Recession differentially shaped retirement expectations and timing in specific sociodemographic groups.

Variation in retirement timing

Despite the historical trends in average retirement age, there remains much individual variation in retirement form and timing. Fisher et al.'s (2016) model of retirement timing based on a thorough review of the literature includes family-related antecedents to retirement such as marital status and caregiving responsibilities, work-related antecedents such as job

characteristics and workplace retirement norms, and individual antecedents such as health, income, wealth, and personal preferences (Fisher, Chaffee, and Sonnega 2016). Given the great social and economic disparities in United States, these antecedents are not uniformly distributed across the population of retirement-age adults. Therefore, while later retirement is generally seen as economically beneficial for individuals, employers, and society (Cahill, Giandrea, and Quinn 2015), it is not equally obtainable across different sociodemographic groups.

For example, Black Americans tend to retire earlier than White Americans due to poor health, unstable employment histories, and experiences of workplace discrimination (Burr et al. 1996; McNamara and Williamson 2004). An individual's educational attainment also affects retirement timing, as high education can lead to longer work life due to favorable job conditions and higher incomes that incentivize work at later ages. The exception to this pattern is those with high education who also have high wealth and thus can afford to retire earlier (Fisher, Chaffee, and Sonnega 2016).

Gender differences in retirement timing depend on time period, family context, and economic status. Some studies show that women are less likely to retire early compared to men due to lower financial status (Shacklock, Brunetto, and Nelson 2009). However, women retire at younger ages than men with the same income, perhaps because women are more often the household's secondary earner (De Preter, Van Looy, and Mortelmans 2015; Evers, De Mooij, and Van Vuuren 2008; Fisher, Chaffee, and Sonnega 2016). Earlier retirement among married women could also be driven by gender differences in age at marriage, education, employment histories, and functional status (Griffin, Loh, and Hesketh 2012). In addition, among healthy unmarried men and women, there is some evidence to suggest that women value retirement more than men (Møller Danø, Ejrnæs, and Husted 2005).

Expectations about retirement timing

Subjective retirement timing is a commonly used construct in research to understand how individuals are planning for retirement and how certain factors influence retirement timing (Fisher, Chaffee, and Sonnega 2016). It has generally been understood that expectations about retirement timing vary according to the same factors that shape actual retirement (Coile and Gruber 2002). While these factors influencing expectations about retirement are relatively well-established, the accuracy with which expectations predict actual labor force status has received increasing research attention.

Unmet expectations about retirement could have adverse consequences for happiness, wealth, and health in old age. Indeed, the life-course framework emphasizes the importance of the timing of role entries and exits and whether timing aligns with socially prescribed norms (Quick and Moen 1998; George 1993). One study using data from before the Great Recession found that working longer than expected and retiring earlier than expected were both associated with significant increases in depressive symptoms (Falba, Gallo, and Sindelar 2008). Further, a more recent study found that life satisfaction was lower for men with unmet expectations for retirement by age 62 (Clarke, Marshall, and Weir 2012). Given these consequences, it is important to understand the probability of facing unmet expectations about retirement timing in current cohorts of middle aged and older adults in the United States.

Certain sociodemographic groups may be at increased risk of experiencing unmet expectations about retirement. For example, despite expectations for long work lives, baby boomers may be facing more challenges in retiring when planned compared to older cohorts, because baby boomers experienced the Great Recession when nearing retirement age. In addition, there is evidence to suggest that women have to exit the labor force early to fulfill

caregiving responsibilities more often than do men (Dentinger and Clarkberg 2002). Also indicating increased risk for unmet expectations, prior research shows that Black Americans may have less agency over retirement timing given comparatively less stable employment, lack of pensions, poorer health, and employment discrimination (Burr et al. 1996; McNamara and Williamson 2004). Much remains to be learned about how the dynamics of the Great Recession, coupled with the aging baby boomers, have shaped changes in retirement expectations and their alignment with realized labor for status across diverse subgroups of aging Americans.

This study

This study used nationally-representative longitudinal data from 1992 to 2016 to answer the research question – What are the retirement timing expectations and behaviors of recent cohorts of older adults in the United States and how do they differ between sociodemographic groups? Therefore, the first objective of this study was to examine expectations about working full time at age 62 by gender, race/ethnicity, educational attainment, and birth cohort. Our next research question was – How do retirement timing expectations align with behaviors, and are there more unmet expectations in certain sociodemographic groups? The second objective was therefore to test group differences in the association between expectations and realized labor force status at 62. We then compared the probability of unexpectedly working and unexpectedly not working by gender, race/ethnicity, educational attainment, and birth cohort. By comparing birth cohorts, who reached age 62 in different time periods, we examine whether unmet expectations about retirement changed around the Great Recession. We hypothesize that disadvantaged groups will experience higher rates of unmet expectations about work at age 62.

Methods

Data and sample

Data for this analysis came from the Health and Retirement Study (HRS), the longest-running nationally-representative longitudinal survey of older adults (ages 51+) in the United States (Sonnega et al. 2014). HRS data collection began in 1992 with individuals born between 1931 and 1941 and their spouses; several other cohorts have since been added to the sample (Sonnega et al. 2014). While participants must be non-institutionalized at baseline, they are eligible for biennial follow up interviews even if they enter institutional settings (Sonnega et al. 2014). The HRS is conducted and distributed by the Institute for Social Research at the University of Michigan and is funded by National Institute of Aging (grant number NIA U01AG009740) (Sonnega et al. 2014). We used the RAND dataset (Version 1), which has been cleaned and compiled by Rand Corporation (Bugliari et al. 2019).

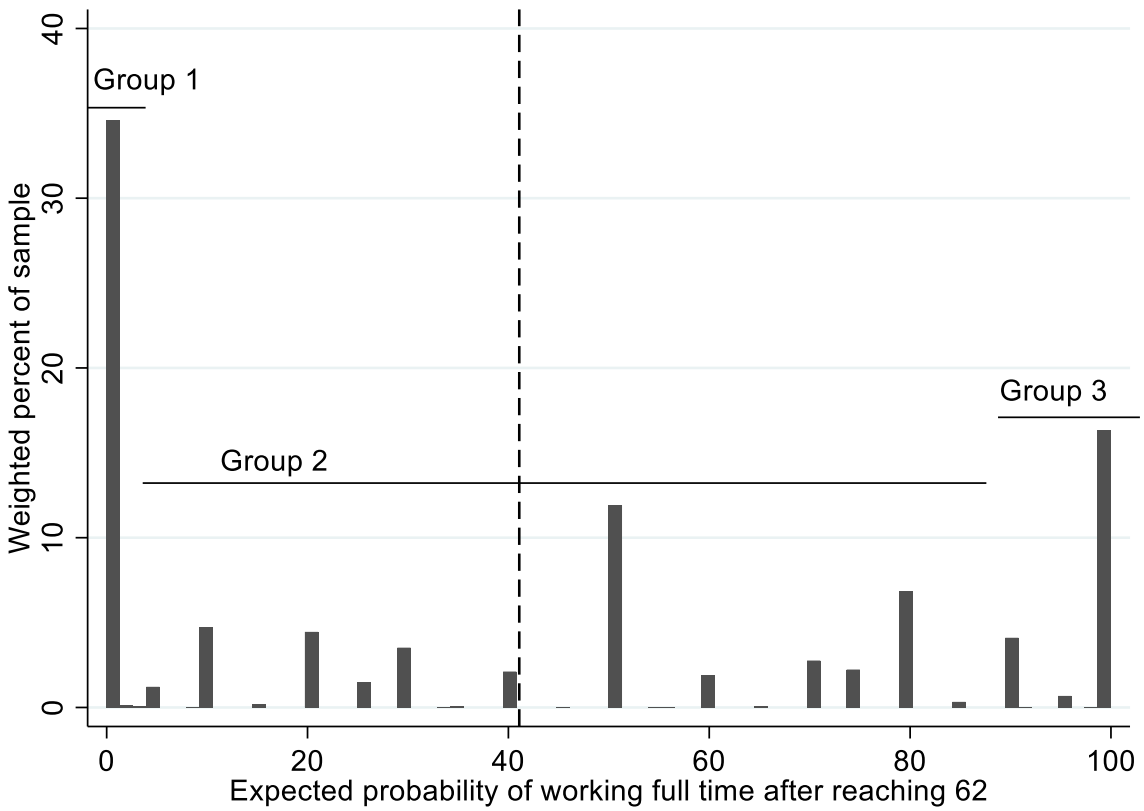
Our observation window spanned from Wave 1 (1992) through Wave 13 (2016), encompassing 40,521 individuals over age 50. To be eligible for our sample, respondents needed to have reported expected probability of working full time at age 62 when they were between ages 51-61 and reported actual labor force status in the first wave after reaching age 62. Expectations were only asked of self-respondents, so those too ill or cognitively impaired to respond without a proxy were not included in this study (Wallace et al. 2000). Applying these criteria, we excluded 13,972 respondents who had no interview between ages 51-61 and 4,017 respondents missing expected probability of working at age 62 (because they were not working full time between ages 51-61, responded via a proxy, had low numeracy, or refused to respond). We then excluded 9,354 respondents who had no interview after reaching age 62 and thus did not have the labor force status outcome. An additional 215 were people missing labor force

status at the first wave after reaching age 62 and 829 respondents were excluded because their labor force status was part-time work, which obscures the distinction between working and retiring. Dropping 7 respondents missing on sociodemographic covariates and 78 respondents with zero weights brought the final analytic sample to a total of 12,049 people (see Figure A-3 in Appendix).

Measures

We used respondent's first reported probability of working full time after reaching age 62, which ranged from 0 to 100. We grouped expected probabilities into three groups (Figure 3-1). Almost 35% of the sample made up group 1 ("no chance"), who reported exactly a zero expected probability of working full time at age 62. Group 2 ("unsure") encompassed the 44% of the sample and reported expected probabilities of work ranging from 1 to 85. About 21% of the sample fell into group 3 ("very likely"), reporting 90-100 expected probability of working full time at age 62.

We compared these expectations against actual labor status at the first wave after reaching age 62. Respondents were coded as either working full time or not working full time (retired, unemployed, disabled, or not in the labor force). Among group 1 who expected no chance of working full time at age 62, working full represents unmet expectations; among group 3 who thought it was very likely they would be working full time at age 62, not working represents unmet expectations.



Group	Group one	Group two	Group three
Expected prob.	0	1-85	90-100
Name	"No Chance"	"Unsure"	"Very likely"
Unweighted count	4,458	5,145	2,446
Weighted percent	34.44	44.38	21.19

Figure 3-1 Distribution of expected probabilities of working full time at age 62 (mean=41.08)

Age in years (centered at 51) was based on the baseline wave when respondents reported expected probabilities. Race and ethnicity were also self-reported at baseline and grouped into four categories— non-Hispanic White, non-Hispanic Black, Hispanic, and non-Hispanic other. Respondents' highest level of education was categorized as having less than a high school

degree, a high school degree or GED, some college or an Associate's degree, and a college degree or higher.

The final sociodemographic variable of interest in this analysis was birth cohort. Baby boomers (made up by HRS's Early Baby Boomer cohort) were born between 1948 and 1953. Pre-baby boomers (made up by HRS's Children of the Depression, HRS Original Cohort, and War Babies) were born between 1924 and 1947. Though numerically uneven, the cohorts were dichotomized this way to capture those who reached retirement age around the Great Recession (baby boomers) compared to those who reached retirement age before this economic downturn. Baby boomers in our sample reported their expectations about work on average in 2004 (interquartile range 2004 to 2005) and reported their labor force status at age 62 on average in 2012 (interquartile range 2012 to 2014). Therefore, for most baby boomers in this sample, the Great Recession occurred after they reported their expectations but before their realized retirement timing. The pre-baby boomer cohort on average reported their expectations in 1995 (interquartile range 1992 to 1998) and reported their labor force status at age 62 in 2002 (interquartile range 2000 to 2008).

Statistical analysis

For the first objective of this study, we examined the weighted and unweighted distribution of the sociodemographic covariates in our sample. We then examined expected probabilities of working at 62 and labor force status at 62 within each sociodemographic group. Adjusted Wald tests calculated the differences in the mean expected probability of working full time at age 62 by gender, race/ethnicity, educational attainment, and birth cohort. In addition, we calculated cross-tabulations of these sociodemographic factors and the three expected probability groups.

For objective two, we ran a series of six logit regression models to test the association between expectations and realized labor force status. The first of these models (Model A) predicted working full time at age 62 by the three expected probability groups while adjusting for gender, race/ethnicity, education, birth cohort, and age when reported expectation. To test if expectations were equally associated with realized labor force status across sociodemographic groups, we ran five more models (Models B-E) that each interacted the expected probability groups with a sociodemographic covariate (see equation 1). As a robustness check, we re-ran these logit models with an additional control of socioeconomic status – total wealth (assets minus debts, per $10,000) at the time of reported expectations.

For the third objective, we calculated the marginal predicted probabilities of unmet expectations for each sociodemographic subgroup based on the interaction models. For Group 1 (0 expected probability), we calculated the predicted probability of working full time and for Group 3 (90-100 expected probability), we took the inverse of the predicted probability of working full time to capture the probability of not working. In both cases, all other covariates were held constant at their distribution in the sample, which approximately represents the U.S. population of adults over age 50.

Equation 1. Logit models of work full time at ages 62

$$Logit(Probability\ of\ working\ full\ time\ at\ 62) = \beta_0 + \beta_1(Age\ at\ expectation) + \beta_2(Female) + \beta_3(Baby\ boomer) + \beta_4(non\text{-}Hispanic\ Black) + \beta_5(Hispanic) + \beta_6(non\text{-}Hispanic\ other\ race/ethnicity) + \beta_7(High\ school\ graduate) + \beta_8(Some\ College) + \beta_9(College\ or\ more) + \beta_{10}(Group\ 2\ \text{“}Unsure\text{”}\ work\ at\ 62) + \beta_{11}(Group\ 3\ \text{“}Very\ Likely\text{”}\ work\ at\ 62) + \boldsymbol{\beta_{12\text{-}k}(Group\ 2\ \text{“}Unsure\text{”}\ *\ Sociodemographic\ factor)} + \boldsymbol{\beta_{12\text{-}k}(Group\ 3\ \text{“}Very\ Likely\text{”}\ *\ Sociodemographic\ factor)} + \varepsilon_{ti}$$

As a robustness check, we tested whether results were sensitive to the thresholds used for creating expectation groups. We re-ran the complete analysis with two alternative groupings – terciles (0, 1-60, 62-100) and ten probability points in the high and low expectation groups (0-10, 15-85, 90-100).

All statistical analyses were conducted in Stata 15 (StataCorp 2017). To yield unbiased estimates and adjust for complex sampling, all analyses took into account clusters and stratification and weighted respondents based on their outcome wave (when labor force status was measured after respondents reached at 62) (Stata's *svy* commands). The HRS respondents that met our inclusion criteria were treated as a non-fixed subpopulation using Stata's *svy, subpop* command (Aneshensel 2013).

Results

Sample

Our final sample consisted of 12,049 individuals who on average reported their expectations at age 54.74 (SD=4.02). As can be seen in Table 3, about 51% was female, 80% was non-Hispanic White, and 50% had a high school level education or less. About 23% of the weighted sample was from the baby boomer birth cohort (born between 1948 and 1953), while the remaining 77% of the sample were pre-baby boomers (born between 1930 and 1947).

Variable	Category	Unweighted count	Weighted % of sample
Gender	Male	5,486	49.41
	Female	6,563	50.59
Race/ ethnicity	NH White	8,291	79.88
	NH Black	2,202	10.29
	NH Other	286	2.68
	Hispanic	1,270	7.15
Educational Attainment	Less than HS	2,550	16.16
	HS or GED	4,226	34.01
	Some College	2,738	23.92
	College +	2,535	25.91
Birth cohort	Pre-baby boomer (1924-1947)	9,380	77.09
	Baby boomer (1948-1953)	2,669	22.91

Table 3 Sample characteristics

N=12,049. NH=Non-Hispanic; HS=High School; GED= General Educational Development

Expectations about full-time work at age 62

The weighted mean expected probability of working full time at age 62 (ranging 0-100) was 41.08 (SD=53.19). The distribution of expectations had notable grouping at 0, 50, and 100 (Figure 1). As mentioned, we grouped respondents by expectations as follows: group 1 ("No chance," 0 probability, 34.44% of sample), group 2 ("Unsure," 1-85 probability, 44.38% of sample), and group 3 ("Very likely," 90-100 probability, 21.19% of sample).

As shown in Table 4, the mean expected probability of working full time at age 62 was significantly higher for men than women (48.19 vs. 34.14, $p<0.0001$). More women thought there was no chance they would be working at age 62 (41.39% vs. 27.32%) and more men thought it was very likely they would be working at 62 (26.53% vs. 15.97%). There were also significant differences in expectations by race/ethnicity ($F(3,54)=26.63$, $p<0.0001$), with the

highest mean expected probability of working full time at age 62 found in non-Hispanic White respondents (42.67) and the lowest expectations found in non-Hispanic Black respondents (31.16). Of all race/ethnicity groups, Black respondents had the highest percentage who thought there was no chance they would be working full time at age 62 (46.27%) and the lowest percentage who thought it was very likely they would be working at age 62 (14.56%). The mean expected probability of working full time at age 62 increased with education ($F(3,54)=96.31$, $p<0.0001$), as did the percentage of respondents who thought it was very likely they would be working at age 62.

Baby boomers had significantly higher mean expected probabilities of working full time at age 62 (44.73) compared to pre-baby boomers (39.99) ($F(1,56)=9.22$, $p=0.0036$). This trend remained consistent and significant when controlling for age when expectations were reported ($p=0.006$). Interestingly, increasing age at expectation (ranging 51-61 years old) was associated with significantly lower expectations of working full time at age 62 ($p<0.001$). Cross-tabulations revealed that, compared to earlier cohorts, a higher percentage of baby boomers were unsure (1-85 probability) about whether they would be working at age 62 (54.16 vs. 41.47). Percentages reporting zero probabilities of working at age 62 and 90-100 probabilities were both lower for baby boomers compared to pre-baby boomers (see Table 4).

Sociodemographic subgroup	Expected prob. of working FT at 62	% "no chance" working FT at 62 (0 prob.)	% "very likely" working FT at 62 (90-100 prob.)	% working FT at 62
Complete sample	41.08	34.44	21.19	33.36
Male	48.19	27.32	26.53	39.94
Female	34.14 F(1,56)= 188.70***	41.39	15.97	26.94 F(1, 56) = 151.53***
NH White	42.67	32.28	22.24	34.19
NH Black	31.16	46.27	14.56	27.42
NH Other	39.29	34.74	19.57	36.87
Hispanic	38.20 F(3,54)= 26.63***	41.38	19.61	31.38 F(3,54)= 8.00**
Less than HS	30.08	51.63	15.45	20.65
HS or GED	37.29	39.44	18.60	29.53
Some College	44.12	29.63	22.75	34.39
College or more	50.10 F(3,54)= 96.31***	21.59	26.72	45.39 F(3,54)= 116.95***
Pre-baby boomer (1924-1947)	39.99	37.03	21.50	31.41
Baby boomer (1948-1953)	44.73 F(1, 56)= 9.22*	25.72	20.12	39.93 F(1,56)= 31.65***

Table 4 Expectations about working full time at age 62 and labor force status at age 62 across sociodemographic groups

FT=Full time; NH=Non-Hispanic; HS=High School; GED= General Educational Development

Probability of working full time after reaching age 62

Table 4 also shows actual retirement timing – the percentage in each sociodemographic subgroup that was working full time after reaching age 62. As might be expected, a significantly higher percentage of men were working full time at this age compared to women (39.94% vs. 26.94%, $F(1,56)=151.53$, $p<0.0001$). White adults were more likely to be working than Black adults at age 62 (34.19% vs. 27.42%, $F(1,56)=19.75$, $p<0.0001$), but White respondents were not significantly different from Hispanic respondents (34.19% vs. 31.37%, $F(1,56)=1.95$, $p=0.1676$) or those of other races/ethnicities (34.19% vs. 36.87%, $F(1,56)=0.40$, $p=0.5275$). The likelihood

of working at age 62 differed dramatically by education ($F(3,54)=116.95$, $p<0.0001$). Only 20.65% of those without high school degrees were working full time at age 62 compared to 45.38% of those with college degrees. Finally, baby boomers were more likely to work full time at age 62 compared to previous cohorts (39.93% vs. 31.41%, $F(1,56)=31.65$, $p<0.0001$).

Comparing working expectations with reality

We next ran logit models to compared expectations with actual labor force status at age 62 (see Table 5). In Model A, which was adjusted for gender, race/ethnicity, education, birth cohort, and age at expectation, expected probability groups were highly associated with actual labor force participation (OR=5.06 and 11.18 for groups 2 and 3 versus 1, $p<0.0001$). In other words, those who thought it was very likely that they would be working full time had 11 times higher odds (95% CI: 9.55, 13.10) of actually working full time at 62 compared to those who thought there was no chance.

With the same sociodemographic adjustments, we then estimated models that included interactions to find that expectations of working full time at age 62 were less consistent with actual labor force participation for minority race/ethnicities compared to White respondents (Model C interaction $F(6,51)=2.39$, $p=0.0411$), especially Black and Hispanic respondents (interaction $F(4,53)=3.30$, $p=0.0173$). In addition, expectations for labor force participation at age 62 were less likely to be realized for low compared to high education groups (Model D interaction $F(6,51)=2.49$, $p=0.0347$), for earlier cohorts compared to baby boomers (Model E interaction $F(2,55)=5.44$, $p=0.0070$), and for those younger at expectations (Model F interaction $F(2,55)=9.47$, $p=0.0003$). There were no significant gender differences in the relationship between expectations and realized labor force participation (Model B interaction $F(2,55)=0.31$,

p=0.7334). These findings did not substantively change when adjusting for total wealth at time of reported expectations.

	Model A: No interactions		Model B: Gender interaction		Model C: Race/ethnicity interaction	
	OR	95% CI	OR	95% CI	OR	95% CI
No chance (0 prob.)	1	(1,1)	1	(1,1)	1	(1,1)
Unsure (1-85)	5.06***	(4.37,5.86)	5.41***	(4.24,6.90)	5.28***	(4.35,6.39)
Very likely (90-100)	11.19***	(9.55,13.10)	11.43***	(9.10,14.36)	12.58***	(10.36,15.28)
Male	1	(1,1)	1	(1,1)	1	(1,1)
Female	0.71***	(0.64,0.78)	0.76*	(0.60,0.97)	0.71***	(0.64,0.78)
NH White	1	(1,1)	1	(1,1)	1	(1,1)
NH Black	1.08	(0.92,1.27)	1.08	(0.92,1.27)	1.52*	(1.04,2.22)
NH Other	1.20	(0.82,1.74)	1.20	(0.83,1.74)	0.76	(0.33,1.75)
Hispanic	1.25	(0.99,1.59)	1.25	(0.98,1.59)	1.53	(0.95,2.47)
Less than HS	0.46***	(0.40,0.54)	0.46***	(0.40,0.54)	0.46***	(0.39,0.53)
GED or HS	0.67***	(0.58,0.78)	0.67***	(0.58,0.78)	0.67***	(0.58,0.78)
Some college	0.71***	(0.60,0.83)	0.71***	(0.60,0.83)	0.71***	(0.60,0.83)
College or more	1	(1,1)	1	(1,1)	1	(1,1)
Pre-baby boomers	1	(1,1)	1	(1,1)	1	(1,1)
Baby boomers	1.22**	(1.08,1.37)	1.22**	(1.08,1.38)	1.21**	(1.07,1.37)
Age at expectation (centered at 51)	0.99	(0.97,1.00)	0.99	(0.97,1.00)	0.99	(0.97,1.00)
Unsure *Female			0.88	(0.62,1.25)		
Very likely *Female			0.98	(0.75,1.27)		
Unsure *NH Black					0.71	(0.42,1.19)
Unsure *NH Other					1.99	(0.65,6.07)
Unsure *Hispanic					0.93	(0.49,1.79)
Very likely *NH Black					0.48**	(0.31,0.77)
Very likely *NH Other					1.24	(0.45,3.42)
Very likely *Hispanic					0.55*	(0.33,0.94)

	Model D: Education interaction		Model E: Cohort interaction		Model F: Age interaction	
	OR	95% CI	OR	95% CI	OR	95% CI
No chance (0 prob.)	1	(1,1)	1	(1,1)	1	(1,1)
Unsure (1-85)	5.11***	(3.72,7.03)	4.59***	(3.91,5.40)	3.72***	(2.92,4.74)
Very likely (90-100)	15.83***	(11.43,21.94)	9.55***	(8.05,11.33)	7.15***	(5.34,9.55)
Male	1	(1,1)	1	(1,1)	1	(1,1)
Female	0.70***	(0.64,0.78)	0.70***	(0.63,0.78)	0.70***	(0.64,0.78)
NH White	1	(1,1)	1	(1,1)	1	(1,1)
NH Black	1.07	(0.92,1.26)	1.09	(0.93,1.28)	1.09	(0.93,1.27)
NH Other	1.21	(0.83,1.75)	1.21	(0.84,1.75)	1.20	(0.83,1.74)
Hispanic	1.25	(0.98,1.58)	1.26	(0.99,1.60)	1.27	(1.00,1.62)
Less than HS	0.52**	(0.35,0.76)	0.46***	(0.40,0.54)	0.46	(0.40,0.54)
GED or HS	0.78	(0.54,1.12)	0.68***	(0.59,0.79)	0.67***	(0.58,0.78)
Some college	0.79	(0.53,1.16)	0.71***	(0.61,0.83)	0.70***	(0.60,0.83)
College or more	1	(1,1)	1	(1,1)	1	(1,1)
Pre-baby boomers	1	(1,1)	1	(1,1)	1	(1,1)
Baby boomers	1.21**	(1.07,1.37)	0.70	(0.47,1.03)	1.22**	(1.08,1.38)
Age at expectation (centered at 51)	0.99	(0.97,1.00)	0.99	(0.97,1.00)	0.92***	(0.88,0.95)
Unsure *Less than HS	1.05	(0.67,1.63)				
Unsure *GED or HS	1.01	(0.68,1.50)				
Unsure *Some college	0.98	(0.66,1.46)				
Very likely *Less than HS	0.61*	(0.38,0.99)				
Very likely *GED or HS	0.56*	(0.36,0.89)				
Very likely *Some college	0.70	(0.44,1.12)				
Unsure *Baby boomers			1.74*	(1.14,2.66)		
Very likely *Baby boomers			2.36**	(1.41,3.95)		
Unsure *Age at expectation					1.08***	(1.03,1.14)
Very likely *Age at expectation					1.12***	(1.06,1.19)

Table 5 Odds ratios for working full time at age 62 when interacting expectations with sociodemographic factors

No chance=expect 0 probability of working full time at age 62 (group 1); Unsure=1-85 probability (group 2); Very likely=90-100 probability (group 3); NH=Non-Hispanic; HS=High School; GED= General Educational Development

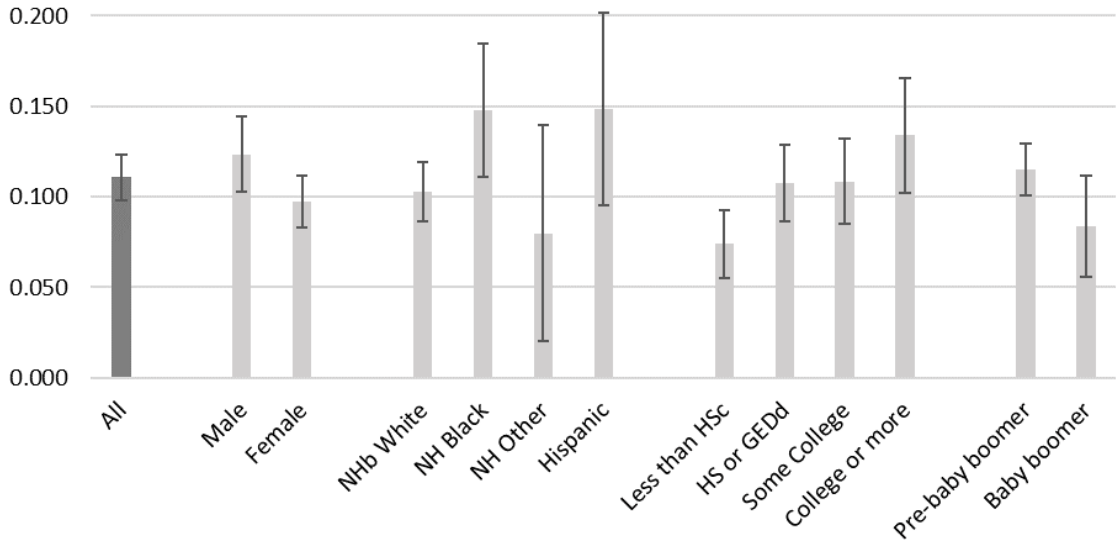
Figure 3-2 depicts predicted probabilities from the main interaction models. For each sociodemographic subgroup, we calculated the adjusted probability of unexpectedly working

among those who thought there was no chance they would be working and of unexpectedly *not* working among those who thought it was very likely they would be working. The first finding to note is that Americans had higher probability of unexpectedly not working (0.430) compared to unexpectedly working at age 62 (0.111). While the gender interaction did not reach statistical significance, men who thought there was no chance of working at age 62 had a slightly higher probability of unexpectedly working than women with that same expectation (0.123 vs. 0.097). Among those who expected to be working, women were more likely than men to be unexpectedly not working (0.462 vs. 0.392).

The race/ethnicity interaction, which did reach statistical significance, followed a different pattern: Black and Hispanic adults had higher probabilities of experiencing both types of unmet expectations compared to White adults and those of other races and ethnicities. For example, the probability of unexpectedly working was 0.103 for White respondents, but was 0.148 and 0.149 for Black and Hispanic respondents respectively. Therefore, Black and Hispanic older adults had nearly 50% higher probability of unexpectedly working at age 62 compared to White older adults. Differences in unexpectedly not working were comparatively smaller – 0.496 and 0.463 for Black and Hispanic respondents respectively.

Among those with low expectations of working at 62, those with college degrees had the highest probabilities of unexpectedly working (0.134), and those without high school degrees had the lowest probability of unexpectedly working (0.074). There was also a clear education pattern among those with high expectations of working at age 62, with each increasing education level exhibiting lower probabilities of unexpectedly not working. In other words, high educational attainment is associated with a high probability of unexpectedly working and a low probability of unexpectedly not working.

A) Predicted probability of not working at age 62 among those who thought it was very likely (90-100 probability) they would be working



B) Predicted probabilities of working at age 62 among those who thought there was no chance (zero probability) they would be working

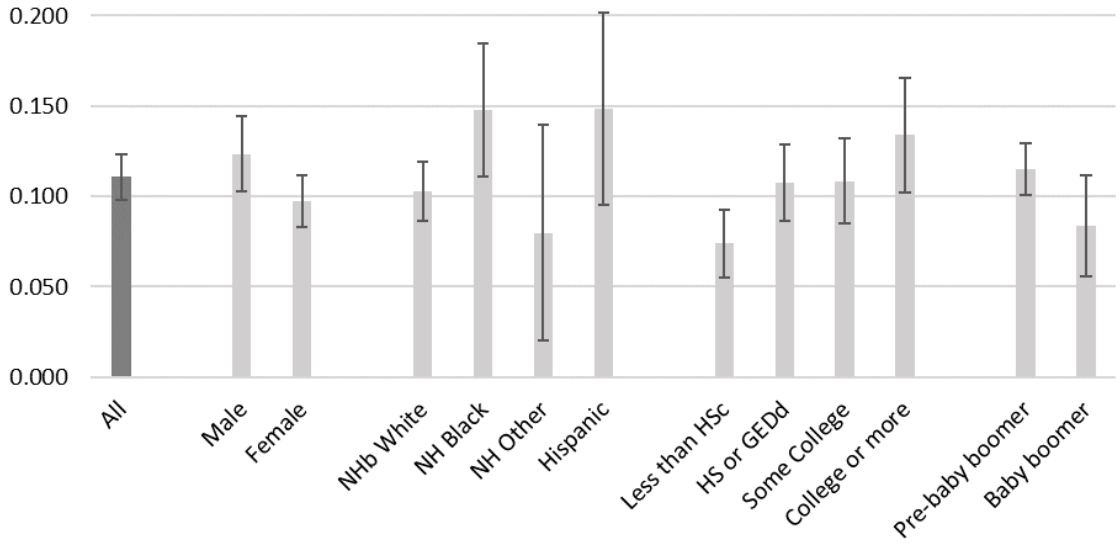


Figure 3-2 (Panel A and B) Distribution of unexpectedly working and unexpectedly not working by sociodemographic subgroups

Interestingly, despite the Recession, baby boomers had lower probabilities of both types of unmet expectations compared to pre-baby boomer cohorts (See Figure 3-2). This finding may be due to the fact that more baby boomers fell into the "unsure" expectation group compared to pre-baby boomers (54.97% and 41.62%, respectively).

Sensitivity analysis

None of the logit models' findings substantively changed when adjusting for total wealth at time of reported expectations. In addition, two alternative methods of categorizing expectations into groups led to overall similar results. When using terciles of expected probabilities, there were more baby boomers in group three (which captured probabilities 62-100) compared to pre-baby boomers. Expectations were still highly associated with realized labor force status, and all interactions were similar to prior models. In the next test, group one contained probabilities 0-10 (rather than only zero) and group three contained probabilities 90-100 (as in original analysis). All results matched the original analysis apart from the interaction between expectation groups and education, which was not statistically significant ($p=0.0637$). With most results consistent across strategies, we present the original grouping because it provides relatively equal sample size to all three groups with logical distinctions of high and low expectations.

Discussion

This study is one of the first to use nationally-representative longitudinal data to examine differences in unmet work expectations at age 62 across sociodemographic subgroups of Americans following the Great Recession. We found that expectations about retirement timing are socially patterned and certain sociodemographic groups experience substantial deviations

between expected and actual labor force status in late life. Understanding how well expectations align with reality in distinct subpopulations is important because the alignment of retirement with prior expectations impacts life satisfaction in the retirement years (Clarke, Marshall, and Weir 2012). In addition, failure to predict labor force exits hinders individuals' ability to estimate the duration of their retirement and plan their finances accordingly.

Our research highlights two different types of unmet expectations – unexpectedly working and unexpectedly not working. We found that it was more common for those with high expectations of working to be unexpectedly out of work at age 62 than for those with low expectations of working to be unexpectedly still in the labor force. In different sociodemographic groups, these two outcomes presented distinct patterns, suggesting that they are driven by separate processes. Evidence from prior research suggests that later-than-expected retirement is associated with flexibility in hours and loss of retiree health insurance, which may be less disruptive than the forces behind earlier-than-expected retirement (namely, forced retirement and illness) (Panis et al. 2002). Therefore, these opposing types of unmet work expectations may be useful constructs for future research investigating the health and life satisfaction consequences of economic events that alter retirement timing.

When looking at differences by sociodemographic groups, we found that Black and Hispanic respondents were more likely to experience both types of unmet expectations compared to Whites. These racial/ethnic differences in unmet work expectations ultimately result from structural factors. In the United States, there are racial/ethnic differences in access to stable and desirable employment over adulthood because minorities tend to experience lower educational opportunities, more workplace discrimination, residential segregation, and other structural constraints (Bailey et al. 2017). Driven by these macro-level factors, racial/ethnic differences in

poor health or unemployment likely contribute to the higher rates of earlier-than-expected retirement among Black and Hispanic adults compared to White adults (Burr et al. 1996; McNamara and Williamson 2004). Indeed, there is evidence that Blacks and Hispanics experience more involuntary labor market exits than do Whites due to joblessness that transitions to retirement (Flippen and Tienda 2000). The fact that racial/ethnic minorities experienced even larger differences in later-than-expected retirement may be due to lower wealth (Bailey et al. 2017) and less stable labor force histories that hinder pension coverage, saving for retirement, and obtaining high incomes that incentivize work (Flippen and Tienda 2000). Misalignment between expected and realized retirement complicates financial planning and thus may contribute to racial/ethnic disparities in poverty risk in old age. Given evidence of the life satisfaction consequences of unmet expectations about retirement, enabling individuals to better align retirement plans and behaviors represents a promising area for intervention to address racial/ethnic disparities in quality of life in old age (Yang 2008; Skarupski et al. 2013).

In our study, older Americans with lower education levels were unexpectedly not working more often than peers with higher education. This finding is in line with a study in Norway that showed that low education and blue-collar workers often cannot stay in the workforce as long as they would prefer (Solem et al. 2016). Similar to the racial/ethnic differences noted above, this pattern could be driven by those with lower educations having more periods of joblessness, poorer health, and lower incomes over their working lives (Aaron and Callan 2011). In addition, the jobs of workers with lower education tend to have low flexibility and high physical demands, which may prevent working into old age (Mermin, Johnson, and Murphy 2007). Conversely, working longer than expected was more common among the advantaged group – those with high education. This aligns with previous research that has

consistently found education to be positively related to retirement age (Fisher, Chaffee, and Sonnega 2016; De Preter, Van Looy, and Mortelmans 2013). High education may result in later-than-expected retirement due to desirable employment opportunities, high quality working environments, and generous salary and benefit compensation (Potočnik, Tordera, and Peiró 2010; Fisher, Chaffee, and Sonnega 2016). Therefore, working longer than expected in this group may be a voluntary decision, rather than a necessity for income or benefits.

Despite wealth losses and increased unemployment during the Great Recession, baby boomers retiring at that time did not experience more earlier-than-expected or later-than-expected retirement compared to cohorts who had previously retired. This finding is in line with some previous research that found that stock market changes and unemployment rates around the recession did not affect expected retirement age (Szinovacz, Davey, and Martin 2015). However, it contradicts several other findings that report the Recession did result in changes in retirement timing (Hurd and Rohwedder 2010; McFall et al. 2011; Ondrich and Falevich 2016; Goda, Shoven, and Slavov 2011). Baby boomers in our study were more likely than their predecessors to be unsure about their work status at age 62 (reporting a 1-85 probability of working full time). This increased uncertainty could be due to how changes in social security policies and an unsteady economy make confident predictions more difficult. Indeed, declines in the stock market during the Recession have been found to result in increased insecurity in or postponement of retirement planning (Szinovacz, Davey, and Martin 2015). This is concerning because those who plan for retirement ultimately have more wealth when they stop working (Lusardi and Mitchell 2007). Baby boomers with 0 probability (“no chance" group) or 90-100 probabilities (“very likely” group) were more accurate in their expectations than pre-baby boomers, which raises the possibility that baby boomers exhibited higher standards of certainty before being

willing to report an expectation at either extreme of the probability range. There is clear evidence that baby boomers are working longer than previous cohorts (Mermin, Johnson, and Murphy 2007), and our findings suggest that this late retirement may be properly anticipated.

In the past, survey research has often used work expectations as a tool for understanding how certain factors like health shocks or financial incentives influence retirement timing. For example, one study asked respondents about the probability they would be working at age 70 conditioned on good health and then conditioned on poor health to try to understand the causal effect of health on retirement (Hudomiet, Hurd, and Rohwedder 2018). Expectations are also useful for forecasting trends in retirement before they occur. In these cases, expectations of retirement timing are proxying actual retirement timing, under the assumption that expected retirement is consistent with realized retirement. Our findings reveal how using expectations to represent actual timing systematically mis-measures retirement timing among minority races, those with high and low educational attainment (compared to middle levels), and older birth cohorts.

These findings should be considered along with the study's limitations. We were not able to ascertain the specific reason for leaving or staying in the workforce, and thus we cannot directly parse out competing processes such as working longer due to insufficient savings or due to enjoyable workplaces. In addition, our paper considers not working at age 62 to represent retirement, but it may represent temporary unemployment for some. This study does not identify changes in expectations between when they are first reported and age 62. However, changes in expectations that lead retirement behaviors to misalign with original expectations are interesting in the same way as traditional unmet expectations. Both scenarios beg the question of why preferences and behaviors changed between these timepoints. Another limitation is that our

sample was restricted by including only those with expectations and labor force status. Missing responses to these items are likely not missing completely at random.

Despite these limitations, our findings clearly highlight how certain social groups face difficulty in predicting retirement timing. This unpredictability likely hinders retirement planning, and such consequences of unmet expectations may differ across diverse groups of older adults. Future research should explore interventions that improve individuals' accuracy in predicting retirement timing and their agency in controlling when they exit the labor force. Interventions that reduce the high rates of unexpectedly not working hold promise to improve the financial, physical, and mental health of these older adults and their families, along with the solvency of the social security program.

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Chapter 4 **Unmet Expectations About Retirement Timing and Subsequent Depressive Symptoms**

Introduction

There are many economic, social, and health factors that might lead an American to retire earlier or later than originally planned. While the economic implications of unexpected retirement timing are often clear or calculable, less is known about the mental health implications of these changes in plans. This paper examines how earlier and later than expected retirement relate to subsequent depressive symptoms in a sample that represents the United States population of older adults. These findings are important to consider given the current economic downturn, which may impact retirement timing for baby boomers.

Background

As the United States prepares for an aging population, there has been a policy push to incentivize longer working lives (Quinn, Cahill, and Giandrea 2011). However, some older adults do not have complete agency over their retirement timing (Abrams, Clarke, & Mehta, 2020, Unpublished manuscript; Flippen and Tienda 2000). For example, retirement might occur earlier than planned due to illness or injury, caregiving responsibilities, or unemployment (Flippen and Tienda 2000; Fisher, Chaffee, and Sonnega 2016). Retirement tends to occur later than planned when an individual has good health, white collar employment, and is incentivized by high income (Fisher, Chaffee, and Sonnega 2016). Recent work using the Health and Retirement Study showed that those expecting to work full time at age 62 have a 0.43 probability

of unexpectedly not working; among those not expecting to work at 62, there was a 0.11 probability of unexpectedly working (Abrams, Clarke, & Mehta, 2020, Unpublished manuscript). If policy changes successfully make longer working lives the norm, there may be even higher incidence of earlier than expected retirement, especially among those with poor health and unstable employment.

Research on the 2008 Great Recession demonstrated the role of economic instability in unrealized retirement plans. For example, there is evidence that wealth losses during the Recession were associated with modest increases in expected retirement age (Hurd and Rohwedder 2010; McFall et al. 2011), decreased probabilities of retirement (Ondrich and Falevich 2016), and increased reported probabilities of working at age 62 (Goda, Shoven, and Slavov 2011). Simultaneously, the Recession led to increased and prolonged unemployment that pushed some into earlier retirement (Gorodnichenko, Song, and Stolyarov 2013; Johnson 2012). To fully understand the consequences of large economic downturns, individual economic insecurity, and policy initiatives for later retirement, it is important to investigate the ramifications of unmet expectations about retirement timing.

Drawing upon sociological theory, early or late retirement can be considered an "off-time event," because it is a major life transition that deviates from normative timetables (Rook, Catalano, and Dooley 1989). Off-time events often have reduced opportunities for social support and increased social disapproval (Rook, Catalano, and Dooley 1989) and thus are considered stressors that predict poor mental health (Quick and Moen 1998; Mossakowski 2011; Rook, Catalano, and Dooley 1989). With this framework, it makes sense that the effect of retirement on mental health depends on whether retirement occurred as planned and preferred (Herzog, House, and Morgan 1991). Indeed, a study using data from before the Great Recession found that unmet

retirement expectations (both early and late) were associated with significant increases in depressive symptoms (Falba, Gallo, and Sindelar 2008). A more recent study found that men but not women exhibited lower life satisfaction when they experienced unmet expectations for retirement timing (Clarke, Marshall, and Weir 2012).

Specifically examining the relationship between unmet expectations about retirement timing and depressive symptoms is important because depression is one of the most common causes of poor quality of life in older adults (Volkert et al. 2013). Depressive symptoms are relatively common in old age (Reynolds and Kamphaus 2013; Alexopoulos 2005) and can have negative effects on physical health and functioning (Bruce 2001; Penninx et al. 2000). Recent findings on rising mortality from "diseases of despair," including drug overdose, suicide, and alcohol-related liver disease, have raised concerns about mental health in mid- and late life (Case and Deaton 2017). Case and Deaton hypothesized that, in conjunction with an increase in opioids supply, social changes in the labor market and in marriage patterns have caused heightened despair (Case and Deaton 2017). However, much work remains to be done connecting these factors to poor mental health at the individual level.

Case and Deaton's findings pertain only to middle-age White Americans, which begs the question – are there racial/ethnic differences in mental health responses to economic and social hardship? While there is some evidence that racial and ethnic minorities experience higher rates of unmet retirement expectations compare to Whites (Abrams, Clarke, & Mehta, 2020, Unpublished manuscript), it remains unknown whether there are group differences in the effects of these unmet expectations. A recent paper by Malat and colleagues posited that higher rates of depression in White compared to Black adults may be due to White's unhealthy responses to setbacks (Malat, Mayorga-Gallo, and Williams 2018). In addition, men and women may respond

differently to unmet expectations about retirement if women's expectations are more closely tied to their husbands work activities than their own (Clarke, Marshall, and Weir 2012). Given the differential economic status and experiences of the Great Recession, it is also possible that the mental health consequences of early or late retirement depend on educational attainment, wealth, occupation type, and birth cohort.

Current study

In this study, we ask: Are unmet expectations about retirement timing associated with subsequent increases in depressive symptoms? And, is this relationship consistent across diverse subpopulations of older Americans? This study uses the longitudinal Health and Retirement Study (waves 1992-2016) to test the association between unmet expectations and depressive symptoms across sociodemographic and economic groups.

Methods

Data and sample

The Health and Retirement Study (HRS) is a longitudinal and nationally-representative sample of adults ages 51 and older in the United States (Sonnega et al. 2014). We used all currently available survey waves (1-13), which include surveys every other year from 1992 to 2016. Respondents in the first wave were born between 1931 and 1941, with more recent cohorts added to the sample over the course of the study. To be eligible, respondents had to be non-institutionalized at baseline, but they remained eligible for follow up interviews even if they entered an institutional setting (Sonnega et al. 2014). The Institute for Social Research at the University of Michigan conducts and distributes the HRS and the National Institute of Aging

funds the study (grant number NIA U01AG009740) (Sonnega et al. 2014). We used the RAND dataset (Version 1), which the Rand Corporation cleaned and compiled (Bugliari et al. 2019).

The HRS has 40,521 respondents ages 51+ with data from at least one wave. For our study, respondents must have reported (between ages 51 and 61) their expectations about working full time at age 62. We excluded 13,997 respondents with no interviews before age 62 and 3,992 respondents who did not report expectations because they responded via proxy, were out of the labor force, had low numeracy, did not know, or refused. Of the remaining 22,532 people, 9,359 had not yet reached age 62 to observe actual labor force status. An additional 234 were missing labor force status at age 62, and 835 were excluded for having part-time labor force status (a decision that was explored in robustness checks). These exclusion criteria left 12,104 respondents, of which 9,242 remained in the final sample because they had no missing values on other key variables (see Figure A-4 in Appendix).

Compared to those who remained in the sample, respondents who were excluded were on average about seven months younger, less likely to be non-Hispanic White, and more likely to have low education levels. To ensure our sample represents the U.S. population over age 50, we adjusted for complex sampling and applied survey weights.

Measures

Unmet expectations about retirement timing were operationalized as a misalignment between respondents' reported expectations about full time work at age 62 and their actual labor force status at 62. Between ages 51 and 61 years old, respondents reported the subjective probability (0 to 100) that they would be working full time after reaching age 62. We used their first response to this question and categorized expected probabilities into three groups. Group 1 ("no chance") reported exactly zero expected probability of working full time at age 62; Group 2

("unsure") reported expected probabilities of work ranging from 1 to 85; Group 3 ("very likely") reported 90-100 expected probabilities of working full time at age 62.

Labor force status was dichotomized as working full time or not working full time (which consisted of being retired, unemployed, disabled, or not in the labor force). Comparing expectations with realized labor force status led to five groups – unsure (Group 2 for expectations), unexpectedly working (Group 1, working full time at 62), unexpectedly not working (Group 3, not working full time at 62), working as expected (Group 3, working full time at 62), and not working as expected (Group 1, not working full time at 62). See Figure 4-1.

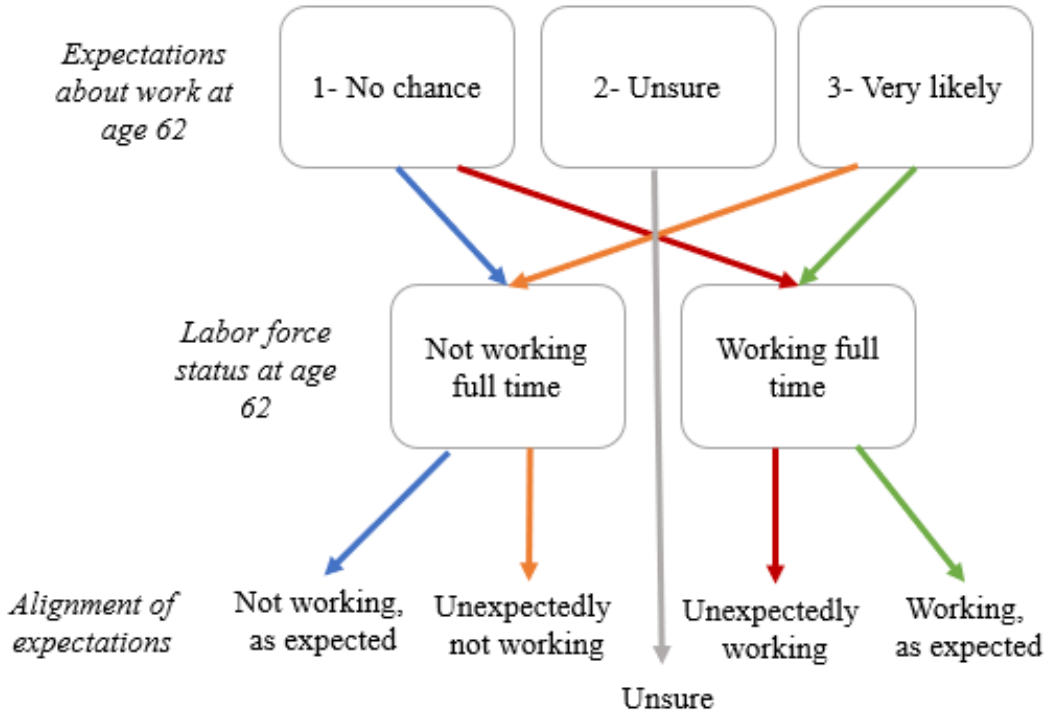

Figure 4-1 Alignment of expectations with realized labor force status

The HRS measures depressive symptoms using the 8-item Center for Epidemiologic Studies Depression scale (CESD-8). Respondents reported whether they felt each of the following eight symptoms "much of the week": felt depressed, everything was an effort, sleep was restless, was happy (reverse coded), felt lonely, felt sad, could not get going, and enjoyed

life (reverse coded). Our depressive symptoms score used the first wave after respondents reached age 62, the same wave in which we observed labor force status. We used the total number of symptoms that were reported, ranging from zero to eight symptoms. Respondents were considered missing on depressive symptoms if they did not answer three or more of the eight CESD items.

The CESD-8 is a common depressive symptom measure for older adults (Karim et al. 2015; Lewinsohn et al. 1997; Turvey, Wallace, and Herzog 1999). A longer version of the scale has been validated against diagnostic interviews in those ages 50 and older, with satisfactory internal consistency and test-retest reliability across gender and age groups (Lewinsohn et al. 1997). In addition, a large psychometric study using older adults in Europe found that the 8-item CESD scores were significantly inversely associated with life satisfaction, happiness, social trust, self-esteem, optimism, subjective health, autonomy, and social relationships (Karim et al. 2015).

Sociodemographic factors in our study included self-reported age in years at baseline wave, gender (male and female), race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and non-Hispanic other), level of educational attainment (less than a high school degree, a high school degree or GED, some college or an Associate's degree, and a college degree or higher), and birth cohort (Pre-baby boomers born between 1924-1947 and baby boomers born between 1948-1953).

The two economic covariates were wealth and occupation type. Total wealth in the wave of reported expectations was calculated as respondents' assets minus debts, grouped into quartiles (-$4,483,000 to $34,300, $34,500 to $104,500, $104,666 to $246,500, $246,700 to 18.4M). Occupation type was based on the job respondents held for the longest tenure. As has been categorized in the prior studies using the HRS, white collar jobs included occupations such

as managerial, professional, sales, and administrative support, while blue collar jobs included occupations such as mechanics, repair, construction, machine operator, transportation, food preparation, and farming (Cahill, Giandrea, and Quinn 2013).

We captured respondents' health at two time points. When considering health as a confounding factor, we used the wave of reported expectations and measured CESD-8 scores, condition count (including high blood pressure, diabetes, cancer, lung disease, heart disease, stroke, psychiatric problems, and arthritis), activities of daily living (ADLs), instrumental activities of daily living (IADLs), and an indicator for having applied for social security insurance or social security disability insurance (SSI/SSDI). When considering health as a potential mediator, we examined changes between the wave of expectations and the first wave after reaching age 62. We created an indicator for increased condition count, increased ADLs or IADLs, and incident applications to SSI or SSDI.

Statistical analysis

The first part of our analysis answered the question of whether unmet expectations about retirement timing relate to subsequent depressive symptoms. We ran a series of negative binomial models predicting depressive symptom count by alignment of expectations with realized labor force status. The first model was unadjusted, the second included sociodemographic factors, the third added economic factors, the fourth added health covariates from the wave of expectations, and the fifth added health declines between expectations and age 62 (see Equation 2). We calculated the marginal predicted number of depressive symptoms at each of the five expectation alignment groups. This hierarchical model approach is useful for separating out the factors that might explain an observed association, for example separately

examining the confounding of health at wave of expectations and the potential mediation of health declines between expectations and age 62.

Equation 2. Fully adjusted negative binomial model of depressive symptom count

$$Pr(\text{Depressive symptoms}) = \beta_0 + \boldsymbol{\beta_1(\text{Unexpectedly working}) +} \boldsymbol{\beta_2(\text{Unexpectedly not working}) + \beta_3(\text{Working as expected}) + \beta_4(\text{Not working as expected})} + \beta_5(\text{Female}) + \beta_6(\text{Non-Hispanic Black}) + \beta_7(\text{Non-Hispanic other race/ethnicity}) + \beta_8(\text{Hispanic}) + \beta_9(\text{Less than high school education}) + \beta_{10}(\text{GED or high school graduate}) + \beta_{11}(\text{Some college}) + \beta_{12}(\text{Baby boomers}) + \beta_{13}(\text{Age at expectation}) + \beta_{14}(\text{Blue collar occupation}) + \beta_{15}(\text{Wealth quartile 2}) + \beta_{16}(\text{Wealth quartile 3}) + \beta_{17}(\text{Wealth quartile 4}) + \beta_{18}(\text{ADLs}) + \beta_{19}(\text{IADLs}) + \beta_{20}(\text{Chronic conditions}) + \beta_{21}(\text{Applied for SSI before expectations}) + \beta_{22}(\text{Increasing chronic conditions}) + \beta_{23}(\text{Increasing ADLs or IADLs}) + \beta_{24}(\text{Applied for SSI between expectations and age 62}) + \varepsilon_{ti}$$

The second part of our analysis answered the question of whether unmet expectations differentially relate to depressive symptoms in different sociodemographic groups. While including sociodemographic, economic, and health confounders (but not the potentially mediating factor of health declines), we then ran models testing interactions between unmet expectations and a series of sociodemographic and economic covariates – age, gender, race/ethnicity, education, birth cohort, occupation type, and wealth. Given the number of statistical tests run to answer this research question, we applied a more stringent standard for statistical significance at alpha=0.01, rather than alpha=0.05.

We ran three sensitivity analyses to test the robustness of our findings. First, we included part-time workers in the group not working full time at age 62. Next, we considered the effect of including an indicator for whether respondents ever reported retirement to be at least partially

forced, rather than desired. Third, we considered different approaches to creating expectation groups.

These analyses were conducted using Stata 15 (StataCorp 2017). Using Stata's *svy* commands, we accounted for clusters and stratification and weighted respondents based on their weight at age 62 to yield unbiased estimates and adjust for complex sampling. The subsample of respondents that met inclusion criteria were considered a non-fixed subpopulation using Stata's *svy, subpop* command (Aneshensel 2013).

Results

In our weighted analytic sample of 9,242 respondents, 50.3% was female, 82% was non-Hispanic White, about 50% had a high school education or less, and 20% was baby boomers (see Table 6). The mean number of depressive symptoms among respondents at reported expectations was 0.93 symptoms (SD=2.55), while the mean at age 62 was 1.28 symptoms (SD=2.79). The distributions of economic and health covariates are shown in Table 6.

Variable	Category	Unweighted: count	Weighted: % or mean (SD)
Expectation alignment with realized labor force status	Unsure	3,980	45.6
	Unexpectedly working	373	3.4
	Unexpectedly not working	891	9.4
	Working as expected	1,071	12.5
	Not working as expected	2,927	29.1
Depressive symptoms at 62, 0-8 (mean)			1.28 (2.78)
Gender	Male	4,198	49.7
	Female	5,044	50.3

Race/ ethnicity	NH White	6,764	82.0
	NH Black	1,480	9.1
	NH Other	199	2.6
	Hispanic	799	6.3
Educational Attainment	Less than HS	1,790	14.3
	HS or GED	3,385	34.7
	Some College	2,043	23.9
	College +	2,024	27.1
Birth cohort	Pre-baby boomer (1924-1947)	8,066	80.0
	Baby boomer (1948-1953)	1,176	20.0
Age at expectations, 51-61 (mean)			54.52 (4.22)
Total wealth, assets minus debts	Q1 (-$4,483,000 to $34,300)	2,313	22.2
	Q2 ($34,500 to $104,500)	2,310	22.6
	Q3 ($104,666 to $246,500)	2,311	25.2
	Q4 ($246,700 to 18.4M)	2,308	29.9
Occupation type	White collar	5,245	59.9
	Blue collar	3,997	40.1
Depressive symptoms at expectation, 0-8 (mean)			0.93 (2.55)
Condition count at expectation, 0-8 (mean)			0.94 (1.56)
ADLs at expectations, 0-5 (mean)			0.11 (0.76)
IADLs at expectation, 0-3 (mean)			0.06 (0.44)
Applied for SSI or SSDI before expectations	No	8,664	96.0
	Yes	578	4.0

Increased conditions	No	4,895	49.5
	Yes	4,347	50.5
Increased ADLs or IADLs	No	8,480	91.8
	Yes	762	8.2
Applied to SSI or SSDI since expectations, before age 62	No	8,767	96.5
	Yes	475	3.5

Table 6 Sample characteristics and distributions of covariates

N=9,242. NH=Non-Hispanic; HS=High School; GED= General Educational Development; ADLs= Activities of Daily Living; IADLs= Instrumental Activities of Daily Living; SSI= Social Security Income

Expectations about work at age 62 were reported at a mean age of 54.5 (SD=4.22). About 46% of the sample had unsure expectations about full time work at age 62. Among those with high and low expectations, it was more common to have met expectations than unmet expectations. Specifically, 29.1% of the weighted sample was not working as expected at age 62, and 12.5% of the sample was working as expected. Only 3.4% of the sample (373 respondents) was unexpectedly working at age 62, and 9.4% of the sample (891 respondents) was unexpectedly not working.

Results from unadjusted and adjusted negative binomial models predicting depressive symptoms by expectation alignment are shown below in Table 7. The categorical variable for expectation alignment groups was significant overall in the unadjusted model ($F(4,56)=14.01$, $p<0.001$), and remained significant after adjusting for sociodemographic characteristics, economic factors, and health at wave of expectations ($F(4,56)= 4.62$, $p=0.003$). In this model, unexpectedly not working was associated with a 1.182 (95% CI=1.033, 1.353) increased incidence rate of depressive symptoms compared to those who were unsure about work status at age 62. Unexpectedly working and meeting expectations about work were not associated with depressive symptoms. The predicted number of depressive symptoms in each expectation alignment group from this model are shown in Figure 4-2, revealing a small increase of about 0.2

predicted depressive symptoms in those who were unexpectedly not working. The significant relationship between unexpectedly not working and depressive symptoms was completely attenuated by adjustments for health declines between expectations and reaching age 62 (IRR=1.101, 95% CI=0.970, 1.249).

Depressive symptoms at age 62	Unadjusted		+ Sociodemographic factors		+ Economic factors		+ Health at expectations		+ Health declines by age 62	
	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI
Unsure	1	(1, 1)	1	(1, 1)	1	(1, 1)	1	(1, 1)	1	(1, 1)
Unexpectedly working	0.923	(0.719, 1.186)	0.862	(0.669, 1.110)	0.914	(0.704, 1.185)	0.946	(0.741, 1.207)	0.999	(0.792, 1.262)
Unexpectedly *not* working	1.247**	(1.078, 1.442)	1.233**	(1.061, 1.433)	1.164*	(1.002, 1.352)	1.182*	(1.033, 1.353)	1.101	(0.970, 1.249)
Working as expected	0.839*	(0.724, 0.973)	0.940	(0.806, 1.096)	0.945	(0.813, 1.097)	0.992	(0.871, 1.129)	1.047	(0.921, 1.191)
Not working as expected	1.358***	(1.235, 1.493)	1.215***	(1.110, 1.331)	1.196***	(1.096, 1.305)	0.919	(0.834, 1.011)	0.917	(0.832, 1.010)
Male			1	(1, 1)	1	(1, 1)	1	(1, 1)	1	(1, 1)
Female			1.167***	(1.076, 1.267)	1.246***	(1.153, 1.347)	1.172***	(1.087, 1.263)	1.194***	(1.112, 1.283)
NH White			1	(1, 1)	1	(1, 1)	1	(1, 1)	1	(1, 1)
NH Black			1.185***	(1.084, 1.296)	1.006	(0.913, 1.109)	0.986	(0.887, 1.096)	0.970	(0.877, 1.074)
NH Other			1.715***	(1.356, 2.168)	1.666***	(1.282, 2.151)	1.538**	(1.199, 1.974)	1.487**	(1.173, 1.887)
Hispanic			1.295***	(1.133, 1.479)	1.148*	(1.008, 1.307)	1.160*	(1.026, 1.312)	1.149*	(1.024, 1.289)
<HS			2.227***	(1.922, 2.581)	1.556***	(1.327, 1.824)	1.423***	(1.226, 1.652)	1.379***	(1.181, 1.612)
GED or HS Grad			1.591***	(1.395, 1.814)	1.278***	(1.118, 1.461)	1.255***	(1.113, 1.414)	1.232***	(1.097, 1.384)
Some College			1.444***	(1.230, 1.695)	1.257**	(1.069, 1.478)	1.200*	(1.040, 1.388)	1.299*	(1.044, 1.376)
Bachelor degree +			1	(1, 1)	1	(1, 1)	1	(1, 1)	1	(1, 1)
Pre-baby boomers			1	(1, 1)	1	(1, 1)	1	(1, 1)	1	(1, 1)

Baby boomers	1.179*	(1.030, 1.349)	1.156*	(1.005, 1.331)	0.936	(0.826, 1.061)	0.948	(0.839, 1.073)
Age at expectation (centered)	0.994	(0.983, 1.006)	0.998	(0.986, 1.010)	0.997	(0.985, 1.009)	1.021***	(1.001, 1.034)
White collar			1	(1, 1)	1	(1, 1)	1	(1, 1)
Blue collar			1.281***	(1.175, 1.398)	1.230***	(1.121, 1.348)	1.210***	(1.105, 1.325)
Wealth Q1			1	(1, 1)	1	(1, 1)	1	(1, 1)
Wealth Q2			0.829***	(0.747, 0.920)	0.970	(0.880, 1.070)	0.964	(0.878, 1.059)
Wealth Q3			0.719***	(0.626, 0.826)	0.888	(0.784, 1.007)	0.912	(0.811, 1.026)
Wealth Q4			0.610***	(0.533, 0.698)	0.791***	(0.692, 0.904)	0.833**	(0.731, 0.950)
Depressive symptoms at expectation					1.184***	(1.161, 1.208)	1.179***	(1.155, 1.203)
ADLS					1.106***	(1.054, 1.160)	1.153***	(1.097, 1.211)
IADLs					1.125**	(1.050, 1.205)	1.172***	(1.088, 1.262)
Condition count					1.166***	(1.136, 1.197)	1.144***	(1.112, 1.178)
Applied to SSI or SSDI before expectation					1.177**	(1.047, 1.324)	1.155*	(1.023, 1.303)
Increased condition count							1.368***	(1.251, 1.497)
Increased ADLs or IADLs							1.918***	(1.720, 2.139)
Applied to SSI or SSDI before age 62							1.561***	(1.397, 1.744)

Table 7 Incidence rate ratios for depressive symptoms count at age 62 by alignment of retirement expectations with realized labor force status

** p<0.05, ** p<0.01, *** p<0.001; NH=Non-Hispanic; HS=High School; GED= General Educational Development; ADLs= Activities of Daily Living; IADLs= Instrumental Activities of Daily Living; SSI= Social Security Income*

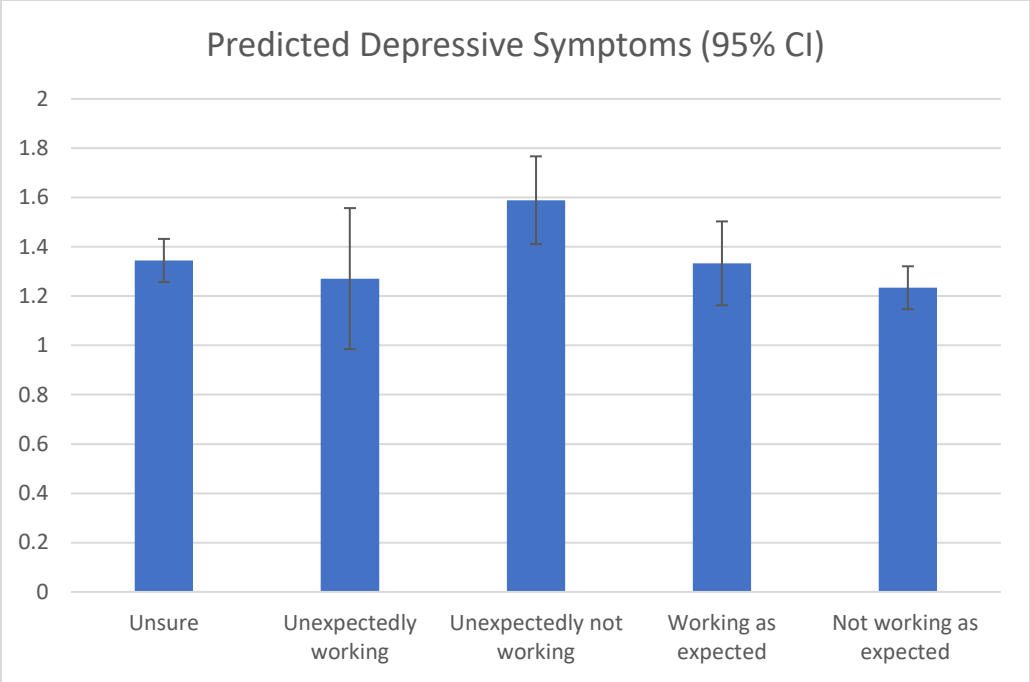

Figure 4-2 Predicted depressive symptoms by expectation alignment groups, adjusted for sociodemographic, economic, and health confounders.

As can be seen in Table 7, the fully adjusted model revealed significantly higher depressive symptoms among women (compared to men), non-Hispanic others and Hispanics (compared to non-Hispanic Whites), those with less than high school education, a high school degree, or some college (compared to those with college degrees), and blue collar workers (compared to white collar workers). Depressive symptoms significantly increased with each year of age. In addition, depressive symptoms at age 62 were significantly positively associated with depressive symptoms at expectation, ADLs, IADLs, condition count, having applied to SSI/SSDI before expectations, increasing chronic conditions after expectations, increasing ADLs or IADLs, and applying for SSI/SSDI for the first time after expectations.

Variable interacting with expectation alignment	Adjusted Wald test for overall interaction	
Age at expectation	F(4,53)= 0.79	p=0.5399
Gender	F(4,53)= 1.15	p=0.3426
Race/ethnicity	F(12,45)= 1.55	p=0.1404
Educational attainment	F(12,45)= 2.01	p=0.0461
Birth cohort	F(4,53)= 2.25	p=0.0759
Occupation type	F(4,53)= 1.64	p=0.1778
Wealth quartile	F(12,45)= 1.22	p=0.2999

Table 8 Interactions of sociodemographic and economic factors with expectation alignment when modeling depressive symptoms

Negative binomial models predicting depressive symptom count at age 62 by alignment of retirement expectations with realized labor force status, interacting alignment with sociodemographic and economic factors while adjusting for sociodemographic, economic, and health covariates.

Next, we tested interactions to determine whether the relationship between unmet expectations and depressive symptoms was consistent across age, gender, race/ethnicity, educational attainment, birth cohort, occupation type, and wealth. While including sociodemographic, economic, and health confounders, none of the seven interactions reached statistical significance at the alpha=0.01 level (see Table 8), meaning that the association between unmet work expectations and depressive symptoms did not differ by these sociodemographic and economic factors.

Sensitivity analyses

As a robustness check, we re-ran the negative binomial models while including those working part time at age 62, grouping part-time workers with the retired, unemployed, and disabled respondents considered not working. Model results were very similar to the original

analysis, with expectation alignment groups significant overall after adjusting for sociodemographic characteristics, economic factors, and health at wave of expectations ($F(4,56)= 3.17$, $p=0.021$). Once again, expectation alignment was no longer significant after adjusting for health declines between expectations and reaching age 62 ($F(4,56)=1.27$, $p=0.2948$). We present the original results because part-time work somewhat obscures the distinction between working and retiring, and thus between met and unmet expectations.

As an additional robustness check, we examined an indicator for whether respondents considered their retirement to be partially or complete forced, rather than desired. Including this variable (which is not part of the RAND dataset) brought the analytic sample down to 7,906 respondents due to missingness. The sample was further reduced to 5,768 respondents after excluding all those still working full time at age 62, as it is not clear how to interpret their perception of retirement when they are currently not retired. Among those remaining, 49.87% of the weighted sample reported that retirement was wanted, whereas 50.13% ever reported that retirement was partially or completely forced. There was a significantly higher proportion of with unexpected retirement among respondents who reported retirement as forced versus desired (15.93% versus 12.16%, $p=0.0009$).

When adding the indicator of forced retirement to the negative binomial model that included expectation alignment, sociodemographic factors, economic factors, and health at expectations, reporting forced retirement was significantly associated with increased depressive symptoms (IRR=1.67, CI=1.52, 1.85). With this added covariate, unexpectedly not working was not associated with depressive symptoms (IRR=1.05, CI=0.92, 1.21), but not working as expected was associated with 0.88 (95% CI=0.81, 0.98) lower incidence of depressive symptoms compared to those who with unsure expectations. Forced retirement did not significantly modify

the relationship between expectation alignment and depressive symptoms (interaction effect, F(2,55)=1.84, p=0.1683) (see Figure A-5 in Appendix).

A final robustness check examined whether results would be consistent if expectation groups were defined as three equally sized terciles (resulting thresholds of expected probabilities: 0, 1-60, and 65-100). As in the original analysis, the alignment of these expectation groups with realized labor force status was statistically significantly associated with depressive symptoms when controlling for sociodemographic characteristics, economic factors, and health covariates (F(4,56)=6.99, p=0.0001). As in the main analysis, this association was driven by higher depressive symptoms among those unexpectedly not working. Unlike the original analysis, this association between unmet expectations and depressive symptoms remained significant after adjusting for health declines between expectations and age 62 (F(4, 56)=3.90, p=0.0075). No interactions with expectation alignment reach statistical significance at the alpha=0.01 level.

Discussion

The main finding from this analysis is that depressive symptoms were slightly higher among respondents who were unexpectedly not working at age 62 compared to those with unsure or met expectations. It is possible that exiting the labor force earlier than expected feels more like unemployment than it does retirement, as it is well-established that unemployment is detrimental to mental health (Waddell and Burton 2006). Depending on how continuous expected probabilities were categorized into groups, the association between unexpectedly not working and depressive symptoms may or may not be completely explained by declines in health. Poor physical health could predict both depressive symptoms and exiting the workforce earlier than expected (Fisher, Chaffee, and Sonnega 2016; Alexopoulos 2005). It is also possible that early retirement for non-health reasons contributes to worse mental and physical health

(Segel-Karpas, Ayalon, and Lachman 2018; Mein et al. 2003). Innovative methods are needed to disentangle the complex and bidirectional relationships between mental health, physical health, and labor force status.

In this study, there was no evidence of differential depressive symptoms in response to unmet expectations by sociodemographic or economic characteristics. This is a surprising finding that contradicts prior work on gender differences in the consequences of unmet expectations about retirement (Mein et al. 2003). It is also surprising to find no difference by educational attainment, wealth, or occupation type, given that retiring earlier or later than expected may have different causes and implications for those with different economic statuses. While prior research had posited that higher rates of depression in White compared to Black adults may be due to White's unhealthy responses to setbacks (Malat, Mayorga-Gallo, & Williams, 2018), we found no racial/ethnic modification of how unmet expectations about retirement timing relate to depressive symptoms. Therefore, the differential prevalence of unmet retirement expectations across sociodemographic groups (Abrams, Clarke, & Mehta, 2020, Unpublished manuscript) does not translate to differential responses to this setback.

Another important finding from this study is that depressive symptoms were not higher among those unexpectedly still working at age 62 (although this outcome was relatively uncommon). These results indicate that adults adapted well, in terms of depressive symptoms, to working longer than expected, for example in response to wealth losses during the 2008 Recession (McFall et al. 2011). This is a timely finding as we currently face another economic downturn due to the COVID-19 outbreak, which is affecting the retirement savings and thus potentially the retirement timing of many Americans currently nearing age 62.

The implications of these results should be considered in light of the study's limitations. First, this study focused on depressive symptoms and does not capture other potential mental health reactions to unmet expectations, such as distress or anxiety. In addition, our results considering forced retirement only capture respondents' perception on their reason for retirement, therefore combining disparate processes such as age discrimination, workplace injuries, or even family pressure. An important limitation is that some variables in this analysis had a non-trivial amount of missing data and we used a complete case analysis. Even so, our analytic sample did not differ dramatically from those excluded from the analysis and we applied survey weights so that the sample better represented the U.S. population of adults over age 50. Finally, the observational nature of this study prohibits causal inference, and thus we cannot be certain of the directionality of the relationships between health declines, unmet retirement expectations, and depressive symptoms.

This analysis also had important strengths worth discussing. The longitudinal nature of HRS allowed us to examine expectations before actual retirement occurred, rather than asking about expectations post-hoc, when respondents may exhibit retrospective bias. In addition, the nationally-representative sample broadens the generalizability of our findings. Overall, this study demonstrates that older Americans are adept at adjusting to unmet retirement expectations, which result in minimal increases in depressive symptoms, especially when considering the role of declines in physical health.

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Chapter 5 **Role of Post-Acute Care Setting in Relationship Between Depressive Symptoms and Post-Hospital Outcomes Among Older Adults**

Introduction

Depressive symptoms are associated with poor physical health outcomes, worse functioning, and higher mortality risk in older adults (Bruce, 2001; Callahan et al., 2005; Cuijpers & Smit, 2002; Cuijpers et al., 2014; Hoffman, Hays, Wallace, Shapiro, & Ettner, 2017), partially due to worse self-care behaviors (Ciechanowski, Katon, Russo, & Hirsch, 2003; DiMatteo, Lepper, & Croghan, 2000; Gonzalez et al., 2008; Kilbourne et al., 2005). Periods directly following acute hospitalizations feature high care needs and pose great health risks, and those with depressive symptoms may need special support. It is currently unknown whether patients with higher depressive symptoms receive more intensive post-acute care and whether this care enhances their recovery. This study aims to fill that gap, and to assess whether more structured post-acute care (such as home health care or rehabilitation in Skilled Nursing Facilities) compared to routine discharges home mutes the negative impact of depressive symptoms on older adults' post-hospital health outcomes. The results have implications for providers to make effective discharge decisions for vulnerable older adults in the context of expansive changes to post-acute care practices.

Effectiveness of varied post-acute care settings

Care transitions out of hospitals are critical opportunities to optimize recovery and rehabilitation when health and functional risks are greatest. In recent years, hospitals have

substantially increased efforts to improve discharge processes and care transitions to help patients expand their capacity for self-care at home, or to provide them with the appropriate level of post-hospital professional services (Brock, Mitchell, Irby, et al, 2013; Coleman, Parry, Chalmers, & Min, 2006). At discharge, one of the highest levels of service intensity is a skilled nursing facility (SNF) for inpatient rehabilitation that includes 24-hour nursing as well as physical, occupational, and speech therapy services (Alcusky, Ulbricht, & Lapane, 2018). Alternatively, a patient may be discharged with a referral to home health, which involves receiving a first visit at the patient's home within 48 hours of hospital discharge and receiving less intensive skilled care than in inpatient rehabilitation (Ackerly & Grabowski, 2014). The lowest intensity discharge disposition involves routine discharges to home without formal care, in which patients often rely on informal care for assistance with post-hospital functional recovery.

The effectiveness of post-acute care is often captured via outcome measures such as physical functioning, cognitive performance, affect, social functioning, and cost of future care (Kane, 2007). The degree to which higher-intensity post-hospital services benefit patients in terms of improving functioning and reducing hospital readmissions is uncertain. There is evidence that home health care is more effective for improving functioning and less costly when compared to skilled nursing facilities or inpatient rehabilitation facilities, specifically for stroke and hip fracture patients (Chen, Kane, & Finch, 2000). In contrast, a study that used propensity score and instrumental variable analysis showed that more intensive rehabilitation settings (in this case, inpatient rehabilitation facilities compared to skilled nursing facilities) led to larger improvements in mobility and self-care (Hong et al., 2019). Similarly, a recent systematic review concluded that increased therapy intensity in an inpatient rehabilitation facility compared to a

skilled nursing facility was associated with better rehabilitation outcomes including functional status and mortality (Alcusky et al., 2018). Hong (2019) and Alcusky (2018) both focused only on post-stroke recovery, and so the inconsistent findings regarding the comparative effectiveness of different post-acute care settings may reflect varying benefits for specific types of patients. Research investigating which settings benefit which specific types of patients is currently lacking (Ackerly & Grabowski, 2014; Burke et al., 2016).

In addition to functional outcomes, there is conflicting evidence on the effectiveness of different post-acute care settings for reducing hospital readmissions. There are high rates of hospital readmissions from SNFs (Mor, Intrator, Feng, & Grabowski, 2010), motivating concerns about the risks relative to the benefits of inpatient rehabilitation for older patients and driving attention to care transitions (Ouslander, Diaz, Hain, & Tappen, 2011). In some cases, inpatient rehabilitation was associated with lower hospital readmissions than SNFs or home health (Hong et al., 2019; Riggs, Roberts, Aronow, & Younan, 2010). These studies may be confounded by indication, as healthier patients are more likely to be discharged home (Werner, Coe, Qi, & Konetzka, 2019). One study addressed this endogeneity by using an instrumental variable – beneficiaries' distance to the closest home health agency and to the closest SNFs (Werner et al., 2019). This rigorous approach revealed that discharge to home health was associated with higher readmission rates than discharge to SNFs (Werner et al., 2019). Being in an inpatient setting might reduce readmissions by investing in clinical services that decrease the need for hospitalization (Mor et al., 2010).

Unique post-hospital needs of patients with high depressive symptoms

The inability to identify the post-hospital setting of maximal benefit for patients has critical implications for patients with high depressive symptoms who have increased health risk.

Depressive symptoms are associated with increased mortality risk (Blazer, Hybels, & Pieper, 2001; Cuijpers & Smit, 2002; Cuijpers et al., 2014; Holwerda et al., 2007; Ng et al., 2007; Schoevers et al., 2009). Two meta-analyses estimated at least a 150% increase in risk of mortality among depressed compared to non-depressed adults, for both major depression and subclinical forms of the condition (Cuijpers & Smit, 2002; Cuijpers et al., 2014). Studies evaluating depression among samples of older adults have also reported greater mortality risk (Holwerda et al., 2007; Schoevers et al., 2009). Depressed patients also have high overall health care utilization and costs (Luber et al., 2001; Luppa et al., 2012), including greater risk of hospital readmission compared to the non-depressed population (Berges, Amr, Abraham, Cannon, & Ostir, 2015; Mitchell et al., 2010; Tully, Baker, Turnbull, & Winefield, 2008). However, evidence on the association between depression and readmissions can be inconsistent, limited by small clinical samples and incomplete adjustment for risk factors that confound the relationship.

Higher mortality risk and greater post-hospital utilization may reflect self-management limitations among depressed individuals. For example, in samples of diabetics, depression is associated with lower acts of self-care including reducing or quitting smoking, reducing or quitting alcohol consumption, exercising, adhering to dietary guidelines, checking feet, and glycemic monitoring (Chan, Lin, Chau, & Chang, 2012; Mut-Vitcu, Timar, Timar, Oancea, & Citu, 2016). Depressive symptoms are also associated with worse adherence to medication regimens in older adults (Hennein et al., 2018; Kilbourne et al., 2005). A third mechanism linking depression to poor health outcomes may be higher caregiving needs (Langa, Valenstein, Fendrick, Kabeto, & Vijan, 2004). Therefore, post-hospital treatment settings need to address

depressed patients' health risks, ability to self-care, as well as availability of informal care at home.

Despite these unique post-hospital needs, it is unclear whether depressed individuals receive more intensive and structured post-hospital support. In fact, depression is not usually assessed in hospital discharge decisions (Bowles et al., 2009). It is possible that hospitals make referrals for post-acute care settings differently for depressed compared to non-depressed patients because of other observable factors like differences in functioning or levels of family support. Post-acute referrals by depression status could also reflect providers' concerns about self-management capacity and motivation to complete intensive physical and occupational therapy (Lenze et al., 2007). However, there is no evidence that depression reduces the benefits of inpatient rehabilitation for functional recovery (Lenze et al., 2007). The potential for patients with high depressive symptoms to receive additional benefits from intensive post-acute care has remained unexplored.

Policy context

One factor that has a large influence on discharge decisions is financial incentives (Ackerly & Grabowski, 2014). Over the past few decades, because of its profitability, post-acute care has been one of the fastest growing categories of Medicare spending, particularly SNFs, which accounted for about half of the $62 billion that Medicare spent on post-acute care in 2012 (Mechanic, 2014). More recently, however, Medicare has bundled care episodes, incorporating acute and post-acute care payments to put pressure on providers to reduce discharges to inpatient rehabilitation facilities and home health care (Curtin, Russell, & Odum, 2017). This may increase the likelihood that discharge decisions are based on financial factors rather than clinical factors, the latter which align care needs with the appropriate post-hospital settings. Given this

momentous change in Medicare post-acute care reimbursement, it is critical to better understand post-hospital care referrals and their impact on functional and health outcomes for the at-risk depressed population.

This study

In this study, we use nationally-representative survey data linked to Medicare claims to evaluate the relationship between depressive symptoms and discharge disposition, and to evaluate whether depressive symptoms are differentially associated with 30-day readmission rates, 30-day fall injuries, 1-year fall injuries, and 1-year mortality according to patients' discharge dispositions. This analysis will illustrate whether the association between depressive symptoms and deleterious outcomes is smaller in more structured post-hospital settings. These findings will answer calls for research that can help avoid excess hospitalizations, long-term nursing home admissions, and other poor health outcomes by better managing care transitions for older individuals with depressive symptoms (Berges et al., 2015).

Methods

Sample

Our data came from the Health and Retirement Study (HRS) linked to Medicare claims data from 2000 to 2014. The HRS is a national, biennial panel dataset consisting of multiple birth cohorts of U.S. adults ages 51 and older, with new cohorts added every six years (Sonnega et al., 2014). HRS is conducted and distributed by the University of Michigan and is funded by the National Institute of Aging (Sonnega et al., 2014).

Approximately 80% of respondents give HRS permission to link their survey data to Medicare claims. We linked beneficiaries' enrollment and inpatient data files to data from HRS

surveys that preceded the date of an index hospitalization. In our sample, HRS interviews were on average around 350 days prior to the hospitalization in Medicare claims. Consistent with Centers for Medicare & Medicaid Services (CMS) methodology, hospitalizations were considered eligible index admissions if the respondent had continuous Parts A/B but no Part C coverage during the month of the index hospitalization and the following month, was age 65 or older at the date of the index admission, was discharged alive and not against medical advice, was treated in an acute care hospital (excluding hospitals in Maryland or Puerto Rico and specialty hospitals), and was not hospitalized for a psychiatric diagnosis, rehabilitation, or cancer treatment (Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation, 2014). The analytic sample with complete data on all model variables included 23,485 eligible index hospitalizations for 7,151 unique older, fee-for-service beneficiaries.

Measures

Our outcomes were identified using Medicare claims. We followed CMS criteria to identify unplanned hospital-wide, all-cause readmissions within thirty days of discharge from the index hospitalization, excluding planned readmissions such as transplants, maintenance chemotherapy, or other planned procedures (Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation, 2014). Next, we identified fall injuries within thirty days and one year following discharge from the index hospitalization, based on a validated algorithm for identifying fall injury episodes from claims data that uses hospital, outpatient, physician, and skilled nursing facility claims (Min et al., 2019). Mortality within one year from discharge was identified using the death date in Medicare enrollment files.

Depressive symptoms were measured using the Center for Epidemiologic Studies Depression short-form scale (CESD-8) in HRS. Respondents were asked to report (yes/no)

whether they felt each of the following eight symptoms “much of the week”: depressed, everything was an effort, sleep was restless, was happy, lonely, sad, could not get going, and enjoyed life. We used the summed the number of symptoms respondents reported (with a score of 1 for 'yes' responses and 0 for 'no' responses; each of 'felt happy' and 'enjoyed life' were reverse coded), ranging from zero to eight symptoms. The CESD-8 is common measure of depressive symptoms in older adults, and it has been validated in prior studies (Karim, Weisz, Bibi, & ur Rehman, 2015; Lewinsohn, Seeley, Roberts, & Allen, 1997; Turvey, Wallace, & Herzog, 1999). We use the continuous symptom count rather than a threshold for high depressive symptoms, because the CESD-8 was designed to be used as a scale, not to identify depression cases (Karim et al., 2015). As a sensitivity analysis, we tested whether conclusions would differ if using an indicator for high depressive symptoms, as has been done in some prior studies (Han, 2002; Ní Mhaoláin et al., 2012; Stevens, Lang, Guralnik, & Melzer, 2008).

We grouped discharge status into three categories of post-hospital settings – 1) home without home health (hereafter “routine home”), 2) home with home health (hereafter “home health”), or 3) Intermediate Care Facility or Skilled Nursing Facility (hereafter “inpatient rehabilitation”). Models adjusted for a number of potential confounding risk factors that might be associated with depressive symptoms and our outcomes of interest. We adjusted for standard sociodemographic factors including age at discharge (from Medicare claims), and HRS data on sex (male, female), and race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and non-Hispanic other). We also adjusted for socioeconomic factors from the HRS including education level (less than high school degree, high school degree or GED, some college or Associates degree, and college or more), total wealth (assets minus debts), dual enrollment status in Medicare and Medicaid, and supplemental insurance status.

We also included measures of family support, which may influence depressive symptoms (Bures, Koropeckyj-Cox, & Loree, 2009; Zunzunegui, Béland, & Otero, 2001) and discharge decisions (Bowles et al., 2009). We used HRS data on marital status, having a child who is alive, living alone, and total weekly hours (from all caregivers) of informal care receipt (0, 1-13, and 14+ hours) (Hoffman, Hays, Wallace, Shapiro, Yakusheva, et al., 2017). Because such support might mediate (rather than confound) the effects of discharge setting on relationships between depressive symptom and our outcomes, controlling for those factors could mute observed differences by discharge disposition.

Therefore, in a sensitivity analysis we ran models without controlling for family support covariates. Given that differences in underlying health and functioning typically drive discharge decisions (Bowles et al., 2009; Werner et al., 2019), we adjusted for a number of health and functional status indicators from the HRS: Activities of Daily Living (ADLs, ranging 0-5), Instrumental Activities of Daily living (IADLs, ranging 0-3), cognition (word recall and mental status, ranging from 0-35, higher scores indicating better cognition) (Lièvre, Alley, & Crimmins, 2008; Suthers, Kim, & Crimmins, 2003), and a count of the number of chronic diseases (ranging from 0-8, measuring whether respondents were ever diagnosed with high blood pressure, diabetes, cancer, lung disease, heart disease, stroke, psychiatric problems, and arthritis).

Statistical Analysis

First, we characterized the analytic sample by reporting the mean and standard deviation of continuous model variables and the count and percentages of categorical variables. Next, we ran a series of multinomial probit models regressing post-hospital setting on depressive symptoms, adjusting for model covariates. We chose probit rather than logistic model specifications because of evidence that the Independence of Irrelevant Alternatives (IIA)

assumption was violated. The IIA states that the relative odds of selection two alternative options are independent of the number of options (Bow & Endersby, 2004). When this assumption is violated, multinomial probit regression models are appropriate because they use independent normal error terms (Bolduc, 1999). For interpretability, we report marginal effects with covariates held at their means. To understand the confounding role of family support and health status, we took a hierarchical approach. Model 1 adjusted for sociodemographic and socioeconomic factors, Model 2 additionally adjusted for family support variables, Model 3 adjusted for health status variables in addition to Model 1 covariates, and Model 4 included all covariates – sociodemographic factors, socioeconomic factors, family support, and health status (see Equation 3).

Equation 3. Multinomial probit regression model of post-hospital setting

$$Pr(\text{Home health}) = \beta_0 + \boldsymbol{\beta_1}\textbf{(Depressive symptoms)} + \beta_2(\text{Age}) + \beta_3(\text{Female}) + \beta_4(\text{Non-Hispanic Black}) + \beta_5(\text{Non-Hispanic other race/ethnicity}) + \beta_6(\text{Hispanic}) + \beta_7(\text{Less than high school education}) + \beta_8(\text{GED or high school graduate}) + \beta_9(\text{Some college}) + \beta_{10}(\text{Wealth}) + \beta_{11}(\text{Dual enrollment}) + \beta_{12}(\text{Supplemental insurance}) + \beta_{13}(\text{Married}) + \beta_{14}(\text{Child alive}) + \beta_{15}(\text{Live alone}) + \beta_{16}(\text{Informal caregiving 1-13 hours/week}) + \beta_{17}(\text{Informal caregiving 14+ hours/week}) + \beta_{18}(\text{ADLs}) + \beta_{19}(\text{IADLs}) + \beta_{20}(\text{Cognition}) + \beta_{21}(\text{Chronic conditions}) + \varepsilon_{ti}$$

$$Pr(\text{Inpatient rehabilitation}) = \beta_0 + \boldsymbol{\beta_1}\textbf{(Depressive symptoms)} + \beta_2(\text{Age}) + \beta_3(\text{Female}) + \beta_4(\text{Non-Hispanic Black}) + \beta_5(\text{Non-Hispanic other race/ethnicity}) + \beta_6(\text{Hispanic}) + \beta_7(\text{Less than high school education}) + \beta_8(\text{GED or high school graduate}) + \beta_9(\text{Some college}) + \beta_{10}(\text{Wealth}) + \beta_{11}(\text{Dual enrollment}) + \beta_{12}(\text{Supplemental insurance}) + \beta_{13}(\text{Married}) + \beta_{14}(\text{Child alive}) + \beta_{15}(\text{Live alone}) + \beta_{16}(\text{Informal caregiving 1-13 hours/week}) + \beta_{17}(\text{Informal caregiving 14+ hours/week}) + \beta_{18}(\text{ADLs}) + \beta_{19}(\text{IADLs}) + \beta_{20}(\text{Cognition}) + \beta_{21}(\text{Chronic conditions}) + \varepsilon_{ti}$$

Finally, we examined whether the relationships between depressive symptoms and our four binary outcomes – 30-day readmissions, 30-day falls, 1-year falls, and 1-year mortality – varied according to patients' post-hospital settings. We used logistic regression models and interacted depressive symptoms with post-hospital setting, while adjusting for all covariates (see Equation 4). We calculated and plotted predicted probabilities of each outcome by depressive symptoms and post-hospital setting. All models used clustered standard errors to account for the clustering of hospitalizations within individuals.

Equation 4. Logistic regression models of four health outcomes by post-hospital setting interacted with depressive symptoms

$$Pr(\text{Health outcome}) = \beta_0 + \boldsymbol{\beta_1(\text{Depressive symptoms}) + \beta_2(\text{Home health}) + \beta_3(\text{Inpatient rehabilitation}) + \beta_4(\text{Depressive symptoms * home health}) + \beta_5(\text{Depressive symptoms * inpatient rehabilitation})} + \beta_6(\text{Age}) + \beta_7(\text{Female}) + \beta_8(\text{Non-Hispanic Black}) + \beta_9(\text{Non-Hispanic other race/ethnicity}) + \beta_{10}(\text{Hispanic}) + \beta_{11}(\text{Less than high school education}) + \beta_{12}(\text{GED or high school graduate}) + \beta_{13}(\text{Some college}) + \beta_{14}(\text{Wealth}) + \beta_{15}(\text{Dual enrollment}) + \beta_{16}(\text{Supplemental insurance}) + \beta_{17}(\text{Married}) + \beta_{18}(\text{Child alive}) + \beta_{19}(\text{Live alone}) + \beta_{20}(\text{Informal caregiving 1-13 hours/week}) + \beta_{21}(\text{Informal caregiving 14+ hours/week}) + \beta_{22}(\text{ADLs}) + \beta_{23}(\text{IADLs}) + \beta_{24}(\text{Cognition}) + \beta_{25}(\text{Chronic conditions}) + \varepsilon_{ti}$$

Results

Of the 23,485 hospitalizations in the analytic sample, 58% were for women, 79% for non-Hispanic Whites, 33% for patients who completed some college or higher, 15% for patients dually eligible for Medicare and Medicaid, and 22% for those with supplemental insurance

(Table 9). The mean age at discharge was 78.5 years old (SD=7.68). According to the HRS interview prior to hospitalization, 51% were married, 93% had a living child, 34% lived alone, and 24% received informal care. On average, the ADL count was 0.70 (SD=1.22), the IADL count was 0.23 (SD=0.58), and the chronic condition count was 3.01 (SD=1.52). Mean depressive symptom count was 2.04 (SD=2.15). The majority of hospitalizations (62%) involved routine home discharges, while 17% were discharged to home health, and 21% were discharged to inpatient rehabilitation. Following hospitalization, 15% of respondents died within one year, 14% had an unplanned 30-day readmission, 13% had a fall injury within one year, and 2% had a fall injury within 30 days.

	Variable	Count (Percent) or Mean (SD)
Independent variable	Depressive symptoms (0-8)	2.04 (2.15)
Socio-demographic factors	Age (65-111)	78.52 (7.68)
	Sex	
	Female	13,698 (58.33)
	Male	9,787 (41.67)
	Race/ethnicity	
	NH White	18,579 (79.11)
	NH Black	3,152 (13.42)
	Hispanic	1,367 (5.82)
	Other	387 (1.65)
Socio-economic factors	Educational attainment	
	Less than HS	7,067 (30.09)
	HS or GED	8,701 (37.05)
	Some college or AS	4,198 (17.88)
	College or more	3,519 (14.98)
	Total wealth ($10k)	364.54 (1008.23)
	Dual enrollment	
	Yes	3,564 (15.18)
	No	19,921 (84.82)
	Supplemental insurance	
	Yes	5,231 (22.27)
	No	18,254 (77.73)
Family support	Marital status	

	Currently married	12,015 (51.16)
	Currently not married	11,470 (48.84)
	Child alive	
	Yes	21,759 (92.65)
	No	1,726 (7.35)
	Live alone	
	Yes	7,990 (34.02)
	No	15,495 (65.98)
	Informal caregiving	
	0 hours per week	17,845 (75.98)
	1-13 hours per week	2,283 (9.72)
	14+ hours per week	3,357 (14.29)
Health factors	ADLs (0-5)	0.70 (1.22)
	IADLs (0-3)	0.23 (0.58)
	Cognition (0-35)	19.83 (5.60)
	Conditions (0-8)	3.01 (1.52)
Modifier	Post-Acute Care	
	Routine home	14,450 (61.53)
	Home health	4,019 (17.11)
	Inpatient rehabilitation	5,016 (21.36)
Outcomes	30-day readmission	
	Yes	3,145 (13.39)
	No	20,340 (86.61)
	30-day falls	
	Yes	411 (1.75)
	No	23,074 (98.25)
	1-year fall	
	Yes	2,860 (12.18)
	No	20,625 (87.82)
	1-year mortality	
	Yes	**3,439 (14.64)**
	No	**20,046 (85.36)**

Table 9 Descriptive statistics of all hospitalizations

N=23,485 hospitalizations, N=7,151 individuals. NH= Non-Hispanic, HS=High School, AS= Associates degree, ADLs=Activities of Daily Living, IADLs= Instrumental Activities of Daily Living

Table 10 shows the results of the first aim of this paper – to determine the association between depressive symptoms and discharge disposition. In Model 1, adjusting for

sociodemographic and socioeconomic factors, the probability of being discharged to home health compared to routine home was on average about a half percentage point higher with each increasing depressive symptom (dydx=0.004, 95% CI=0.001, 0.007). Therefore, 17.6% of patients with two depressive symptoms (the sample mean) were discharged to home health, while two standard deviations higher at six symptoms, the rate increased to 19.0%. The probability of being discharged to inpatient rehabilitation compared to routine discharges home was 1.6 percentage points higher with each increasing symptom (dydx=0.016, 95% CI=0.012, 0.019), so that 19.7% of patients with two depressive symptoms were discharged to SNFs compared to 26.5% with six symptoms. The association between depressive symptoms and inpatient rehabilitation remained significant in Models 2 and 3 that additionally adjusted for family support and health status respectively, but not when both factors where included in the model (Table 2). The association between depressive symptoms and home health was completely attenuated by additional adjustment for factors included in Models 2-4.

Home health compared to routine home	Model 1: Sociodemographic and socio-economic factors	Model 2: Model 1 + Family support	Model 3: Model 1 + Health status	Model 4: Model 1 + Family support + health status
Depressive symptoms	0.004 (0.001, 0.007)**	0.002 (-0.001, 0.005)	-0.001 (-0.004, 0.002)	-0.001 (-0.004, 0.002)
Age	0.002 (0.001, 0.003)***	0.002 (0.001, 0.003)***	0.002 (0.001, 0.003)***	0.002 (0.001, 0.03)***
Sex				
Female	0.013 (0.000, 0.026)	0.010 (-0.004, 0.024)	0.013 (0.000, 0.026)	0.012 (-0.002, 0.026)
Male	--	--	--	--
Race/ethnicity				
NH White	--	--	--	--
NH Black	0.043 (0.023, 0.063)***	0.036 (0.016, 0.057)***	0.040 (0.020, 0.060)***	0.037 (0.017, 0.058)***
Hispanic	0.044 (0.011, 0.077)**	0.038 (0.006, 0.072)*	0.045 (0.011, 0.078)**	0.043 (0.010, 0.076)*
Other	-0.059 (-0.095, -0.022)**	-0.063 (-0.099, -0.027)**	-0.066 (-0.101, -0.031)***	-0.067 (-0.102, -0.031)***
Educational attainment				
Less than HS	--	--	--	--
HS or GED	0.001 (-0.016, 0.017)	0.002 (-0.014, 0.019)	0.003 (-0.014, 0.019)	0.003 (-0.014, 0.019)
Some college or AS	0.012 (-0.009, 0.032)	0.014 (-0.006, 0.035)	0.013 (-0.008, 0.034)	0.013 (-0.007, 0.034)
College or more	-0.002 (-0.023, 0.018)	0.000 (-0.021, 0.020)	-0.002 (-0.023, 0.019)	-0.002 (-0.023, 0.019)
Total wealth ($10k)	0.000 (0.000, 0.000)	0.000 (0.000, 0.000)	0.0001 (0.000, 0.000)*	0.0001 (0.000, 0.000)*
Dual enrollment	0.026 (0.004, 0.047)**	0.020 (-0.002, 0.041)	0.015 (-0.005, 0.036)	0.015 (-0.005, 0.035)
Supp. insurance	0.006 (-0.009, 0.021)	0.006 (-0.009, 0.021)	0.006 (-0.008, 0.021)	0.006 (-0.009, 0.021)
Married		-0.011 (-0.030, 0.008)		-0.009 (-0.028, 0.010)
Child alive		0.024 (-0.000, 0.048)		0.024 (0.000, 0.048)*
Live alone		-0.013 (-0.031, 0.005)		-0.013 (-0.031, 0.005)
Informal caregiving				
0 hours per week		--		--
1-13 hours per week		0.027 (0.007, 0.047)**		0.012 (-0.010, 0.033)
14+ hours per week		0.057 (0.037, 0.078)***		0.028 (0.005, 0.052)*
ADLs			0.019 (0.013, 0.025)***	0.016 (0.010, 0.023)***
IADLs			0.004 (-0.009, 0.016)	-0.002 (-0.015, 0.010)
Cognition			0.000 (-0.001, 0.002)	0.001 (-0.001, 0.002)
Conditions			0.009 (0.005, 0.013)***	0.008 (0.004, 0.013)***

Inpatient rehab. compared to routine home	Model 1: Sociodemographic and socio-economic factors	Model 2: Model 1 + Family support	Model 3: Model 1 + Health status	Model 4: Model 1 + Family support + health status
Depressive symptoms	0.016 (0.012, 0.019)***	0.011 (0.007, 0.014)***	0.006 (0.002, 0.009)**	0.004 (0.000, 0.007)
Age	0.013 (0.012, 0.014)***	0.011 (0.009, 0.012)***	0.010 (0.009, 0.011)***	0.009 (0.007, 0.010)***
Sex				
Female	0.038 (0.022, 0.055)***	0.012 (-0.004, 0.029)	0.042 (0.027, 0.058)***	0.021 (0.005, 0.038)*
Male	--	--	--	--
Race/ethnicity				
NH White	--	--	--	--
NH Black	-0.030 (-0.056, -0.004)*	-0.031 (-0.057, -0.006)*	-0.059 (-0.083, -0.035)***	-0.056 (-0.079, -0.032)***
Hispanic	-0.077 (-0.109, -0.044)***	-0.073 (-0.105, -0.040)***	-0.096 (-0.126, -0.066)***	-0.087 (-0.118, -0.057)***
Other	-0.084 (-0.133, -0.035)**	-0.093 (-0.137, -0.049)***	-0.106 (-0.151, -0.061)***	-0.108 (-0.148, -0.068)***
Educational attainment				
Less than HS	--	--	--	--
HS or GED	0.033 (0.013, 0.053)**	0.037 (0.018, 0.057)***	0.052 (0.032, 0.071)***	0.054 (0.034, 0.073)***
Some college or AS	0.027 (0.002, 0.051)*	0.031 (0.007, 0.055)*	0.052 (0.027, 0.076)***	0.054 (0.030, 0.078)***
College or more	0.036 (0.010, 0.062)**	0.040 (0.051, 0.066)**	0.068 (0.041, 0.095)***	0.072 (0.045, 0.098)***
Total wealth ($10k)	-0.0001 (0.000, 0.000)*	-0.000 (0.000, 0.000)	0.000 (0.000, 0.000)	0.000 (0.000, 0.000)
Dual enrollment	0.074 (0.045, 0.103)***	0.044 (0.017, 0.072)**	0.037 (0.009, 0.064)**	0.019 (-0.006, 0.044)
Supp. insurance	-0.014 (-0.032, 0.004)	-0.014 (-0.032, 0.004)	-0.009 (-0.027, 0.009)	-0.008 (-0.026, 0.010)
Married		-0.029 (-0.053, -0.005)*		-0.028 (-0.052, -0.004)*
Child alive		-0.076 (-0.109, -0.044)***		-0.073 (-0.105, -0.042)***
Live alone		0.059 (0.035, 0.083)***		0.057 (0.033, 0.080)***
Informal caregiving				
0 hours per week		--		--
1-13 hours per week		0.107 (0.080, 0.133)***		0.051 (0.025, 0.045)***
14+ hours per week		0.078 (0.054, 0.102)***		-0.011 (-0.037, 0.014)
ADLs			0.039 (0.031, 0.046)***	0.037 (0.030, 0.045)***
IADLs			-0.003 (-0.016, 0.010)	0.002 (-0.012, 0.015)
Cognition			-0.008 (-0.010, 0.006)***	-0.008 (-0.010, -0.007)***

Conditions	0.006 (0.001, 0.011)*	0.007 (0.002, 0.012)**

Table 10 Multinomial probit marginal effects (95% confidence intervals) from adjusted models predicted post-hospital setting by depressive symptoms

*N=23,485, *<0.05, **<0.01,***<0.001; NH= Non-Hispanic, HS=High School, AS= Associates degree, Supp. Insurance = Supplemental Insurance, ADLs=Activities of Daily Living, IADLs= Instrumental Activities of Daily Living*

In logistic regressions testing the study's second aim, there was not a significant relationship between depressive symptoms and each of 30-day and 1-year falls across all post-hospital settings (Table 11). There was a marginally significant association between depressive symptoms and 1-year mortality in routine discharges home (OR=1.04, 95% CI=1.00, 1.07); this association also did not significantly vary across settings. For 30-day readmissions, odds were lower for each additional depressive symptom for patients discharged to inpatient rehabilitation settings compared to routine discharges home (OR=0.95, p=0.027). As illustrated in Figure 5-1, the probability of a 30-day readmission increased with more depressive symptoms for patients discharged to routine home (from 9% with zero symptoms to 15% with eight symptoms) and for patients referred to home health (from 14% to 23%). However, the probability of a readmission was relatively unchanged across depressive symptoms for those treated in inpatient rehabilitation settings (from 17% at zero symptoms to 19% at eight symptoms).

In a sensitivity analysis using an indicator for high depressive symptoms (four to eight symptoms) rather than a continuous symptoms count, model results were consistent with those in the main analysis – odds were lower for increasing depressive symptoms in inpatient rehabilitation at SNFs compared to routine discharges home (OR=0.78, p=0.024), while interactions were not significant when modeling the other outcomes. Results were also robust to removing family support covariates to conceptualize these factors as potential mediators. Odds of readmissions with each additional depressive symptom were lower (OR=0.95, p=0.017) in inpatient rehabilitation compared to routine home, while interactions were not significant when modeling falls and mortality.

	30-day readmission	30-day fall	1-year fall	1-year mortality
Depressive symptoms	1.03 (1.00, 1.06)*	1.02 (0.94, 1.11)	1.01 (0.97, 1.05)	1.04 (1.00, 1.07)
Post-acute care				
Routine home	--	--	--	--
Home health	1.47 (1.26, 1.70)***	2.41 (1.61, 3.63)***	1.70 (1.43, 2.02)***	1.80 (1.53, 2.11)***
Inpatient rehab.	1.70 (1.46, 1.97)***	2.74 (1.86, 4.06)***	2.04 (1.72, 2.42)***	2.84 (2.43, 3.32)***
Interaction				
Depressive sym. x routine home	--	--	--	--
Depressive sym. x Home health	1.00 (0.96, 1.05)	0.97 (0.86, 1.11)	1.02 (0.97, 1.09)	0.98 (0.93, 1.03)
Depressive sym. x Inpatient rehab.	0.95 (0.91, 0.99)*	0.95 (0.85, 1.06)	0.99 (0.94, 1.04)	0.98 (0.93, 1.02)
Age	1.01 (1.00, 1.01)*	1.02 (1.00, 1.04)*	1.02 (1.01, 1.03)***	1.03 (1.02, 1.04)***
Sex				
Female	0.78 (0.70, 0.86)***	1.21 (0.94, 1.57)	1.33 (1.14, 1.54)***	0.62 (0.54, 0.71)***
Male	--	--		
Race/ethnicity				
NH White	--	--	--	--
NH Black	1.17 (1.02, 1.34)*	0.89 (0.61, 1.30)	0.65 (0.52, 0.82)***	0.84 (0.69, 1.02)
Hispanic	0.93 (0.76, 1.13)	1.07 (0.62, 1.84)	1.09 (0.78, 1.52)	0.89 (0.67, 1.18)
Other	0.72 (0.53, 0.97)*	1.65 (0.70, 3.89)	1.97 (1.21, 3.20)**	0.80 (0.47, 1.37)
Educational attainment				
Less than HS	--	--	--	--
HS or GED	1.04 (0.92, 1.18)	1.59 (1.16, 2.17)**	1.35 (1.12, 1.62)**	1.01 (0.87, 1.18)
Some college or AS	0.89 (0.76, 1.04)	1.21 (0.80, 1.81)	1.30 (1.05, 1.63)*	0.92 (0.76, 1.2)
College or more	0.90 (0.77, 1.06)	1.69 (1.15, 2.49)**	1.66 (1.33, 2.08)***	0.87 (0.71, 1.08)
Total wealth ($10k)	1.00 (0.99, 1.00)	1.00 (0.99, 1.00)	1.00 (0.99, 1.00)	1.00 (0.99, 1.00)
Dual enrollment	1.23 (1.07, 1.43)**	1.12 (0.80, 1.58)	1.00 (0.81, 1.23)	0.99 (0.83, 1.20)
Supplemental insurance	0.96 (0.85, 1.08)	1.11 (0.83, 1.49)	1.12 (0.95, 1.31)	0.96 (0.84, 1.11)
Married	0.80 (0.70, 0.91)**	0.96 (0.68, 1.36)	1.00 (0.81, 1.22)	0.84 (0.70, 1.01)
Child alive	1.00 (0.83, 1.21)	1.08 (0.70, 1.64)	1.05 (0.82, 1.34)	0.95 (0.78, 1.15)

Live alone	0.88 (0.77, 1.00)	0.92 (0.66, 1.28)	1.16 (0.95, 1.40)	0.93 (0.78, 1.11)
Informal caregiving				
0 hours per week	--	--	--	--
1-13 hours per week	1.09 (0.94, 1.26)	1.23 (0.87, 1.73)	1.10 (0.88, 1.37)	1.23 (1.01, 1.50)*
14+ hours per week	1.33 (1.13, 1.56)***	1.15 (0.79, 1.66)	1.18 (0.95, 1.46)	1.73 (1.42, 2.10)***
ADLs	1.03 (0.98, 1.08)	1.01 (0.91, 1.12)	1.02 (0.96, 1.09)	1.01 (0.95, 1.07)
IADLs	0.90 (0.82, 0.99)*	0.89 (0.71, 1.11)	0.94 (0.83, 1.07)	0.86 (0.77, 0.97)*
Cognition	0.99 (0.98, 1.00)	0.97, 0.94, 0.99)**	0.98 (0.97, 0.99)**	0.97 (0.95, 0.98)***
Conditions	1.12 (1.09, 1.16)***	1.18 (1.09, 1.28)***	1.18 (1.13, 1.24)***	1.13 (1.08, 1.18)***

Table 11 Odds ratios (95% confidence intervals) from adjusted logistic regression models predicting outcomes by depressive symptoms interacted with post-acute care settings

*N=23,485. *<0.05, **<0.01,***<0.001; NH= Non-Hispanic, HS=High School, AS= Associates degree, ADLs=Activities of Daily Living, IADLs= Instrumental Activities of Daily Living*

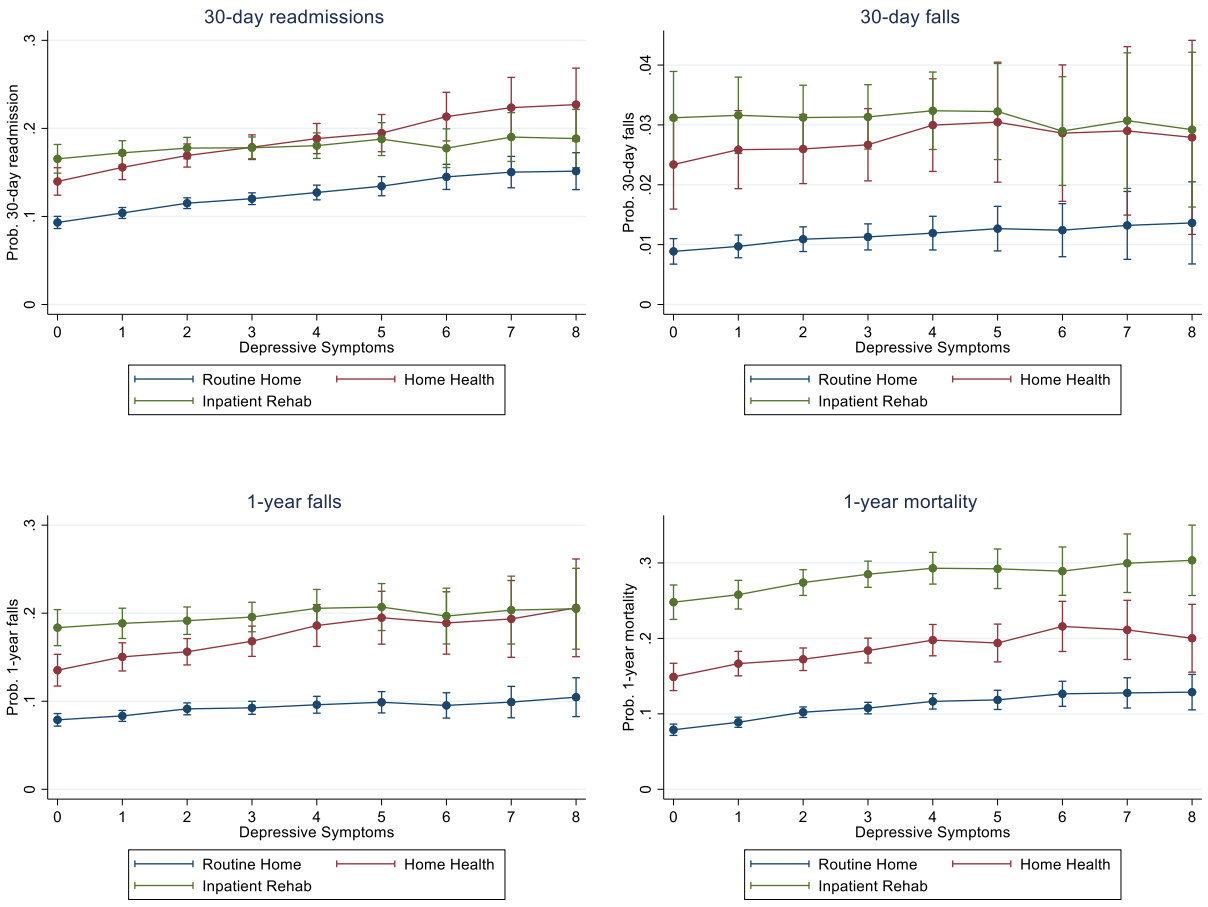

Figure 5-1 Predicted probabilities (with 95% confidence intervals) of each outcome by depressive symptoms and post-acute care setting from fully adjusted logistic regression interaction models

Discussion

Overall, our results showed that inpatient rehabilitation compared to routine discharges home reduced excess readmissions among patients with high depressive symptoms, but did not modify the risk that depressive symptoms pose for falls or mortality. Therefore, discharging a patient with high depressive symptoms to a SNF would be incentivized to avoid readmission penalties (Patel, Wright, & Hay, 2017), but would simultaneously inflict the patient with high costs that may not have health returns.

Previously, it had been shown that discharge decisions were shaped largely by factors such as care available at home, hospital length of stay, health and functional status, and financial incentives (Ackerly & Grabowski, 2014; Bowles et al., 2009; Werner et al., 2019). This study revealed a positive relationship between depressive symptoms and referrals to home health or inpatient rehabilitation when adjusting for sociodemographic and socioeconomic factors. Adjusting for family support attenuated the association with home health, suggesting that, within similar levels of family support, depressive symptoms were not considered for home health referrals. Because the associations between depressive symptoms and health outcomes were similar with and without home health, factors other than depressive symptoms should continue to be used for home health referrals.

At the same levels of family support and health status, patients with high depressive symptoms were no more likely to be discharged to a SNF or intermediate care facility, despite the fact that these inpatient rehabilitation settings reduced readmissions associated with high depressive symptoms. Prior studies have highlighted concerns about the "revolving door" between hospitals and SNFs because of the high rates of readmissions from these facilities (Mor et al., 2010). Our results also show high readmission rates from SNFs, but add a new

understanding of how SNFs might reduce excess readmissions for vulnerable patients. Patients with high depressive symptoms in SNFs had similar readmission rates to those with low depressive symptoms, and even had lower rates of readmissions that those with similarly high symptoms in home health. Therefore, in not considering depressive symptoms above and beyond health and family support differences, hospitals may be missing opportunities to refer vulnerable patients to post-acute care settings that could prevent hospital readmissions.

While prior studies have found a positive association between depressive symptoms and subsequent falls (Hoffman, Hays, Wallace, Shapiro, & Ettner, 2017), there was not a significant relationship in any post-hospital setting in our adjusted analysis. The marginally significant positive association between depressive symptoms and mortality in our study was consistent with the direction of this association in prior studies (Blazer et al., 2001; Holwerda et al., 2007; Ng et al., 2007), and was not reduced in home health or inpatient care settings. Removing family support factors as a sensitivity analysis revealed that the null interactions for falls and mortality were not due to an over-adjustment of the potential mechanism of family support. One interpretation of the significant interaction for readmissions but not falls or mortality is that inpatient rehabilitation reduces excess readmissions by providing the clinical services sought when returning to the hospital, but does not improve the clinical trajectories or health outcomes of patients with high depressive symptoms. Our study confirms prior findings that patients with and without high depressive symptoms respond similarly to post-hospital rehabilitation in terms of measures of health and functioning (Lenze et al., 2007).

These results should be interpreted in the context of this study's strengths and limitations. One limitation is our observational study design, which, despite rigorous adjustment for confounding using a broad set of survey and claims-based variables, cannot capture all

unobservable factors associated with depressive symptoms, post-acute care, and health outcomes. Given that sicker patients are more commonly discharged to higher-intensity care settings (Werner et al., 2019), there is risk of residual confounding, even after risk-adjustment; for this reason, our results likely underestimate any benefits from high-intensity care for patients with greater depressive symptoms. Another limitation is that an average of approximately one year passed between the HRS interview and each hospitalization, a time period in which we were unable to observe changes in depressive symptoms, economic status, health status, or family support. Random noise in these right-side variables will likely bias our estimates towards a null effect.

Despite these limitations, this study is strengthened by its rich data and large sample. Most studies of hospital readmissions are limited to small samples using clinical data. In contrast, this study exploited the powerful combination of both claims data and extensive survey data, with a large sample size for statistical power and representativeness. Measures of health status, socioeconomic status, and family support captured important context for a more complete picture of patient well-being and the home environment. Another strength of this study was the use of multiple outcomes measuring different aspects of health and functioning in short- and long-term time frames. These multiple outcomes enabled us to parse out the specific benefit of inpatient rehabilitation for readmissions at high depressive symptoms, but not for other important markers of the clinical trajectory.

In conclusion, discharging patients with high depressive symptoms to SNFs or intermediate care facilities may reduce readmissions associated with depressive symptoms, making this a financially-sound decision for hospitals. For the patient, the financial and other

costs of inpatient rehabilitation may not be worthwhile, as intensive post-acute care does not appear to reduce the risk of falls or mortality associated with depressive symptoms.

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Chapter 6 **Conclusion and Future Directions**

Overview

My dissertation examined depressive symptoms late in life, motivated by concern about the health of the growing aging population (Centers for Disease Control and Prevention (CDC), 2003) and rising suicide, drug-use, and despair in midlife (Case & Deaton, 2017). I funded this research by applying for and receiving a T32 training grant from the National Institute on Aging, as well as the Angus Campbell Scholars Award from the University of Michigan Institute for Social Research and the Rackham Predoctoral Fellowship. During my doctoral studies, the complex relationship between retirement timing and health emerged as a focal area I will continue to pursue in the coming years. This chapter will discuss the implications of this dissertation research and ideas for my future research agenda.

Implications of findings

The first empirical paper of my dissertation (Chapter 2) focused on the demography of mental health, examining sociodemographic differences in how depressive symptoms change over ages 51-90. Prior research on depression curves over the life course had heavily relied on cross-sectional data (Cairney & Krause, 2005; Mirowsky & Ross, 1992). My analysis leveraged the longitudinal Health and Retirement Study, multi-level modeling, and flexible indicators for age groups to differentiate between age and cohort effects while capturing trends in the population of concern for high despair. This method revealed that educational attainment drives large disparities in mental health in mid- and late life, pointing to the long-term health

consequences of this early life exposure. In addition, depressive symptoms were substantially higher among Hispanic Americans compared to other racial/ethnic groups, calling for future research into the unique mental health needs of the aging Hispanic population. This finding is consistent with findings that the lower mortality in Hispanic Americans is not accompanied by lower levels of disability or morbidity (Melvin et al. 2014). Consistent with trends in deaths of despair, depressive symptoms in midlife were especially high among recent birth cohorts compared to prior cohorts (Case & Deaton, 2017). This finding adds depressive symptoms to the list of alarming trends, including worsening physical functioning and mortality, in middle- and older-aged Americans (Bezruchka, 2012; Martin, Freedman, Schoeni, & Andreski, 2010; Seeman, Merkin, Crimmins, & Karlamangla, 2010).

Next steps in this research will examine the mechanisms and pathways that explain why depressive symptoms are high in midlife and growing worse over time. For example, future research could take a life course perspective to explore which aspects of midlife (e.g. job strain, relational stress, changing parenting roles, etc.) contribute to higher depressive symptoms in middle age compared to older ages. In addition, it will be important to explore the potential role of decreasing mental health stigma and increasing use of metal health services in cohort differences in reported depressive symptoms in late life.

My second and third empirical papers (chapters 3 and 4) focused on retirement timing and mental health. I compared retirement expectations in ages 51-61 to actual labor force status at age 62 to evaluate whether unmet expectations about retirement timing relate to depressive symptoms. This study design tested the hypothesis that setbacks late in life might differentially relate to depressive symptoms in Black and White older adults (Malat, Mayorga-Gallo, & Williams, 2018). In addition, the timing of the HRS allowed me to explore how the Great

Recession of 2008 might have contributed to increased unmet expectations about retirement timing and therefore potentially increased depressive symptoms in recent birth cohorts.

The first paper from this study (Chapter 3) described retirement expectations and realizations across diverse groups of older Americans. Whereas researchers have often used HRS' expected retirement timing as an outcome to test the effects of social, economic, and health factors on retirement (for example, (Hudomiet, Hurd, & Rohwedder, 2018)), few have critically examined how expectations align with realized retirement timing. In doing so, my study found that Black and Hispanic Americans were more likely than White Americans to be unexpectedly working and unexpectedly not working at age 62. In addition, low educational attainment was associated with higher probability of unexpectedly not working. These findings demonstrate how the societal and personal benefits of longer work and predictable retirement are not equally attainable across the population of older adults in America.

The second paper that resulted from this project (Chapter 4) turned to the question of how unmet expectations about work at age 62 relate to subsequent depressive symptoms. The results highlight the adaptability of older adults to delayed retirement and suggests that there need not be concern about the mental health implications of delayed retirement among those who lost wealth during the Great Recession. The significant but small increase in depressive symptoms among those unexpectedly not working was explained by health declines. Therefore, poor health may be the common cause of leaving the labor force earlier than expected and experiencing declines in mental health. Future research attention should be directed at mitigating health-related early labor force departures, which differentially occur among disadvantaged groups in America. Despite compelling hypotheses from prior studies, I found no evidence of differential resilience in response to setbacks based on race (nor gender, educational attainment, or birth

cohort). I have many new research questions I would like to pursue based on the findings of these two chapters, and that research agenda will be outlined below.

In the fifth chapter of this dissertation, I used Medicare claims data to examine discharge disposition by depressive symptoms, and how post-hospital setting might modify the relationship between depressive symptoms and health outcomes. This research was motivated by the increased burden of depressive symptoms among those with other health conditions (Alexopoulos, 2005; Alexopoulos et al., 2002) and the detrimental effects of depressive symptoms on chronic disease outcomes (Egede & Ellis, 2010; Ng et al., 2007). Despite the high costs of post-acute care, there has been a poor understanding of which types of patients benefit most from specific post-acute care settings, hindering any ability to match depressed patients to post-hospital care suits their unique needs (Ackerly & Grabowski, 2014; Burke et al., 2016; Mechanic, 2014). This study showed that depressive symptoms were associated with increased likelihood being referred to home health or inpatient rehabilitation compared to routine discharge home, explained by differences in family support factors and health status.

Not considering depressive symptoms above and beyond their correlation with family support and physical health represents a missed opportunity to prevent excess readmissions in Skilled Nursing Facilities. While much of the prior research on depressive symptoms and hospital readmissions was conducted in small samples with minimal controls, we provided evidence from a large sample and well-controlled model showing that depressive symptoms are associated with increased risk for 30-day readmissions at home with and without home health, but not in SNFs. Post-acute care settings did not modify the relationships between depressive symptoms and each of falls and mortality. Therefore, SNFs may reduce excess readmissions by providing the clinical services sought in the hospital, but without improving the clinical

trajectory of patients. These results indicate that referring patients with high depressive symptoms to SNFs is a financially-sound decision for hospitals but not a beneficial decision for patients' health and functioning.

Attrition from mortality, study drop out, and proxy response are present throughout these chapters, as in all longitudinal aging research, and the implications of attrition/survival bias warrant further discussion (Banks, Muriel & Smith 2011; Langa, Llewellyn, Lang, et al. 2009). In this dissertation, respondents who needed proxies to complete the HRS survey were not included in analytic samples, because proxies do not provide information on depressive symptoms. In Chapter 2, excluding proxy respondents, who tend to be sicker and more cognitively impaired, may result in an underestimate of depressive symptoms in the population and especially in the oldest old. In Chapters 3, excluding proxies, who most likely are not working full time, may underestimate expectedly and unexpectedly not working. Therefore, the association between unexpectedly not working and depressive symptoms in Chapter 4 may be biased towards the null. In Chapter 5, excluding proxies may result in an underestimate of the association between depressive symptoms and health outcomes. It is not clear whether the interaction between post-hospital setting and depressive symptoms in predicting hospital readmissions would hold among the most impaired that are not in the analytic sample.

Along with attrition via proxy response, mortality and study drop-out contribute to healthy survival bias. In the descriptive analyses of Chapters 2 and 3, mortality is not a concern because we are not interested in characterizing the depressive symptoms or unmet expectations of those who did not survive to be part of the population of interest. In Chapter 4, survival bias may, like excluding proxies, result in an underestimation of the association between unexpectedly not working and depressive symptoms. The analytic sample in Chapter 5 is 65

years old or older and thus represents a select group who survived to that age. The results may not be generalizable to younger ages.

Despite the implications of attrition, the four empirical chapters of this dissertation provides a rich interdisciplinary look at social factors related to depressive symptoms in the aging population and examine one aspect of health services that may address the harmful repercussions of depressive symptoms on health outcomes. This research has solidified my interest in retirement and health, raising several important questions that I want to answer during my postdoctoral training.

Next Steps

In the next step of my academic career, I will be a Sloan Postdoctoral Fellow on Work and Aging at the Harvard Center for Population and Development Studies. In that capacity, I want to leverage my unique interdisciplinary background to broaden the scope of my research from retirement timing and depressive symptoms to work and health at large. One of the key findings from my dissertation is that disadvantaged older adults – according to race/ethnicity and education – have less agency in their retirement timing. Therefore, policies that push for later retirement, such as increases in Social Security's full retirement age, may inadvertently penalize specific groups of older adults who cannot extend their working lives. This leads to a two-pronged research agenda – investigating mechanisms for the inequity in retiring as late as desired and testing policies that might enable longer work for those of low education or low wage occupations.

Improvements in life expectancy over the past several decades have partially motivated the push for longer working lives, but illness and disability are not necessarily occurring at later ages (Crimmins, Zhang, & Saito, 2016). While recent cohorts are retiring later on average

(Mermin, Johnson, & Murphy, 2007), it is unclear whether this trend is driven by subpopulations with good health and white-collar employment. Adults in disadvantaged populations experience poor health earlier and more often (Hayward, Miles, Crimmins, & Yang, 2000; Link & Phelan, 2010), but we do not know if these poor health events have greater labor force consequences than they do in advantaged workers. In other words, does the same level of illness and disability differentially relate to labor force exits depending on education level or occupation type?

Premature exits from the labor force may further perpetuate social, economic, and health disparities because of the benefits of work. Preventing early retirement is important for maximizing individuals' economic standing, because retiring early forgoes Social Security's financial incentives for later retirement and extends the period living on savings. In addition to these economic benefits of delaying retirement, there is growing consensus that work is good for health because it meets psychosocial needs, is central to identity in social roles, and improves socioeconomic status (Waddell & Burton, 2006). There is also strong evidence that the cognitive engagement of work tasks in old age is beneficial to preventing cognitive decline (Adam, Bonsang, Grotz, & Sergio, 2013; Bonsang, Adam, & Perelman, 2012; Meng, Nexø, & Borg, 2017; Mosca & Wright, 2018; Rohwedder & Willis, 2010). Therefore, efforts to promote economic and health equity in late life should include interventions for avoiding or delaying illness-related premature departures from the labor force.

The second arm of this research will explore how specific public and employer policies can enable more equitable access to longer working lives. Relevant public policies include protections against age and disability discrimination. International comparisons using HRS and sister studies could be an enlightening tool for comparing retirement timing in different policy contexts. For example, the U.K. has reformed their disability insurance program to encourage

disabled adults to transition back into the labor force (Stuart Adam, Bozio, & Emmerson, 2010). In the US, some states are implementing innovative policies to help adults stay at and return to employment post illness or injury, for example, by coordinating medical recovery to facilitate continued employment and enhancing communication between workers, employers, and health care professionals ("S@W/R2W Research & RETAIN Demonstration Projects," n.d.).

Federal and state policies can be blunt tools, and much remains to be learned regarding the promise of employer-level policies to retain older employees. For example, older adults prefer flexible hours (Siegenthaler & Brenner, 2000), a benefit that may be important for prolonging working lives (Koc-Menard, 2009; Loretto & Vickerstaff, 2015). But, is this benefit more common among those already at a high probability of retiring late? How does education relate to access to benefits that prolong working lives, such as medical leave, family leave, disability accommodations, or retraining opportunities? Do these workplace benefits have larger effects on those with low educational attainment? It will be important to understand how federal, state, and local governments can incentivize employers to implement effective policies for extending working lives.

Together, these research ideas will build upon my dissertation by identifying policy mechanisms to shift the social and economic circumstances related to late-life depression and well-being at large. I hope this research will propel the next phase of my career as an aging and health policy research.

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Appendix

Dep. Symptoms	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age groups						
51-55	1.00	1.00	1.00	1.00	1.00	1.00
56-60	0.971*	0.968*	0.966	0.977	0.932*	0.960
61-65	0.911***	0.905***	0.900***	0.917***	0.864***	0.793
66-70	0.904***	0.893***	0.882***	0.916***	0.846***	0.979
71-75	0.964	0.934***	0.883***	0.968	0.968	1.050
76-80	1.114***	1.066**	1.039	1.124***	1.104	1.300***
81-85	1.292***	1.220***	1.292***	1.302***	1.319***	1.525***
86-90	1.495***	1.396***	1.589***	1.504***	1.722***	1.730***
Gender						
Male		1.00	1.00	1.00	1.00	1.00
Female		1.272***	1.266***	1.272***	1.272***	1.271***
Race/Ethnicity						
NH White		1.00	1.00	1.00	1.00	1.00
NH Black		1.349***	1.349***	1.496***	1.346***	1.350***
NH Other		1.432***	1.432***	1.510***	1.427***	1.434***
Hispanic		1.267***	1.267***	1.341***	1.249***	1.270***
Education						
<HS		2.546***	2.545***	2.554***	2.654***	2.544***
GED/HS Grad		1.762***	1.762***	1.757***	1.736***	1.763***
Some College		1.428***	1.428***	1.425***	1.378***	1.429***
College+		1.00	1.00	1.00	1.00	1.00
Birth Cohort						
AHEAD		1.00	1.00	1.00	1.00	1.00
CODA		1.037	1.038	1.045	1.025	0.952
HRS		0.929**	0.932**	0.941*	0.922**	0.972
War Babies		1.010	1.012	1.024	1.011	1.255***
Early baby boomers		1.068	1.070	1.080	1.074	1.323***
Mid baby boomers		1.077	1.079	1.089	1.083	1.312***
Overall interaction			Chi-sq. (7) = 60.22, p<0.0001			
51-55 # male			1.00			
51-55 # female			1.00			

56-60 # male	1.00
56-60 # female	1.004
61-65 # male	1.000
61-65 # female	1.009
66-70 # male	1.000
66-70 # female	1.020
71-75 # male	1.000
71-75 # female	1.095**
76-80 # male	1.000
76-80 # female	1.041
81-85 # male	1.000
81-85 # female	0.921*
86-90 # male	1.000
86-90 # female	0.828***
Overall Interaction	Chi-sq(21) =150.55, p<0.0001
51-55 # NH White	1.00
51-55 # NH Black	1.00
51-55 # NH Other	1.00
51-55 # Hispanic	1.00
56-60 # NH White	1.00
56-60 # NH Black	0.956
56-60 # NH Other	0.975
56-60 # Hispanic	0.975
61-65 # NH White	1.000
61-65 # NH Black	0.927*
61-65 # NH Other	0.987
61-65 # Hispanic	0.973
66-70 # NH White	1.000
66-70 # NH Black	0.861***
66-70 # NH Other	0.959
66-70 # Hispanic	0.938
71-75 # NH White	1.000
71-75 # NH Black	0.821***
71-75 # NH Other	0.922
71-75 # Hispanic	0.915
76-80 # NH White	1.000
76-80 # NH Black	0.773***
76-80 # NH Other	0.761**
76-80 # Hispanic	0.803***
81-85 # NH White	1.000
81-85 # NH Black	0.675***

81-85 # NH Other	0.774*	
81-85 # Hispanic	0.773***	
86-90 # NH White	1.000	
86-90 # NH Black	0.668***	
86-90 # NH Other	0.617*	
86-90 # Hispanic	0.652***	
Overall Interaction		Chi-sq(21) = 153.26, p<0.0001
51-55 # <HS		1.00
51-55 # GED/HS		1.00
51-55 # Some Col.		1.00
51-55 # College+		1.00
56-60 # <HS		1.030
56-60 # GED/HS		1.063
56-60 # Some Col.		1.041
56-60 # College+		1.000
61-65 # <HS		1.056
61-65 # GED/HS		1.046
61-65 # Some Col.		1.084
61-65 # College+		1.000
66-70 # <HS		1.066
66-70 # GED/HS		1.047
66-70 # Some Col.		1.101*
66-70 # College+		1.000
71-75 # <HS		0.913
71-75 # GED/HS		0.970
71-75 # Some Col.		1.017
71-75 # College+		1.000
76-80 # <HS		0.904
76-80 # GED/HS		0.965
76-80 # Some Col.		1.037
76-80 # College+		1.000
81-85 # <HS		0.812***
81-85 # GED/HS		0.938
81-85 # Some Col.		1.052
81-85 # College+		1.000
86-90 # <HS		0.666***
86-90 # GED/HS		0.852*
86-90 # Some Col.		0.894
86-90 # College+		1.000
Overall Interaction		Chi-sq(17) =

	118.38, p<0.0001
51-55 # AHEAD	1.00
51-55 # CODA	1.00
51-55 # HRS	1.00
51-55 # War Babies	1.00
51-55 # Early BB	1.00
51-55 # Mid BB	1.00
56-60 # AHEAD	1.00
56-60 # CODA	1.00
56-60 # HRS	1.108**
56-60 # War Babies	1.023
56-60 # Early BB	0.990
56-60 # Mid BB	1.000
61-65 # AHEAD	1.000
61-65 # CODA	1.312
61-65 # HRS	1.345
61-65 # War Babies	1.123
61-65 # Early BB	1.085
61-65 # Mid BB	1.000
66-70 # AHEAD	1.000
66-70 # CODA	1.254*
66-70 # HRS	1.103
66-70 # War Babies	0.822*
66-70 # Early BB	0.972
66-70 # Mid BB	1.000
71-75 # AHEAD	1.000
71-75 # CODA	1.229***
71-75 # HRS	1.049
71-75 # War Babies	0.753***
71-75 # Early BB	1.000
71-75 # Mid BB	1.000
76-80 # AHEAD	1.000
76-80 # CODA	1.059
76-80 # HRS	0.977
76-80 # War Babies	1.000
76-80 # Early BB	1.000
76-80 # Mid BB	1.000
81-85 # AHEAD	1.000
81-85 # CODA	0.995
81-85 # HRS	1.000
81-85 # War Babies	1.000
81-85 # Early BB	1.000
81-85 # Mid BB	1.000

86-90 # AHEAD						1.000
86-90 # CODA						1.000
86-90 # HRS						1.000
86-90 # War Babies						1.000
86-90 # Early BB						1.000
86-90 # Mid BB						1.000
var(cons[ID])	3.459***	2.984***	2.986***	2.985***	2.978***	2.985***

Table 12 Incidence rate ratios for increasing depressive symptoms

*Health and Retirement Study 1994-2014, N= 178,003 depressive symptom observations. NH = Non-Hispanic; HS = High School Graduate; GED = General Education Development; Some col.= Some college; AHEAD = Asset and Health Dynamics Among the Oldest Old; CODA= Children of the Depression; HRS = original Health and Retirement Study; var(cons[ID])= Variance component corresponding to the random intercept; Some levels of birth cohort-by-age group interaction omitted because no observations in that sample or collinearity with reference group; *=p<0.05, **=p<0.01, ***=p<0.001*

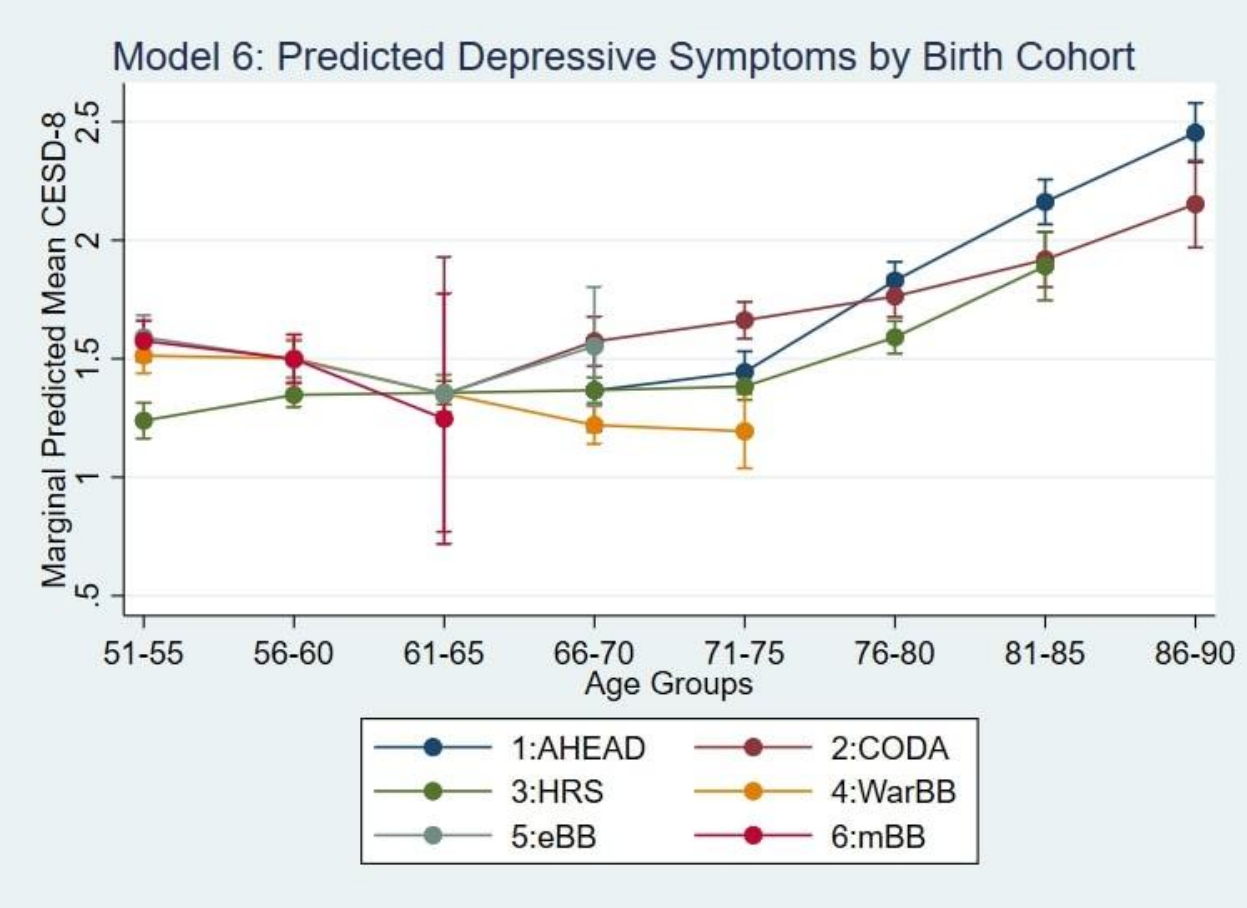

Figure A- 1 Adjusted predicted depressive symptoms from interaction between age groups and birth cohort

Health and Retirement Study 1994-2014, N= 178,003 depressive symptom observations. AHEAD = Asset and Health Dynamics Among the Oldest Old; CODA= Children of the Depression; HRS = original Health and Retirement Study; WarB = War Babies; eBB = Early Baby Boomers; mBB= Mid Baby Boomers

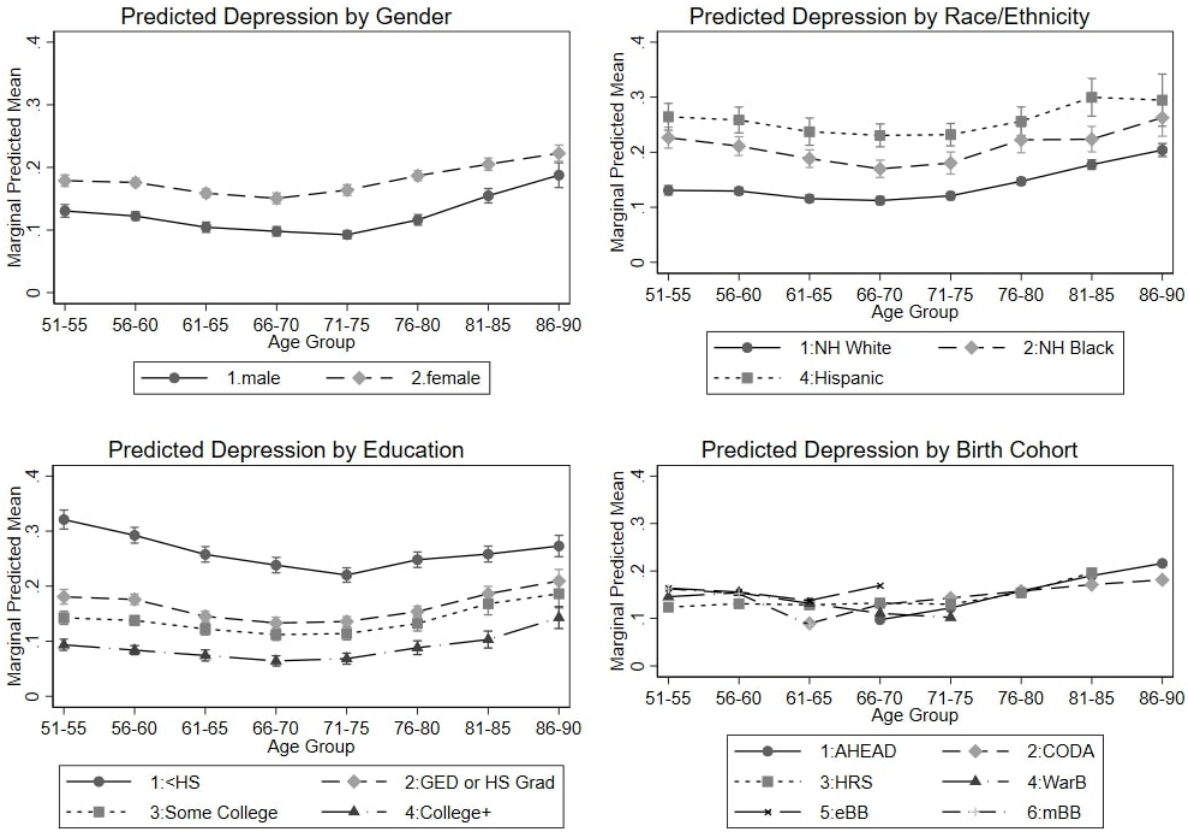

Figure A- 2 Adjusted predicted probabilities of high depressive symptoms (4-8) from interactions between age groups and sociodemographic factors

Health and Retirement Study 1994-2014, N= 178,003 depressive symptom observations. NH = Non-Hispanic; HS = High School; GED = General Education Development; AHEAD = Asset and Health Dynamics Among the Oldest Old; CODA= Children of the Depression; HRS = original Health and Retirement Study; WarB = War Babies; eBB = Early Baby Boomers; mBB= Mid Baby Boomers. Confidence Intervals not plotted for birth cohort graph because CODA ages 61-65 produced interval out of range.

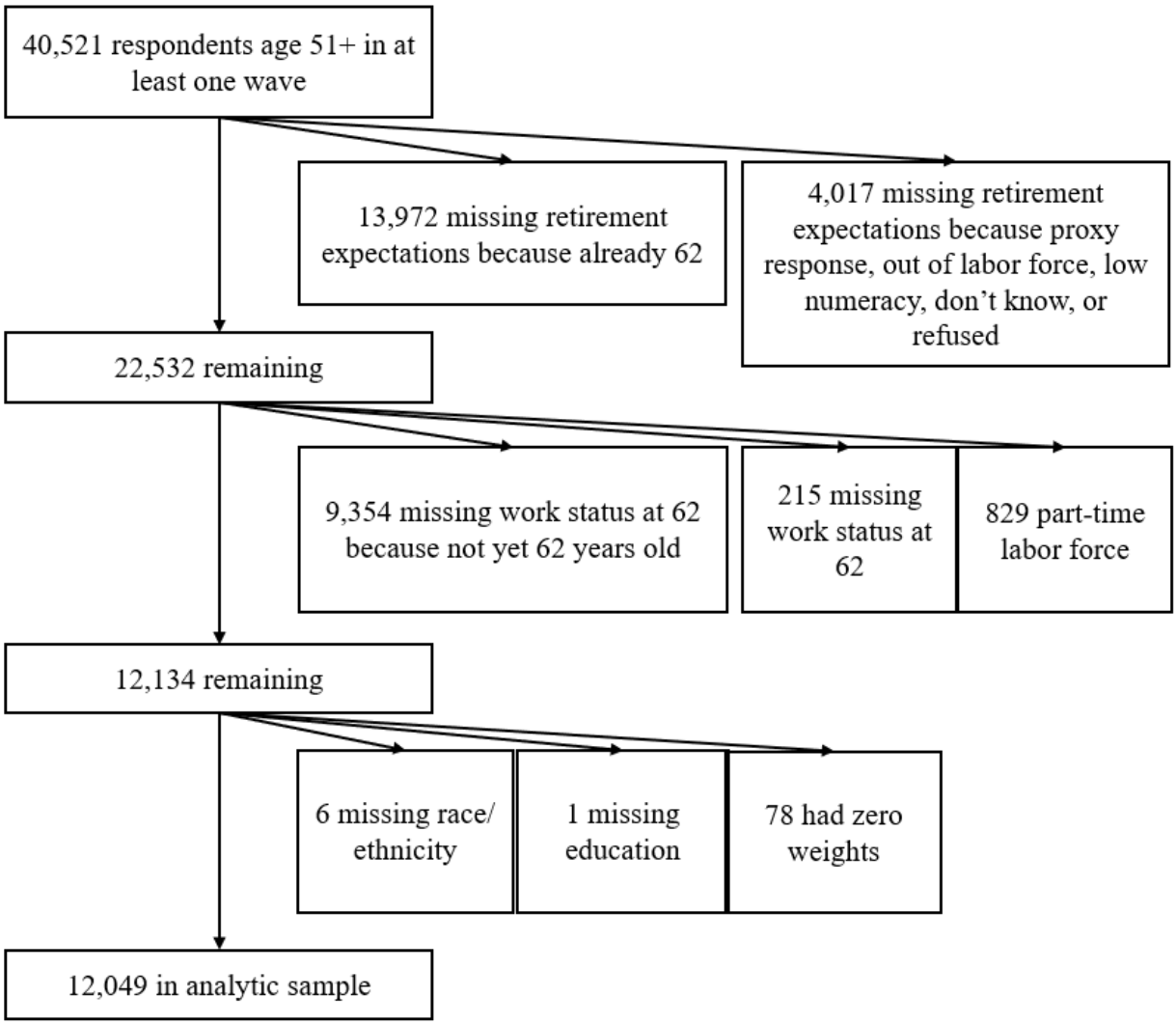

Figure A- 3 Flow chart of sample inclusion for Chapter 3

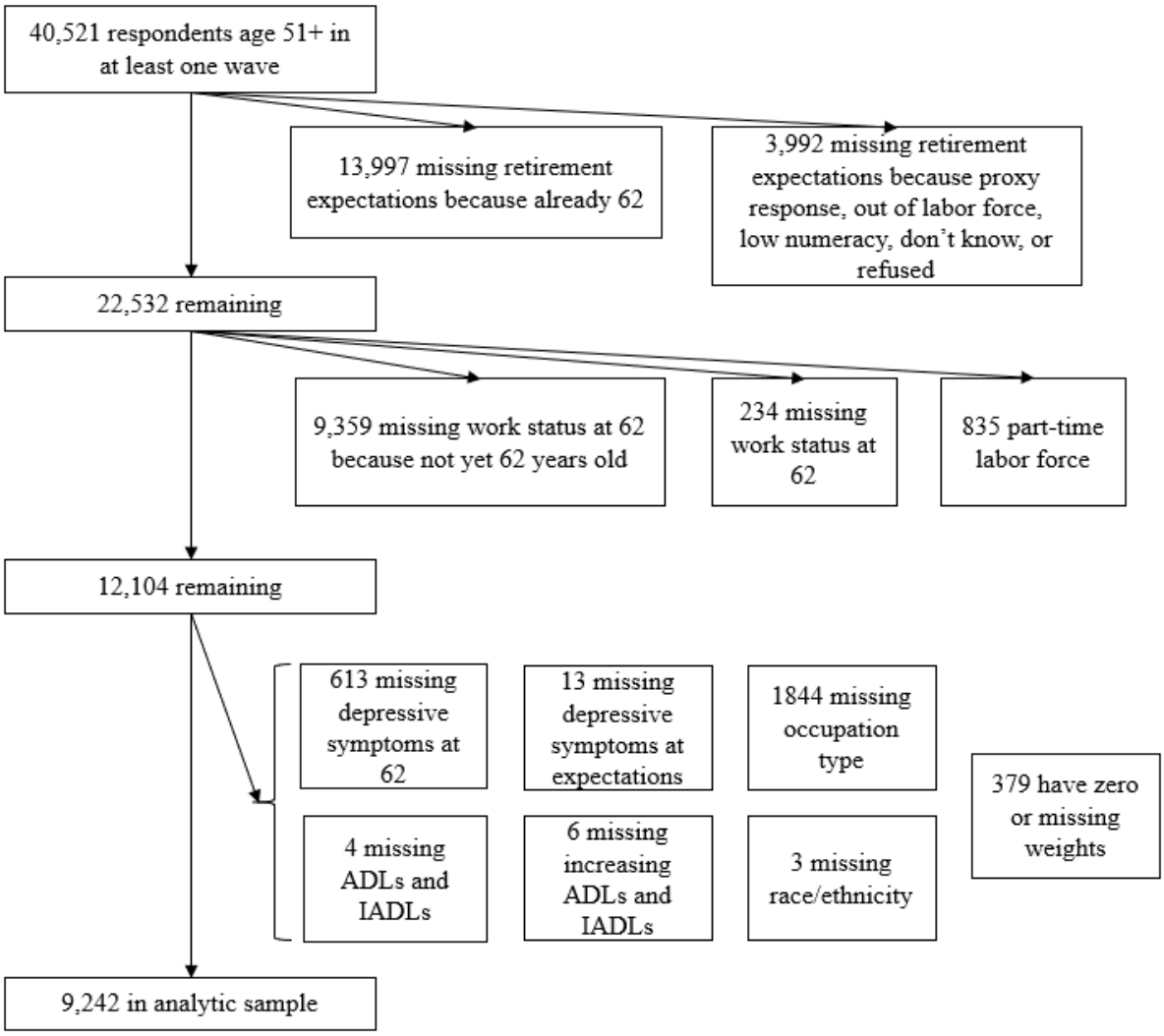

Figure A- 4 Flow chart of sample inclusion for Chapter 4

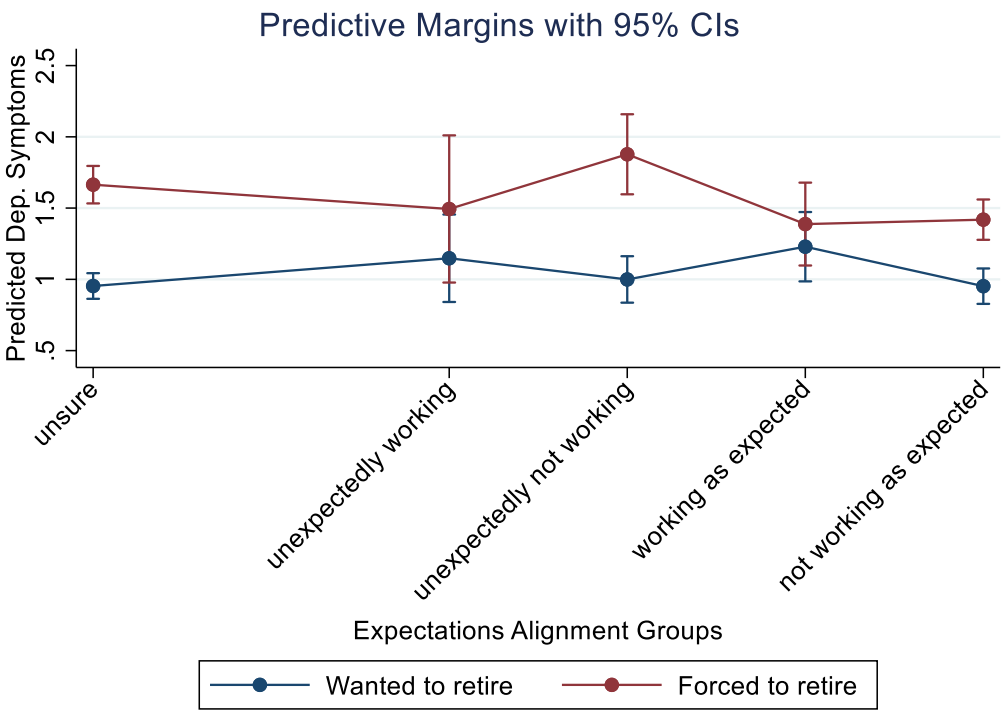

Figure A- 5 Predicted number of depressive symptoms by alignment of expectations with realized labor force status and by forced retirement

Adjusted for sociodemographic factors, economic factors, and health at wave of expectations