5-6-2024

Lifecourse Patterns of Productive Engagement among Rural and Urban Older Adults

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A dissertation presented to the Brown School of Washington University in St. Louis in partial fulfillment of the requirements for the degree of Doctor of Philosophy

May 2024

St. Louis, Missouri

Acknowledgments

I would like to thank my chair, Dr. Nancy Morrow-Howell, for shepherding this dissertation to completion and providing excellent mentorship throughout my doctoral studies. I would also like to thank my committee members, Dr. Abigail Barker, Dr. Shenyang Guo, Dr. Timothy McBride, and Dr. Sojung Park, for their invaluable feedback.

For the generous support provided by the New York Community Trust through a Grand Challenges for Social Work Doctoral Award, I am very grateful. I would also like to acknowledge the Gerontology Interest Group and the Sequence Analysis Association for offering helpful feedback at various stages of this dissertation.

This dissertation would not have been possible without the support of my family and friends. I would like to thank my grandmother Grace, my aunts Lisa and Esther, my uncle Bruce, my parents Daniel and Jennifer, my brother Jeremiah, and my wife Jenny, along with her wonderful family, for their unwavering love and support. Special thanks to Andrew and Linda, Joshua and Bethany, and Ryan and Jessie for their friendship and hospitality, especially during the pandemic. To my longtime mentors, Joanna, Diane, Brice, and Tracy, thank you for always believing in me.

Finally, I want to acknowledge my congregations both in the U.S. and in Taiwan for their constant prayers. Soli Deo gloria!

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May 2024

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Abstract

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Many older adults are engaged in productive activities that have important ramifications for health in later life. However, little is known about rural-urban patterns of productive engagement across the lifecourse. This dissertation used six waves (2008, 2010, 2012, 2014, 2016, 2018) of the nationally representative Health and Retirement Study to identify patterns of working, volunteering, and caregiving activities over a ten-year period using multichannel sequence analysis and cluster analysis. The antecedents of the patterns were studied using multinomial logistic regression, and the associations of the patterns with longstanding rural-urban disparities in cognitive functioning and self-rated health were studied using multiple linear regression and ordinal logistic regression, respectively. This study found conceptually meaningful patterns of productive engagement that varied by rural/urban residence and age groups. Furthermore, rural respondents had a significantly lower likelihood than urban respondents of being in the pattern of ‘increasing high-intensity volunteering’ and the pattern of ‘decreasing part-time working,’ after controlling for gender, age, education, marital status, race, religious affiliation, income, and number of diagnosed health problems. Finally, the patterns of ‘increasing high-intensity volunteering,’ ‘decreasing full-time working and low-intensity volunteering,’ and ‘decreasing full-time working and high-intensity volunteering' were significantly associated with higher cognitive functioning scores in 2018; the pattern of 'decreasing full-time working and low-intensity volunteering' was significantly associated with higher self-rated health in 2018; and the pattern of 'steady caregiving and decreasing volunteering and working' was associated with lower self-reported health in 2018. These findings may inform programs and policies aimed at narrowing rural-urban health disparities and increasing the productive engagement of rural and urban older adults.

Chapter 1: Introduction

In the Salzburg Seminar of 1982, Robert N. Butler first coined the term "productive aging" to combat what he saw as a persistent trend in how society viewed older adults as dependent and burdensome (Butler & Gleason, 1985). With declining fertility, it is now expected that by 2050, the population of older adults aged 60 and above will be equal to those aged 15 and younger. This increase in the proportion of older people is again accompanied by the worry that older adults will become a burden to society (Harper, 2014). Butler's concept of productive aging remains relevant today, because it advances "older adults' capacity to make economic contributions through employment, volunteering, and caregiving" and society's ability to increase and support that capacity (Morrow-Howell, Gonzales, Matz-Costa, et al., 2016, p. 4). Inherent in this view is that older adults are not passive buoys in the tides of demographic change but active partakers in the grand challenge of population aging. The purpose of this dissertation is to explore and quantify in novel ways how older adults engage in productive activities, focusing especially on the dimension of time across individuals' lifecourse, the dimension of place between both rural and urban America, and the effects of these productive activities on health in later life. In this introduction, the literature on productive engagement and rural-urban health disparities is reviewed before laying out the aims and scope of this dissertation.

1.1 Background

1.1.1 Productive Engagement in Later Life

Following the Salzburg Seminar, many scholars continued to contemplate Butler's call to reassess the assets of later life, though there was no commonly accepted definition of productive aging. In the National Research Council report on productive activity, Morgan (1986, p. 74) defined productive activities as "activities that produce goods or services that otherwise would have to be paid for." This broad definition encompasses such activities as housework, time helping friends, caring for others who are ill, and taking courses or lessons (Morgan, 1986, p. 92). Herzog et al. (1989) defined productive aging as any activity that produces goods or services, whether paid or not, including activities such as housework, child care, volunteer work, and help to family and friends. Building on Herzog's definition, Bass et al. (1993, p. 6) defined productive aging as "any activity by an older individual that produces goods or services, or develops the capacity to produce them, whether they are to be paid for or not." They focused on a narrower definition than Herzog, calling attention to activities that could be assigned some economic value, as well as emphasizing the employment and voluntary sectors where older adults are at a disadvantage. Later, Bass & Caro (1996) developed the first conceptual framework of productive aging, identifying individual, situational, environmental, and social policy factors as determinants of engagement in productive activities.

In light of these challenges, Sherraden et al. (2001) advanced a framework that focused on a more limited but quantifiable set of productive behaviors (activities that produce goods and services, whether paid or not); potential determinants of these behaviors (sociodemographics, public policy, individual and institutional capacity); and the potential outcomes of these behaviors at the individual, family, and societal levels. They included institutional capacity in the framework to explain the variance in productive behaviors and to open the possibility for policy and program innovations. The framework does not include activities directed towards the self, such as capacity-building from Caro and Bass (1996), in order to focus on behaviors that result in economic or social contributions. Because the label "productive aging" may imply "unproductive aging," they named their model "productivity in later life."

Morrow-Howell and Wang (2013) extended Sherraden et al. (2001) by encapsulating their framework within a larger sociocultural context to support cross-cultural work in practices and policies. Using the World Health Organization’s active aging framework, they also modified the antecedents of the model to include socio-demographics, the economic environment, the physical environment, and public policies and programs. The physical environment includes urban and rural contexts, residential arrangements, and community infrastructure. Following Sherraden et al. (2001), they considered factors such as urban/rural residence as less likely to be modifiable and recommended targeting policies and programs to increase engagement.

Further extending previous work, Morrow-Howell and Greenfield (2015) used ecological systems theory to develop a model with three levels of antecedents: (a) individual, (b) community, and (c) societal, reflecting a gradient of environments from proximal to distal. Their model also theorizes that the effects of productive engagement may recursively affect the antecedents of productive engagement, reflecting the ecological perspective that there are mutual interactions between individuals and their environments. Finally, the model considers the intensity, regularity, and duration of productive activities, as well as multiple productive activities simultaneously.

The assumed linearity between constructs related to productive behaviors is a limitation of the aforementioned conceptual models. Recognizing that relationships between constructs may be more accurately modeled as feedback loops or circular causality, Morrow-Howell et al. (2017) used a system dynamics approach to re-conceptualize productive engagement. Examples of feedback mechanisms are reinforcing feedback loops (e.g., increasing volunteers in an organization with the capacity to recruit volunteers further increases the organization’s capacity) and balancing loops (e.g., family caregiving to meet health needs prevents further health declines). One of the key contributions of this model is that it captures processes that both build up and deplete human capital, perhaps the most significant "dividend" of productive engagement.

Critics have lauded productive aging scholars for counteracting ageist stereotypes, but they caution that elevating productivity as the highest ideal may marginalize older adults who exhibit "unproductive aging" (C. Estes, 2001; Hosltein, 1999). Riley and Riley (1994) demonstrated that productivity may be constrained in some societies and called attention to the importance of opportunity structures. Along similar lines, Martinson (2006) asserted that older adults may or may not have the choice to engage in productive activities, and those who choose not to should be honored. Indeed, for many people, productivity and even health are lesser concerns compared to meaningful social relationships (Laceulle, 2018). Using a political economy perspective, Estes and Mahakian (2001) inquired if an overt focus on the individual neglects how productive behaviors are conditioned by inequalities in race, class, and gender. They argued that unless the structural and socially produced nature of aging is seriously considered, the productivity label inherent in productive aging would only reproduce biomedical ways of thinking, that is, older adults as frail, worthless, or unproductive.

In summary, the historical progression from Butler's concept of "productive aging" to recent developments in productive engagement frameworks has led to a consideration of both micro and macro-level forces (i.e., the environment) and an emphasis on the applied nature of the framework for practice and policy interventions. As Sherraden et al. (2001) argue, focusing on institutions has the applied purpose of taking local variations into account. However, the empirical literature on productive engagement has seldom considered the characteristics of rural places. Few studies have paid attention to the dynamics of small towns and communities.

1.1.2 Rural-Urban Health Disparities

Rural health disparities among older Americans are well-documented. Examples include the rural morality penalty (Afifi et al., 2022; Cosby et al., 2019; Miller & Vasan, 2021), widening disparities in life expectancies (National Academies of Sciences, Engineering, and Medicine et al., 2018; Singh & Siahpush, 2014), lower cognitive functioning (Sharp & Gatz, 2011; Weden et al., 2018), and worse self-rated health (Cohen et al., 2018; Henning-Smith et al., 2021; Monnat & Beeler Pickett, 2011). Research has identified promising targets to address these disparities, such as elevated mid-life blood pressure for dementia risk (Levine et al., 2020) and the role of education on dementia risk and general health (Henning-Smith et al., 2021; Sharp & Gatz, 2011). However, even after controlling for sociodemographic status, persistent disadvantages in cognitive functioning and self-rated health among rural older adults remain largely unexplained (Cohen et al., 2018; Weden et al., 2018).

Cognitive Functioning. Several studies have observed a rural-urban gap in cognitive functioning. Using Census definitions of urbanicity on the 2000 and 2010 Health and Retirement Study (HRS) data, Weden et al. (2018, pp. 168–170) found that the rural-urban disparity in dementia and cognitive impairment without dementia (CIND) was narrowed by improvements in rural education but persisted even after controlling for other sociodemographic factors. The authors make two conjectures: one, that education may indirectly improve cognitive functioning via working, and two, that the persistent rural disadvantage may be explained by fewer opportunities for social engagement. Using the 2000-2016 waves in the HRS, Glauber (2022) also found evidence for lower cognitive functioning among rural older adults, compared to urban older adults, as well as a rural penalty when living in a rural and depopulated county. Rural was defined in the study as rural-urban continuum codes (RUCC) 4-9 or nonmetropolitan counties.

These disparities persisted even after controlling for race and ethnicity, gender, age, education, income, region, employment status, marital status, physical health, depression, and the county's racial-ethnic composition, age structure, economic and educational disadvantage, and health care shortages. Similar to Weden and colleagues (2018), Glauber also suggests that the lack of social engagement and the loss of community spaces for such engagement might alleviate the persistent disparity in cognitive functioning. A third study, by Lawrence et al. (2023), used the 1996-2016 waves of the HRS to assess urban-suburban-exurban differences in cognitive functioning. They found that the persistent differences in cognitive functioning in their sample were already present at the baseline age of 50, suggesting that explanations for the gap may lie in earlier mid-life or early-life processes. Additionally, after controlling for education, early-life finances, and baseline health, they found a robust exurban-urban gap in cognitive functioning that they believe might be explained by factoring in additional health behaviors and social support.

Self-Rated Health. Research has shown a persistent disadvantage in self-rated or self-reported health among rural older adults. Cohen et al. (2018) used the 2012 Behavioral Risk Factor Surveillance System (BRFSS) sample to assess the relationship between negative self-reported health and seven measures of rurality (RUCC, urban influence codes [UIC], rural-urban commuting area [RUCA], distance to nearest metropolitan area, population size, population density, and percent urban according to the U.S. Census). While negative self-reported health was related to decreasing urbanicity in all seven measures, the directions of the associations were mixed for high-income counties.

1.1.3 Methodological Concerns

Rural is commonly defined using ecological definitions that focus on physical and demographic characteristics, such as population density, land size, and isolation from urban centers. Each definition has its unique strengths and limitations, and there is no single definition that is universally preferred. For example, the U.S. Census Bureau's rural/urban classification scheme aims to clearly separate and differentiate urban and rural territory, while the Office of Management and Budget's (OMB) taxonomy focuses on integrating urban and rural areas based on socioeconomic ties (Isserman, 2005). Depending on how the subcategories of these two definitions are combined, the rural population in the U.S. can vary between 10% to 28% of the total population or 26-79 million individuals (Hart et al., 2005). Also, the OMB approach of measuring economic interdependence with commuting patterns may not always be an accurate proxy of access to services (K. J. Mueller et al., 2020). This dissertation uses the U.S. Department of Agriculture's (USDA) Economic Research Service (ERS) *rural-urban continuum codes* (RUCC or Beale codes), which are based on OMB-defined metropolitan-nonmetropolitan areas. Metropolitan areas are subdivided into three codes based on population sizes: (1) 1 million or more individuals, (2) 250,000 to 1 million individuals, and (3) less than 250,000 individuals. Nonmetropolitan (micropolitan and outside core based statistical areas) areas are subdivided into six codes, based on degree of urbanization and adjacency to a metropolitan area (USDA ERS, 2020). The publicly available HRS files contain collapsed RUCC codes (the full codes are only available under special agreement): Urban areas are defined as counties in metro areas of 1 million population or more (RUCC 1); suburban areas are counties in metro areas of 250,000 to 1 million population (RUCC 2); and ex-urban areas consist of counties in metro areas of fewer than 250,000 population and non-metro counties (RUCC 3-9).

1.2 Aims and Scope of Dissertation

Using a three-paper model, this dissertation will explore three aims: (1) lifecourse patterns of productive engagement, (2) antecedents of lifecourse patterns of productive engagement, and (3) outcomes of lifecourse patterns of productive engagement. Each paper introduces a different conceptual framework for approaching the question of interest. Chapter 2 draws from lifecourse sociology and uses multichannel sequence analysis and cluster analysis to explore conceptually meaningful clusters or patterns of engagement. Chapter 3 investigates the antecedents of the patterns found in Chapter 2, drawing upon productive engagement frameworks. Chapter 4 uses the NIA Health Disparities Research framework to measure the associations between the patterns of engagement in Chapter 2 to longstanding health disparities in cognitive functioning and self-rated health. All three papers share the same sample selected from the Health and Retirement Study. The overarching implications for policy, practice, and research of all three papers are discussed in Chapter 5.

Chapter 2: Lifecourse Patterns of Productive Engagement

2.1 Introduction

Research on productive aging has focused on the activity engagement of older adults as workers, caregivers, and volunteers. Studies have shown that engagement in these activities may offset the fiscal burden of population aging, contribute to the welfare of families and society, and improve the health and economic well-being of older adults (Gonzales et al., 2015; Lupton et al., 2010). This chapter reviews the literature on the levels of engagement in working, volunteering, and caregiving activities before reviewing the literature that has investigated multiple activities simultaneously.

2.1.1 Literature Review

Working. In general, labor force participation in rural America is lower than in urban America, because a greater proportion of older adults in rural America drop out of the labor force (U.S. Census Bureau, 2016). According to the 2011-2015 American Community Survey 5-year estimates, among people in their prime working ages (16 to 64 years), rural areas had an overall labor force participation rate of 59.2%, compared with 64.2% in urban areas (U.S. Census Bureau, 2016). At the county level, there has been growth in employment in 1,108 nonmetro counties, while 877 nonmetro counties saw no changes or a decline in employment (USDA ERS, 2019a). The unemployment rates of older adults age 60 and above between metro and nonmetro counties are comparable: 5.2% in the first half of 2012 in nonmetro counties, compared to 6.4% in metro counties. The unemployment rates in nonmetro and metro counties have both steadily declined following the Great Recession of 2007-2010 (USDA ERS, 2012). However, the nonmetro unemployment rate peaked at a rate of 13.6% in mid-April during the COVID-19 pandemic (USDA ERS, 2020). Census data show that self-employment rates of the population age 15 and over are higher in rural areas than suburban and urban areas; however, there has been a consistent decline of rural entrepreneurs over the last three decades, in part due to population aging (Wilmoth, 2017). Another trend among older working Americans is towards transitional retirements, such as bridge jobs, phased retirement, unretirement, and labor market reentry. In a sample of older adults aged 51-61 in 1992, it was found that 57% of career men and 54% of career women left a full-time career for a bridge job (Cahill et al., 2015). However, this trend of delaying retirement is less likely to continue for older women, whose labor force participation rate has been on the decline for two decades (Krueger, 2017). The workforce in rural America is becoming increasingly racially and ethnically diverse, particularly in the South and West (Rowlands & Love, 2021). Hispanic/Latino populations in small-town America nearly doubled from 1.4 to 2.7 million between 1980 and 2000, stemming long-term population decline in many rural counties since the 1950s USDA ERS, 2005). Along the Pacific Coast and regions in the High Plains, many rural Hispanic/Latino populations have “immigrated to work in meatpacking plants, farms or industries like construction, oil, and timber, or to start businesses” (Rowlands & Love, 2021). Nonmetro Blacks currently outnumber nonmetro Hispanics, but Hispanics are projected to become the largest minority group in rural America by about 2025. Despite the economic growth that has partly led to this diversification, nonmetro Hispanics lag behind non-Hispanic Whites in income, home ownership, and are more likely to live in poverty (USDA ERS, 2005). Black women have also been found to have low levels of net worth and net financial assets across the life course (Brown, 2012). In terms of age, the labor force participation rate is expected to grow from 17.5% in 1996 to 30.2% in 2026 for the age 65 to 74 group, and 4.7% in 1996 to 10.8% in 2026 for the age 75 and older group (U.S. Bureau of Labor Statistics, 2019b).

Volunteering. The proportion of volunteers among older adults age 65 and older in the U.S. has risen from about 10% in 1965 to 24% in 2015 (Chambré, 2020). According to a volunteer supplement of the Current Population Survey, which collected data on volunteers over a year, older adults volunteer at a lower rate than those in midlife but contribute more hours overall: a median of 94 hours for volunteers age 65 and above, compared to 36 hours for volunteers under age 35 (Bureau of Labor Statistics, 2016). In comparison, the American Time Use Survey, which collects data for a single day and therefore has less recall bias, shows that between 2011 and 2015, individuals age 65 and above had the highest rates of volunteer activity; about 9 percent of this age group volunteered on an average day versus 6 percent of the population age 15 and over (Turner et al., 2020). The locus of volunteering for older adults is most commonly in religious organizations, followed by social and community service groups and health-related organizations (Tang & Morrow-Howell, 2008). While not often captured in volunteering datasets, older adults also engage in short-term, episodic volunteering and informal volunteer work, such as helping friends and neighbors (Martinez et al., 2011). Zedlewski and Schaner (2006) estimate that more than half of Americans age 55 and older engage in informal volunteer work.

Caregiving. In 2020, there were an estimated 28.6 million American caregivers age 50 and over caring for an adult or child with special needs (AARP & NAC, 2020). Of all the caregivers in the U.S. in 2020—including caregivers of all ages—it is estimated that 12% live in a rural area (AARP & NAC, 2020). Drawing from the National Study of Caregiving, the National Academies of Sciences, Engineering, and Medicine (2016) estimated that 10.4 million older adults age 55 and older were caregivers of Medicare beneficiaries (age 65 and older) with health or functioning needs and an additional 4.9 million older adults age 55 and older were “high-need caregivers” who cared for Medicare beneficiaries with probable dementia or who need help with at least two self-care activities (i.e., bathing, dressing, eating). Data from the American Time Use Survey between 2017 and 2018 show that 19.0 million age 55 and older “eldercare” providers—57.8% of whom were female—provided unpaid care to an individual age 65 and older who needs help because of an age-related condition (U.S. Bureau of Labor Statistics, 2019a). Caregiving arrangements and the intensity of care vary widely. Caregivers with multiple recipients constitute 24% of all caregivers of adults; many caregivers live with their recipient (40%); and caregivers provide on average 24 hours of care every week (AARP & NAC, 2020). The proportion of spousal caregivers caring for partners with self-care or indoor mobility needs for four or more years increased from 45.5% in 1999 to 64.1% in 2015; about one in three caregivers of older adults are employed and juggle competing responsibilities; and caregivers of persons with dementia put in 47.5 hours of care in 2015 (Wolff et al., 2018). Some grandparent caregivers raise grandchildren on their own (skipped generation or custodial grandparenting), while others live with their adult child and grandchildren (coparenting); collectively, it is estimated that 3 million middle-aged and older grandparent caregivers care for nearly 6 million children (Hayslip et al., 2019). Caregivers who live in a rural area more often care for multiple people, more often report that they have choice in taking on care, and provide more hours of care on average, compared to caregivers in a suburban or urban setting (AARP & NAC, 2020). Finally, while the out-migration of younger individuals in rural regions may seem to create a burden on rural caregiving, this relationship has not been clearly established in the literature (Goins et al., 2011).

Multiple Productive Activities. Increasingly, scholars have considered two or more productive activities simultaneously. For example, Kim & Ferraro (2014) found that the number of roles for productive activities (work, volunteering, caregiving, and attending meetings) was related to reduced bodily inflammation, and McDonnall (2011) examined how engaging in work, informal helping, and volunteering reduced depression among older persons with dual sensory loss. A strength of McDonnall's (2011) work is its use of multi-level modelling to consider the relative impact of multiple activities longitudinally from 1993 to 2006. Volunteering emerged in both studies as having the strongest effect relative to the other productive activities, showing that such research crucially considers both the combined and relative effects of multiple activities. In more recent research, Choi et al. (2016) found using five waves (2000-2008) of the HRS that volunteering and full-time or part-time work were both associated with a slower decline in functional health than nonparticipants. Using the 2010 wave of the HRS, Amano et al. (2020) investigated patterns of social engagement among people with cognitive impairment no dementia (CIND) and identified three latent classes: informal social engagement only, formal and informal social engagement, and low social engagement.

2.1.2 Conceptual Framework

A major gap in the current literature is that productive engagement activities have not been investigated as holistic lifecourse patterns. This study draws upon lifecourse sociology to identify key characteristics of productive engagement patterns, and this is presented in the conceptual model in Figure 1. The left hand side of the model consists of the 'experienced states' (Studer & Ritschard, 2016, p. 483) of productive engagement—working, volunteering, and caregiving. The characteristics of these states are explored on the right hand side of the model. First, one of the core principles of the lifecourse paradigm is 'timing' (Elder et al., 2003). The same event, such as beginning part-time work or becoming a caregiver, may have different effects on individuals, depending on its timing in the life course. In his study of children of the

Great Depression, Elder (2003) found that birth cohorts in the early 1920s differed drastically from birth cohorts in the later 1920s, because of the differential timing of their exposure to harsh labor conditions and environments. Second, it is important to specify the spell 'duration' or time spent in distinct successive states to better identify and differentiate prototypical trajectories (Settersten & Mayer, 1997). Third, the 'distribution' provides information on the total time spent in each state (Studer & Ritschard, 2016, p. 483). Fourth, the concept of 'sequencing' refers to the order in which events occur in an individual's life, and this has been emphasized in demographic life course analysis (Studer & Ritschard, 2016). Finally, the lifecourse paradigm focuses on geographical 'place,' because the places that individuals experience over their lifetime may play a role in later-life outcomes. For example, in the Iowa Youth and Families Project (IYFP), which considered the relationship between economic hardship and psychological well-being among 451 rural families in Iowa, attachment to the land and different levels of agriculturalism were important predictors for the psychological well-being of the participants (Conger, 1994).

Drawing from this framework, this paper aims to generate new insights and hypotheses on the timing, duration, and sequencing of individuals' engagement patterns across geographical places. Due to the novelty of these characteristics, potential patterns are described here instead of specific hypotheses. Working patterns may include patterns where participants are both working and volunteering simultaneously and patterns where volunteering follows full-time or part-time employment. Volunteering patterns may include patterns of both low-intensity and high-intensity volunteering, both with and without simultaneous engagement in working. Caregiving patterns may consist largely of caregiving alone, not simultaneously engaged with working or volunteering. Furthermore, caregiving is likely to be more prominent in the later waves, when participants are older and have more care needs. When comparing a younger age group with an older age group, it is likely that the younger age group would be dominated by working-related engagement patterns, while the older age group would have more volunteering and caregiving patterns, albeit in a downward trend, due to declines in health and functional limitations.

2.2 Methods

2.2.1 Data

The Health and Retirement Study (HRS) is sponsored by the NIA (grant number NIA U01AG009740) and is conducted by the University of Michigan. This study used the following public survey datasets from the HRS: (a) the RAND HRS Longitudinal File 2020 (V3) (HRS, 2023c), (b) the Cross-Wave Census Region/Division and Mobility File (Final V9.0) (HRS, 2023d), and (c) the 2008, 2010, 2012, 2014, 2016, and 2018 RAND HRS Fat Files (HRS, 2017, 2021a, 2021b, 2022, 2023a, 2023b).

To study lifecourse patterns of productive engagement, two sample schemes with overlapping ages were formed. In Scheme 1, the study sample was limited to respondents who responded to every biennial wave between 2008 to 2018 (n = 8,023), not in a nursing home in any of the waves to focus on community-dwelling adults (n = 7,738), had no missing geographical data and did not change geographical regions (n = 6,741)[1], and between ages 51-60 in 2008 (n = 2,027). After removing 35 (1.7%) respondents with missing values in the study variables, the final sample size contained 1,992 respondents with 11,952 observations. In Scheme 2, the study sample was limited to the same inclusion criteria as Scheme 1, except the respondents were between ages 61-70 in 2008 (n = 2,658). After removing 47 (1.8%) respondents with missing values in the study variables, the final sample size contained 2,611 respondents with 15,666 observations. Both samples were followed over a ten-year period, to

[1] Glauber (2022) found that around 3% of respondents from the 2000-2016 waves of the HRS who lived in a rural area also spent at least one other wave in an urban location.

have sufficient statistical power and heterogeneity of patterns, as previous studies have shown (Carr et al., 2022; van der Horst et al., 2017). Two age groups were constructed to explore both age effects and birth cohort effects, with the understanding that the two effects are inseparable in this analysis. Furthermore, by using overlapping age groups, similar patterns of engagement should arise in each age group. This serves as a cross-validation of the findings, which is critical given that both age groups involve a substantial loss of cases due to attrition or death over the ten-year observation period—37.7% in Scheme 1 and 43.7% in Scheme 2.

2.2.2 Variables

The main independent variables for the multichannel sequence analysis were working, volunteering, and caregiving. Using terminology from the sequence analysis literature, each level in these categorical variables are "states," and the list of all the states that an individual can be in is the "alphabet" (Gabadinho et al., 2011). The working variables were drawn from the "Labor Force Status" variables in the RAND HRS Longitudinal File, which defines full-time work as working 35+ hours per week and 36+ weeks per year; and part-time work as working fewer hours than full-time work (HRS, 2023c). Full-time work and part-time work were coded as states "A" and "B," respectively, as originally defined in the RAND variable, but the categories unemployed, partly retired, retired, disabled, and not in labor force were collapsed to "C" = Not Working. The volunteering variables were drawn from the HRS Core, which asks, "Have you spent any time in the past 12 months doing volunteer work for religious, educational, health-related or other charitable organizations?" (HRS, 2017). Individuals who answered yes were then probed the number of hours they volunteered. This variable was evenly coded into three states: "D" = Non-Volunteer, "E" = volunteering 50 hours or less (low-intensity), and "F" = volunteering more than 50 hours (high-intensity). Caregivers were coded "G" = Caregiver, if they were either a spousal caregiver, a grandchild caregiver, or a parental caregiver; respondents were coded “H” = Non-Caregiver if they were none of the above. Spousal caregivers were defined as respondents whose spouses reported that they were their primary or secondary Activities of Daily Living (ADLs) or Instrumental Activities of Daily Living (IADLs) helper; grandchild caregivers were respondents who answered yes to the question, “Did you [or your husband/wife/partner/] [or your] [late/husband/wife/partner] spend 100 or more hours in total … [since Previous Wave] … taking care of [grand or great-grandchildren/grandchildren]?”; and parental caregivers were respondents who answered yes to the question, “How about another kind of help: Did you [or your] [late/husband/wife/partner] spend a total of 100 or more hours … [since Previous Wave] … helping your [(deceased)/parents/mother/father/mother (and/or her husband)/father (and/or his wife)] with basic personal activities like dressing, eating, and bathing?” (HRS, 2017).

To study geographical variations in the independent variables, the HRS Cross-Wave Census Region/Division and Mobility File was used to obtain the Rural-Urban Continuum Codes (RUCC) of the participants. The publicly available HRS files contains three categories (the full codes are only available under special agreement): “Urban” (code 1) areas are defined as counties in metro areas of 1 million population or more; “suburban” (code 2) areas are counties in metro areas of 250,000 to 1 million population; and “ex-urban” (codes 3-9) areas are counties in metro areas of fewer than 250,000 population and non-metro counties. In this study, “rural” is defined as “ex-urban,” even though it is an imperfect measure of rurality and consists of both small metro counties and non-metro counties (Sun et al., 2022). “Urban” is defined as a collapsed variable using RUCC 1-2.

2.2.3 Analytical Strategy

To identify and describe lifecourse patterns of productive engagement, this study carried out: (1) multichannel sequence analysis (MSA), (2) cluster analysis, (3) visualizations, (4) sequence characterization, and (5) missing data analysis.

Multichannel Sequence Analysis. First, MSA was used to model the joint trajectories of three productive activities: working, volunteering, and caregiving. Prior to performing MSA, the Hopkins' statistic was used to validate if each sample scheme contained identifiable clusters. The Hopkins' statistic (*H*) seeks to reject the null hypothesis that the data are unclusterable, with values of 0-0.3 indicating regularly-spaced data, values around 0.5 indicating random data, and values 0.7-1 indicating clustered data. Because the test assumes a Beta distribution, a recommended 10% sampling rate was used to test each sample scheme (Hopkins & Skellam, 1954; Maechler et al., 2022). To prepare the data for MSA, state sequence objects were created for each domain separately—working, volunteering, and caregiving. As examples, for Scheme 1, the sequences of the modal states at each position were: (1) A-A-C-C-C-C (two waves of full-time work followed by four waves of not working) for the working domain; (2) D-D-D-D-D-D (not volunteering in all waves) for the volunteering domain; and (3) H-H-H-H-H-H (not a caregiver in all waves). These objects were combined into an extended alphabet in the multidomain level. For example, an individual's sequence was coded as: A+D+H-A+D+H-C+D+H-C+D+H-C+D+H-C+D+H. The longest common subsequences (LCS) distance measure was then used at this multidomain level to create a dissimilarity matrix consisting of pairwise dissimilarities between sequences (Ritschard et al., 2023). This strategy is referred to as building a joint typology that has "independence from domain costs and distances" (IDCD) (Ritschard et al., 2023, p. 290).[2] Because incorporating individuals of different ages at baseline attenuates the

[2] I thank Dr. Gilbert Ritschard for directing me to this approach during a Sequence Analysis Association workshop on January 25, 2024. In an earlier draft, I had invoked the function seqMD with method = "LCS," which computed

ability to make inferences about the timing of activities, the LCS was an appropriate choice as matches based on the LCS are less sensitive to timing. LCS also overcomes the challenges of using optimal matching (OM), which has been criticized due to the difficulty of determining and interpreting substitution and indel operations (Elzinga, 2003; Liao et al., 2022a; Wu, 2000). OM in the context of MSA also typically requires "that states occur independently in each domain" (Ritschard et al., 2023, p. 298), which would not be appropriate in the current study, given evidence, for example, that volunteering is more likely when work is discontinued—the "activity substitution" hypothesis (Carr et al., 2022; Herzog et al., 1989, p. 130; Mutchler et al., 2003, p. 1271). Sampling weights were not incorporated in the multichannel sequence analysis, as there was no clear guidance in the literature.

Cluster Analysis. Second, partitioning around medoids (PAM) clustering was performed on the dissimilarity matrix to obtain cluster memberships. "Clusters" will be used interchangeably in this study with "patterns" and "lifecourse patterns of productive engagement" (LPPEs). Given *k* clusters, the PAM algorithm selects *k* medoids or representative sequences and assigns the remaining sequences to the nearest medoid (L. Kaufman & Rousseeuw, 2009, p. 40). The PAM algorithm is well suited for sequence analysis, because it provides information on the dissimilarity between sequences and medoids, which can be used to assess cluster quality (Piccarreta & Studer, 2019). The optimal number of *k* clusters was determined by using majority rule among several cluster quality indices (weighted average silhouette width, Hubert's gamma, point biserial correlation, and Hubert's C coefficient), silhouette plots via the R package *factoextra* (Kassambara & Mundt, 2020), and theoretical value with respect to the extant literature. The stability of the cluster assignment was assessed using a bootstrap distribution of

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dissimilarities with optimal matching and the cost additive trick (CAT). While the analysis led to similar clusters as the ones presented here, it had violated the independence assumption behind CAT.

the Jaccard coefficient with 50 resampling iterations. Cluster stability “means that a meaningful valid cluster should not disappear easily if the data is changed in a non-essential way,” and a mean Jaccard similarity value of 0.75 or more indicates a valid, stable cluster, while a value between 0.6 and 0.75 indicates clusters with patterns but uncertainty as to which individuals belong to those clusters (Hennig, 2007, p. 258, 2023, p. 44).

Visualizations. Finally, to study the characteristics of the sequences for each sample scheme, the R package *ggseqplot* (Raab, 2022) was used to create chronograms/sequence distribution plots (Billari & Piccarreta, 2005) and sequence frequency plots (Müller et al., 2008). Sequence distribution plots depict the relative distributions of activities by year and cluster, while sequence frequency plots display the most common sequences per cluster. Due to the difficulty of distinguishing 18 different activity combinations using unique colors, the activity states were divided into caregiving states (9 states), represented as shades of green, and non-caregiving states (9 states), represented as shades of red. Darker greens (e.g., caregiving plus working) and darker reds (e.g., working plus volunteering) correspond to engagement in either a greater number or a greater intensity of activities. For example, full-time work and high-intensity volunteering are shaded darker than part-time work and low-intensity volunteering. Caregiving alone is shaded light green, while not engaging in working, caregiving, or volunteering is shaded light orange. These color choices simplify the presentation of the clusters but represent a trade-off in terms of distinguishing different activity patterns. Therefore, the naming of the patterns was carried out by carefully inspecting distributions and using additional visualization tools, such as the modal states plot (Gabadinho et al., 2011).

Sequence Characterization. To further describe the longitudinal nature of the sequences, the sequences were described using four indices: (a) complexity index (Gabadinho et al., 2011), (b) mean spell duration, (c) number of transitions, and (d) number of visited states (Ritschard, 2023). The complexity index (normalized; ranges from 0 to 1) takes into account the diversity of the states and the number of occurrences of each state, with higher values indicating greater unpredictability of state arrangements in the sequences. To illustrate the other indices, the sequence "A+D+H-A+D+H-C+D+H-C+D+H-C+D+H-C+D+H" contains a mean spell duration of (2 + 4) / 2 = 3, one transition from A+D+H to C+D+H, and two (distinct) visited states.

Missing Data Analysis. Due to the small amount of missingness (< 2%) in each age group, imputation methods, such as the MICT algorithm developed by Halpin (2012), were not considered in this study. In Emery's (2023, p. 120) review of methods for dealing with missing data, he argues that "the current approaches available for handling missing data in multichannel sequences do not provide complete satisfaction." Specifically, the MICT algorithm, currently considered the preferred method for addressing missing data in sequence analysis, is only able to treat "each channel separately, thereby ignoring the association between the channels" (Emery, 2023, p. 121). This rendered the MICT approach inappropriate for this study, which could not reject the null hypothesis that the associations between the domains are zero. For example, in Scheme 1, the Pearson's correlation coefficients between (a) volunteering and working sequences and (b) volunteering and caregiving sequences were $r = .020$, $p < .001$ and $r = .021$, $p < .001$, respectively. Nevertheless, to minimize the effects of missing data due to attrition and death, two overlapping age groups were used to cross-validate the findings.

To test the amount of missing data bias in the two sample schemes in the present study, which contain complete observations from 2008-2018, two other samples that meet the same study inclusion criteria but have incomplete observations up till 2018 due to either attrition or death were formed. Bivariate tests were conducted between these two pairs of samples on the following baseline 2008 variables: Gender (0 = Male, 1 = Female), age in years (continuous), years of education (continuous; ranging from 0 to 17 years), marital status (dichotomized to 0 = Not Married, 1 = Married), race (1 = White/Caucasian, 2 = Black/African American, 3 = Other), religious preference (dichotomized to 0 = No Religious Preference, 1 = Has Religious Preference [Protestant, Catholic, Jewish, and Other]), total household income (logged; continuous), number of diagnosed health problems (continuous; ranging from 0 to 8, including high blood pressure, diabetes, cancer, lung, heart condition, stroke, psychiatric, arthritis), self-rated health in 2008 (1-5; higher scores indicate better health), and total cognitive functioning in 2008 (ranges from 0-27 points; higher scores indicate better cognitive functioning).

Survey Weights. Due to the exploratory nature of this study, and the lack of guidance on conducting sequence analysis and cluster analysis with complex survey data, this study did not use survey weights to make inferences to the general US population. This is a limitation that may result in oversampled individuals in the HRS—Blacks, Hispanics, and Florida residents—being over-emphasized in the results (Fisher & Ryan, 2018, p. 2). However, descriptive analyses and chi-square tests (with Rao-Scott second-order correction) of the proportion of productive engagement activities by year and geography were weighted using the baseline 2008 person-level analysis weights (HRS, 2023c) and conducted via the R packages *survey* (Lumley, 2004) and *srvyr* (Ellis & Schneider, 2023).

Analytical Software. All analyses were conducted in R version 4.3.2 (R Core Team, 2023). Additional R packages that were used included *haven* (Wickham et al., 2023) for importing HRS datasets, *tidyverse* (Wickham et al., 2019) for data manipulation; *sjlabelled* (Lüdecke, 2022) for cleaning variables; *hopkins* (Wright, 2023) for clusterability analysis; *cluster* (Maechler et al., 2022) for PAM clustering; *WeightedCluster* (Studer, 2013) for cluster quality measures; *fpc* (Hennig, 2023) for assessing cluster stability; *viridis* (Garnier et al., 2024) for its color palettes; *patchwork* (Pedersen, 2024) for combining plots; and *kableExtra* (Zhu, 2024) for constructing tables. The R package *TraMineR* was used to create state sequence objects (Gabadinho et al., 2011), conduct MSA (Ritschard et al., 2023), and calculate longitudinal characteristics (Ritschard, 2023). This study was deemed exempt by the Washington University in St. Louis Human Research Protection Office (#202210130).

2.3 Results

The null hypothesis that the data contain nonclusterable data was rejected, according to the Hopkins' statistic—Scheme 1: $H = 0.91$, $p < .001$; Scheme 2: $H = 0.89$, $p < .001$. After comparing the two sample schemes with comparable samples with incomplete data—including participants who dropped out subsequently due to attrition or death—the Scheme 1 sample was found to have significantly better self-rated health, more full-time workers, and better cognitive functioning score on average (Table 3). The Scheme 2 sample was found to have significantly more females, fewer rural respondents, better self-rated health, more high-intensity and low-intensity volunteers, younger, more years of education, more household income, fewer number of diagnosed health problems, and higher total cognitive functioning scores (Table 4).

2.3.1 Scheme 1 Results

Descriptive Statistics. Table 1 presents the distribution of older adults ages 51-60 in 2008 who were engaged in working, volunteering, and caregiving activities from 2008 to 2018. Working activities generally followed a downward trend, while the proportion of older adults engaged in both volunteering and caregiving activities remained relatively stable. There were statistically significant differences in working activities by geography in 2008, $F(3.62, 202.49) =$

2.57, p = .045, and in caregiving activities by geography in 2010, $F(1.96, 109.98) = 4.21$, p = .018.

Multichannel Sequence Analysis and Cluster Analysis. For the MSA analyses, there were 1,431 unique sequences among 1,992 total sequences. The sequences were categorized as LPPEs using PAM clustering. An eight-cluster solution (k = 8) was chosen based on several cluster quality indicators (average silhouette width [weighted], Hubert's gamma, Hubert's C coefficient, and point biserial correlation) and comparing visualizations with known trajectories and transitions in the literature (e.g., Y. Lee & Tang, 2015) (Figure 2). The stability of the eight-cluster assignment was assessed using a bootstrap distribution of the Jaccard coefficient with 50 resampling iterations; one cluster was above the recommended Jaccard similarity value of .75, four clusters were between .60 and .75, and three clusters were below .60.

Plot Interpretation. Figure 3 shows the state distribution plots of the eight-cluster solution, while Figure 4 shows sequence frequency plots containing the 20 most frequent sequences per cluster. State distribution plots contain discrete scales on the x-axis that correspond to each biennial wave in the study observation period (2008-2018) and continuous scales on the y-axis that correspond to the relative frequency of the states. For example, in Cluster 1, the light orange color corresponds to not engaging in working, volunteering, or caregiving and roughly 70% of the 456 respondents in the cluster are not engaging in the year 2008, roughly 75% in 2010, and so on. The green lines, which correspond to caregiving, show that only a small percentage (~3%) of the 456 respondents in this cluster were caregivers in any given wave. State frequency plots contain the same x-axis as the state distribution plots but the relative frequency of a given sequence on the y-axis. The 'total coverage' value of 56.4% in Cluster 1 means that the 20 most frequent sequences in Cluster 1 accounted for 56.4% of all sequences in Cluster 1. The percentages of the y-axis labels do not add up to 56.4%, even though the 20 most common sequences are printed out, because overlapping y-axis labels were removed for a cleaner presentation. The results of each cluster, using both the state distribution plots and the state frequency plots, are presented below.

Cluster 1: Steady Limited Productive Engagement. Cluster 1 was the largest cluster, containing a total of 456 (22.9%) individuals age 51-60 in 2008. The modal sequence (26.8%) was ‘steady limited productive engagement (PE)’—not engaged in working, volunteering, or caregiving across the ten-year observation period (as denoted by the light orange color). The second most common trajectory consisted of individuals who transitioned from full-time work to non-engagement in working, volunteering, or caregiving (7.7%). Other sequences contained limited engagement interspersed with short periods of caregiving alone, the timing of which appears random. The 20 most common sequences covered more than half (56.4%) of all trajectories within the cluster.

Cluster 2: Decreasing Full-Time Working. Cluster 2 contained 330 individuals or 16.6% of the total sample. The trend of decreasing full-time (FT) work can be seen in the ladder-like pattern in Figure 3, with decreasing proportions of full-time workers over the ten-year observation period. Figure 4 shows that the timing of transitioning from full-time work to non-engagement in working, volunteering, and caregiving varied in duration, with some individuals working longer than others, before ceasing work.

Cluster 3: Increasing High-Intensity Volunteering. There were 283 individuals or 14.2% of the sample in cluster 3. The modal pattern in this cluster contained individuals who were high-intensity volunteers throughout the observation period (7.4%). Less common were individuals who were working full-time and volunteering at a high-intensity level simultaneously for the first two to six years, before transitioning to high-intensity volunteering alone.

Cluster 4: Steady Full-Time Working. Cluster 4 contained 271 individuals or 13.6% of the sample. The modal sequence (17%) contained full-time work throughout the observation period. Like the previous clusters, a small minority of sequences contained caregiving engagement at various timings. The proportion of those engaged in full-time work remained relatively steady in each wave, except the final two waves, where there was a tapering off of working engagement.

Cluster 5: Decreasing Full-Time Working & Low-Intensity Volunteering. Cluster 5 contained 236 individuals or 11.8% of the sample. Similar to Cluster 2, Cluster 5 exhibited a gradual stepwise decline in the proportion of individuals engaged in full-time work. The darker purple color, in contrast to the lighter red in Cluster 2, denotes that the individuals were simultaneously engaged in full-time work and low-intensity volunteering. The proportion of individuals engaged in low-intensity volunteering remained steady, even as working engagement decreased throughout the observation period.

Cluster 6: Steady Caregiving & Decreasing Volunteering and Working In Cluster 6, there were 157 individuals or 7.9% of the sample. The most frequent sequences contained varying durations of caregiving alone, from two waves to the entire length of the observation. There was considerable heterogeneity in the timing of events in cluster 6, with individuals becoming a caregiver in the beginning, middle, and end of the observation period, or transitioning in and out of caregiving. Caregiving durations also varied, from a single wave to all six waves. Engaging in volunteering in addition to working and volunteering was more common near the beginning of the sequences, rather than the end of the sequences. Thus, this cluster was named for its steady proportions of individuals engaged in caregiving and decreasing engagement in volunteering and working.

Cluster 7: Decreasing Full-Time Working & High-Intensity Volunteering. There were 140 individuals or 7.0% of the sample. The dominant patterns in this cluster consisted of individuals working full-time and engaged in high-intensity volunteering (dark purple). In the last two waves, full-time work decreased, while high-intensity volunteering remained steady throughout the observation period.

Cluster 8: Decreasing Part-Time Working. There were 119 individuals or 6.0% of the sample. The proportion of individuals engaged in part-time work (dark orange) steadily declined, with the modal sequences consisting of individuals transitioning from part-time work to non-engagement in working, volunteering, or caregiving. Less common sequences in this cluster contained individuals who engaged in part-time work in shorter durations or in combination with volunteering and caregiving.

2.3.2 Scheme 2 Results

Descriptive Statistics. Table 2 presents the distributions of productive engagement activities for older adults ages 61-70 in 2008. Similar to the Scheme 1 results, there were generally declines in working activities, while the proportion of older adults engaged in volunteering and caregiving activities remained relatively uniform in the ten-year period. There were statistically significant differences in volunteering activities by rural/urban geography in 2012, $F(2.94, 153.06) = 2.86$, $p = .040$.

Multichannel Sequence Analysis and Cluster Analysis. MSA yielded 1,414 unique sequences among 2,611 total sequences. The sequences were categorized as LPPEs using partitioning around medoids (PAM) clustering. A six-cluster solution ($k = 6$) was chosen based on several cluster quality indicators (Figure 2). The stability of the six-cluster assignment was assessed using a bootstrap distribution of the Jaccard coefficient with 50 resampling iterations; four clusters were above the recommended Jaccard similarity value of .75, and two clusters were between .70 and .75. Figure 5 shows the state distribution plots of the six-cluster solution, and Figure 6 shows the 20 most frequent sequences in each cluster.

Cluster 1: Steady Limited Productive Engagement. There were 758 individuals (29.0%) in Cluster 1. The modal (48.3%) pattern was not engaging in working, volunteering, or caregiving. Less frequent patterns were preceded by a wave of full-time work or contained short durations of caregiving engagement. The 20 most frequent patterns represented a large majority of all patterns (84.6%), which corresponds to the low complexity scores of 0.12 and 0.13 for rural and urban participants in this cluster, respectively. Urban participants tended to have shorter spell durations than rural participants, but the difference was only marginally significant, $p < .10$.

Cluster 2: Steady High-Intensity Volunteering. There were 442 individuals (16.9%) in Cluster 2. The modal (20.6%) pattern consisted of full-time work throughout the observation window. However, on average, both rural and urban participants visited two states and experienced two state transitions. Multi-activity engagement was more common near the early waves, compared to the later waves. The 20 most common patterns accounted for nearly half of all patterns, corresponding to the low complexity scores of 0.29 and 0.27 for rural and urban participants, respectively.

Cluster 3: Decreasing Volunteering. There were 401 individuals (15.4%) in Cluster 3. There was no modal pattern that dominated the patterns. Rural and urban participants both visited three states on average and experienced three state transitions on average. High-intensity volunteering was more common in the early waves, compared to the later waves. Both high-intensity and low-intensity volunteering decreased over time. Overall, the patterns of volunteering in this cluster exhibit high complexity (rural = 0.45, urban = 0.46), with a diversity of different timings of starting, stopping, or sustaining volunteering.

Cluster 4: Decreasing Full-Time Working. There were 401 individuals (15.4%) in Cluster 4. The proportion of older adults engaged in full-time work in this cluster gradually decreased over time. The most frequent patterns in this cluster begin with full-time work with varying duration, followed by non-engagement in working, volunteering, or caregiving. There were no statistically significant differences between rural and urban participants with respect to complexity or the other measures of sequence characteristics in Table 5.

Cluster 5: Decreasing Caregiving. There were 385 participants (14.7%) in Cluster 5. The proportion of caregivers in this cluster gradually declined over time, with very few caregivers simultaneously working or volunteering. The 20 most common patterns accounted for about a third (34.8%) of all patterns within the cluster. There was no dominant modal pattern; the timing of caregiving appears random with varying durations. There were no statistically significant differences between rural and urban sequence characteristics.

Cluster 6: High-Intensity Volunteering and Caregiving. There were 224 individuals (8.6%) in Cluster 6. The most common patterns consisted of high-intensity volunteers who volunteered throughout the observation window with varying spells of caregiving. Similar to Cluster 5, the caregiving patterns do not have a distinguishable pattern. The individuals in this cluster had the most transitions and most visited states, compared to the other clusters. On average, individuals had more than three transitions and more than three visited states. Both rural and urban participants in this cluster had the highest complexity scores, 0.51 and 0.49, respectively, compared to the other clusters.

2.4 Discussion

This study sought to discover if there are patterns of productive engagement when taking into account key lifecourse characteristics. Using multichannel sequence analysis on two overlapping age groups, this study found lifecourse patterns of productive engagement with greater diversity and complexity than previously described in the literature. Past studies that investigated multiple activities allocated groups based on the types of activities and the intensity of the activities (Amano et al., 2022; Carr et al., 2022; Morrow-Howell et al., 2014a); however, the groups contained limited information on the timing and ordering of activities. For example, this study observed decreasing engagement in part-time employment in the ages 51-60 group but not in the ages 61-70 group, suggesting that the timing of—and opportunities for—part-time employment may be biased towards early-old age. This is a concerning finding, given that previous research has correlated part-time employment and flexible work arrangements in later life with multiple health benefits (McDonough et al., 2017).

Another finding was that caregiving patterns were more pronounced in the ages 61-70 group, with one cluster exhibiting decreasing caregiving activities with shorter spells and another cluster exhibiting steady caregiving engagement simultaneously with high-intensity volunteering. The combination of care work with high-intensity volunteering, typically seen as a discretionary activity, lends support to past research that ruled out care work as necessarily competitive to working or volunteering activities (van der Horst et al., 2017). This is similar to the finding that a small segment of older adults are “super helpers” who participate in multiple activities with moderate to high intensity (Burr et al., 2007, p. 272). However, McNamara &

Gonzales' (2011, p. 498) found that parental or spousal caregiving contributes to volunteering cessation, and it is possible that the inclusion of grandparent caregiving may be masking this effect. In summary, Clusters 5 and 6 in Scheme 2 provide support for both a competitive view of caregiving, in which caregiving constrains the opportunity to engage in additional activities, as well as a complementary view of caregiving, in which caregiving occurs simultaneously with high-intensity volunteering.

This study also found variations in patterns by age groups. Compared to Scheme 1, Scheme 2 contained two patterns where the modal sequences contained caregiving activities: one in which caregiving activities declined over time (Cluster 5) and another in which steady caregiving was accompanied by high-intensity volunteering (Cluster 6). The older age group in Scheme 2 also exhibited more homogeneous patterns compared to Scheme 1. For example, roughly a third of the caregiving pattern's sequences in Scheme 2 were represented by the 20 most frequent sequence patterns, in contrast to roughly a quarter of the patterns in the comparable cluster in Scheme 1. This is supported by the complexity analysis, which also showed that the patterns of non-engagement in Scheme 2 were less unpredictable than the patterns in Scheme 1. Furthermore, Scheme 2 was best represented by only six clusters, two of which exhibited similar patterns as Scheme 1: (a) Steady limited productive engagement and (b) Decreasing full-time working. The remaining four clusters consist of two patterns of volunteering and two patterns of caregiving, showing an absence of working in later life and also more flexible modes of engaging in volunteering and caregiving. While these show a clear difference in patterns of engagement by the age groups, further work is needed to separate age, period, and cohort effects, which may interact in complex ways (Rotolo & Wilson, 2004).

There were several limitations in this study. First, the operationalization of caregiving in this study may include false positives, as HRS asks if either the respondent or their late spouse is a parental or grandchild caregiver. It is possible that the respondents identified as parental or grandchild caregivers in this study were not directly providing care. Future work should focus on spousal carers alone, which can be identified unambiguously.[3] Second, the lack of stability in the clusters suggests the need for further work. Testing different clustering algorithms, such as Ward's hierarchical cluster algorithm, *k*-means clustering, or fuzzy clustering, may enhance cluster stability. As Studer (2018, p. 224) argues, the fuzzy clustering approach, in which sequences can be assigned to multiple clusters, may be especially promising, because there might be cases where a sequence is between two sequence types and should not be assigned to a single cluster membership. While this study only used the PAM algorithm for clustering, the use of two overlapping age groups reproduced two similar patterns of engagement, thus serving as a cross-validation of the existence of conceptually meaningful clusters. Third, focusing on respondents with complete information in working, caregiving, and volunteering activities across six waves or ten years of data is problematic for two reasons: (1) focusing on a select group of individuals who are healthier than those who have dropped out due to attrition or death and (2) excluding participants who are productive in other activities such as taking classes or meeting with friends. Future research should truncate the observation window or implement imputation techniques for minimizing these issues. At the time of this writing, novel multiple imputation techniques for MSA—the MICT-timing and MICT-timing random forest algorithms—have been developed but

[3] It should be noted that spousal caregivers cannot be identified exhaustively, because if only one of the respondents completes the survey, there would be no information on whether the non-responding spouse received help from their partner.

not yet released to the public (Emery, 2023, p. 172). Furthermore, additional activities should also be considered, to expand the field's understanding of activity engagement in later life.

This study also has several strengths. The use of a ten-year observation window to aggregate lifecourse patterns is an improvement over prior studies that used latent class analysis (LCA) to study profiles of engagement activities in a two-year period (Amano et al., 2022; Chen et al., 2019; Morrow-Howell et al., 2014). A major weakness of LCA for longitudinal data is that it does "not take into consideration the time correlation between variables" (Barban & Billari, 2012, p. 768). This study overcomes this limitation by investigating the timing of activities using multichannel sequence analysis.

Chapter 3: Antecedents of Lifecourse Patterns of Productive Engagement

3.1 Introduction

In the previous paper, lifecourse patterns of productive engagement among older adults in the United States were discovered using multichannel sequence analysis and cluster analysis. The goal of this chapter is to investigate the antecedents of those patterns.

3.1.1 Literature Review

Past studies have examined the antecedents of a combination of activity domains in later life. Focusing on older adults aged 55 and older in the U.S., Burr et al. (2007) investigated clusters of paid work, volunteering, caregiving, informal helping, and home maintenance activities; they found statistically significant relationships between the clusters and several individual characteristics (e.g., age, marital status, and functional status). For example, they found that higher education was associated with the “helpers” cluster (mostly volunteering and informal helping activities) as compared to the “home maintainers” cluster (mostly home maintenance activities), and they found a higher likelihood of being in the “home maintainers” cluster with increasing age, a lower likelihood of being in the “worker, volunteer” and “super helper” clusters with increasing age, and a curvilinear relationship between age and the “helper” cluster, with the middle age group having the greatest likelihood of being in the cluster (Burr et al., 2002, p. 273). Croezen et al. (2009, p. 778) examined clusters of social engagement activities—voluntary, physical, visiting, hobby, work, and care—of Dutch older adults aged 65 or older and found that the older adults in the “caregiver” clusters had a high share of mental health problems; individuals in the “leisure engaged” cluster had a higher educational level and good overall health; and older adults in the “productive engaged” group were mostly men, had a high educational level, and had good overall health. Using data between 2008 and 2010 of the

Health and Retirement Study, Morrow-Howell et al. (2014b) related five activity profiles (constructed using 36 activity measures) with antecedents and found that lower socioeconomic status was correlated with the “Low Activity” profile, compared with the other profiles; men were more likely than women to be in the “Low Activity” profile; and White older adults were more likely to be in the “Physically Active” and “Working” profiles, compared to African American older adults.

3.1.2 Conceptual Framework

Productive engagement frameworks have theorized the role of antecedents in predicting working, caregiving, and volunteering activities. Sherraden et al. (2001) advanced a framework of “productivity in later life” that focused on a limited but quantifiable set of productive behaviors (activities that produce goods and services, whether paid or not); potential determinants of these behaviors (sociodemographics, public policy, individual and institutional capacity); and the potential outcomes of these behaviors at the individual, family, and societal levels. Morrow-Howell and Wang (2013) extended Sherraden et al. (2001) by encapsulating their framework within a larger sociocultural context to support cross-cultural work in practices and policies. Using the World Health Organization’s active aging framework, they also modified the antecedents of the model to include socio-demographics, the economic environment, the physical environment, and public policies and programs. The physical environment includes urban and rural contexts, residential arrangements, and community infrastructure. Morrow-Howell and Greenfield (2015) used ecological systems theory to develop a model with three levels of antecedents: (a) individual, (b) community, and (c) societal, reflecting a gradient of environments from proximal to distal. Their model also considers the intensity, regularity, and duration of productive activities, as well as multiple productive activities simultaneously.

The life course perspective can also guide the selection of predictors of multiple trajectories of productive engagement. Diverse trajectories can arise from cumulative dis/advantages through early experiences such as family and educational systems (Dannefer & Settersten, 2010). Education, for example, is a consistent predictor of volunteering behavior, with higher educational levels correlated with higher rates of volunteering (Chambré, 2020). Yet, education is not the only “interindividual divergence” and interacts with a complex array of forces (Dannefer, 2003, p. 327). Those with a higher educational level who have a chronic disease are less likely to quit paid employment than those with a chronic disease with a lower educational level (Scharn et al., 2019, p. 140)—this illustrates how multiple factors may interact in diverse ways.

3.2 Methods

3.2.1 Data

To investigate the antecedents of lifecourse patterns of productive engagement, this study used the nationally representative Health and Retirement Study (HRS), which is sponsored by the NIA (grant number NIA U01AG009740) and is conducted by the University of Michigan. The HRS sample is representative of the U.S. population age 51 and above and “based on a multi-stage area probability design involving geographical stratification and clustering and oversampling of certain demographic groups” (Sonnega et al., 2014, p. 577). This study is a follow-up to a previous study (Chapter 2) that analyzed the effects of lifecourse patterns of engagement between 2008-2018, which used the following HRS datasets: (a) the RAND HRS Longitudinal File 2020 (V3) (HRS, 2023c), (b) the Cross-Wave Census Region/Division and Mobility File (Final V9.0) (HRS, 2023d), and (c) the 2008, 2010, 2012, 2014, 2016, and 2018 RAND HRS Fat Files (HRS, 2017, 2021a, 2021b, 2022, 2023a, 2023b). This present study drew upon additional sociodemographic and geographical variables from (a) the RAND HRS Longitudinal File 2020 (V3) (HRS, 2023c) and (b) the Cross-Wave Census Region/Division and Mobility File (Final V9.0) (HRS, 2023d). The study sample was limited to respondents who responded to every biennial wave between 2008 to 2018, because it remains unclear how to handle missing data in sequence analysis (Piccarreta & Studer, 2019) (n = 8,023), not in a nursing home in any of the waves to focus on community-dwelling adults (n = 7,738), had no missing geographical data and did not change geographical regions (n = 6,741), and were between ages 51-60 in 2008 (n = 2,027). The final sample size contained 1,992 respondents with 11,952 observations. To assess the representativeness of the current sample, bivariate comparisons between the present study sample and a larger sample including respondents who later dropped out due to attrition or death revealed that the present study sample tended to have better self-rated health, more full-time working individuals, and a higher total cognitive functioning score at the 2008 baseline wave (Table 3).

3.2.2 Variables

The dependent variable is lifecourse patterns of productive engagement (LPPEs), a nominal variable constructed in a previous study (Chapter 2) using multichannel sequence analysis followed by partitioning around medoids (PAM) clustering. LPPEs summarize 10-year sequences of working (full-time, part-time, not working), volunteering (more than 50 hours, 50 hours or less, no volunteering), and caregiving (caring for a spouse, grandchild, or parent and not a caregiver) states. An eight-cluster solution was found to be optimal, therefore this variable was coded from 1-8.

The independent variables include both rurality and sociodemographic variables found in the productive engagement literature. Rurality was defined using the publicly available HRS

Rural-Urban Continuum Codes (RUCC), which contain three categories (the full codes are only available under special agreement): “Urban” (code 1) areas are defined as counties in metro areas of 1 million population or more; “suburban” (code 2) areas are counties in metro areas of 250,000 to 1 million population; and “ex-urban” (codes 3-9) areas are counties in metro areas of fewer than 250,000 population and non-metro counties. In this study, “rural” is defined as “ex-urban,” even though it is an imperfect measure of rurality and consists of both small metro counties and non-metro counties (Sun et al., 2022). The reference category is “urban” or a collapsed variable using codes 1-2.

The sociodemographic variables include gender (0 = Male [reference category], 1 = Female), age in years (continuous), years of education (continuous; ranging from 0 to 17 years), marital status (dichotomized to 0 = Not Married [reference category], 1 = Married), race (1 = White/Caucasian [reference category], 2 = Black/African American, 3 = Other), religious preference (dichotomized to 0 = No Religious Preference [reference category], 1 = Has Religious Preference [Protestant, Catholic, Jewish, and Other]), total household income (logged; continuous), and number of diagnosed health problems (continuous; ranging from 0 to 8, including high blood pressure, diabetes, cancer, lung, heart condition, stroke, psychiatric, arthritis).

3.2.3 Analytical Strategy

Missing Data. Missingness in the dataset was inspected prior to statistical analyses. Fewer than 1% of the sample had missing data in the study variables, resulting in a loss of 16 out of 1,992 cases if listwise deletion were used. Little’s Missing Completely at Random (MCAR) test was conducted using the R package *naniar* (Tierney & Cook, 2023), and the null hypothesis that the data are MCAR could not be rejected, $\chi^2(40) = 38.43$, $p = .54$. However, longitudinal cohorts such as those in the HRS are likely to suffer from non-random attrition due to unobservable characteristics (Kapteyn et al., 2006). Lu & Shelley (2023, p. 447) used different approaches to test for the missingness mechanism in two-wave longitudinal HRS data and determined that the data were likely to be missing at random (MAR), though they could not rule out the possibility of not missing at random (NMAR). Further, the sample from this present study already represents a truncated sample due to missing data from the preceding analysis in Chapter 2. Assuming a MAR mechanism, multivariate imputation by chained equations (MICE) is an appropriate strategy for dealing with the missing data problem. Based on the rule of thumb that the number of imputations should be equal or greater than the percentage of incomplete cases (White et al., 2011), 20 multiply imputed datasets were created via chained equations using the R package *mice* (Buuren & Groothuis-Oudshoorn, 2011). Missing values were imputed using predictive mean modeling for continuous variables, proportional odds model for ordinal variables, and logistic regression for dichotomous variables. Trace plots were inspected for each imputed variable to look for adequate mixing and convergence around a stable mean (Enders, 2022).

Multinomial Logistic Regression. To determine the characteristics of LPPEs, two multinomial logistic regression models were fitted on the multiply imputed dataset. Model 1 predicted LPPEs by rural/urban status. Model 2 added to Model 1 the following baseline 2008 sociodemographic variables: Gender, age, education, marital status, race, religious preference, income, and number of diagnosed health problems. The results were pooled using Rubin's (1976) rule.

Survey Weights. Following the recommendation of HRS (n.d., p. 2), both models were weighted using baseline 2008 person-level analysis weights (HRS, 2023c). HRS sampling weights permit inference to the non-institutionalized U.S. population, account for the oversampling of individuals in the HRS—Blacks, Hispanics, and Florida residents (Fisher & Ryan, 2018, p. 2), and account for “differential probability of selection and differential non-response in each wave” (Sonnega et al., 2014, p. 578). Clustering and stratification variables were also used to improve variance estimation given the geographic clustering of the sample (Fisher & Ryan, 2018, p. 2). Model fit statistics, such as AIC and BIC, in the context of complex survey data is still an area of research under development (Lumley & Scott, 2015); therefore, as a sensitivity analysis, non-weighted models were fitted and their model fits were assessed to ensure that they were within reasonable thresholds.

Analytical Software. Additional R packages that were used included *tidyverse* (Wickham et al., 2019) for importing data and data cleaning; *survey*, *mitools*, and *svyVGAM* (Lumley, 2004, 2019, 2023) for survey-weighted multinomial logistic regression with multiple imputation; and *tableone* (Yoshida & Bartel, 2022) and *table1* (Rich, 2023) for descriptive analyses. All analyses were conducted in R version 4.3.2 (R Core Team, 2023). This study was deemed exempt by the Washington University in St. Louis Human Research Protection Office (#202210130).

3.3 Results

In Model 1, there were two statistically significant findings (Table 7). First, the relative risk ratio comparing rural to urban respondents of being in the cluster “2. Decreasing full-time work” versus being in the reference cluster “1. Steady limited productive engagement” would be expected to decrease by a factor of 0.77, all other things being equal. Second, the relative risk ratio of being in the cluster “3. Increasing high-intensity volunteering” versus being in the cluster “1. Steady limited productive engagement” would be expected to decrease by a factor of 0.62 for rural respondents compared to urban respondents.

In Model 2, there were both statistically significant sociodemographic and geographical associations with the LPPEs (Table 8). Due to the difficulty of interpreting the magnitudes of the effects, only the directions of the significant findings are interpreted below. Compared to the reference cluster of steady limited productive engagement, being male was positively associated with clusters that had a modal pattern involving full-time working (clusters 2, 4, and 5). Being female was positively associated with “3. Increasing high-intensity volunteering” and “8. Decreasing part-time working.” Younger ages were positively associated with clusters involving full-time working (clusters 4, 5, and 7) and part-time working (cluster 8). With the exception of “8. Decreasing part-time working,” all of the clusters were positively associated with a higher educational level, compared to the reference cluster. Being married was negatively associated with being in the cluster “2. Decreasing full-time working,” but positively associated with clusters involving volunteering (clusters 3 and 7), caregiving (cluster 6), and part-time working (cluster 8). Black or African Americans were less likely to be in the clusters “4. Steady full-time working” and “8. Decreasing part-time working.” Religious affiliation was positively associated with all of the clusters, except “2. Decreasing full-time working,” “4. Steady full-time working,” and “7. Decreasing full-time working and high-intensity volunteering.” Higher income was positively associated with all of the clusters, except “7. Decreasing full-time working and high-intensity volunteering.” Having fewer diagnosed health problems was positively associated with all of the clusters, except “6. Steady caregiving and decreasing volunteering and working” and “8. Decreasing part-time working.” Finally, being rural was negatively associated with “3. Increasing high-intensity volunteering” and “8. Decreasing part-time working,” compared to the reference category.

3.4 Discussion

This study's findings contribute to a greater understanding of rural-urban differences in productive engagement in later life.

First, rural participants were less likely than urban participants to be in the cluster of increasing high-intensity volunteering versus the reference cluster of not engaging in working, caregiving, or volunteering. This finding perhaps represents the continuation of a downward trend in rural voluntary association membership, documented over the period 1994-2004 (Painter II & Paxton, 2014). The persistence of this gap, after controlling for sociodemographic variables, suggests that other contextual factors may be driving the rural/urban differences. For example, nonprofits in rural communities reported fewer increases in overall donations compared to nonprofits in urban areas between 2015 and 2019 (Faulk et al., 2021, p. 28). Besser (2009, pp. 187–188) further points to generational effects, such as Robert Putnam's (2000) thesis on the aging of the "civic generation," as well as the aging of rural towns, whereby older residents "may 'retire' from active engagement." Despite this finding of a net rural disadvantage, it is also important to note that several factors contribute to a narrowing of the rural-urban volunteering gap, such as education, racial homogeneity, and congregational density (Paarlberg et al., 2022, p. 117). Indeed, in this paper's model building, a significant rural effect disappeared after controlling for key social determinants of health, such as gender, education, and income. This shows that rurality, taken alone, is unable to tease apart the dimensions of place, such as the physical environment, community effects, or the effects of social practices (Dixon & Welch, 2000, pp. 258–259). Determining which of these facets of rural places are most amenable to change will be important for further reducing the rural-urban divide in volunteering.

Second, rural respondents were less likely than urban respondents to exhibit the pattern of "8. Decreasing part-time working" compared to "1. Minimal productive engagement." This is not surprising, as overall labor force participation rates between metropolitan and nonmetropolitan areas, after tracking closely together during the Great Recession, have become more divergent during the subsequent recovery period (2010-2019). In 2019, nonmetropolitan employment was still 3% below pre-Great Recession employment levels, while metropolitan employment had risen 10% above pre-Great Recession levels (U.S. Department of Agriculture Economic Research Service, 2019). Historically, nonstandard work, defined as both part-time work and contingent work (e.g., jobs lasting less than a year), were more prevalent in nonmetro areas than metro areas (McLaughlin & Coleman-Jensen, 2008, p. 655). This change in trend deserves attention, as part-time work can mean different things to older adults and lead to varying outcomes. In the case of older workers looking for flexible working options or phased retirement, part-time work could provide protective benefits such as delaying cognitive decline or the onset of long-term care (Tomioka et al., 2018) and improving life satisfaction (Chang & Yen, 2011). When part-time work is involuntary, then there may be continued occupational stress and a lack of health or insurance benefits (Donnelly & Schoenbachler, 2021). Future work should further characterize the nature of part-time work in this cluster to understand the implications of the rural-urban differential.

This study is not without limitations. First, the operationalization of the productive engagement variables do not capture important characteristics such as the volitional nature of working or the type of volunteering activity that a respondent engaged in. Second, Long (1997, p. 161) suggests using a likelihood ratio test to test that an independent variable has no effect on the dependent variable. Due to software limitations, this test was performed using a non-weighted multinomial logistic regression model and found that the overall model contained at least one significant predictor. Future work should extend this test to the survey-weighted regression model as well.

Chapter 4: Outcomes of Lifecourse Patterns of Productive Engagement

4.1 Introduction

In the preceding two chapters, lifecourse patterns of productive engagement were identified among older adults in the United States and the antecedents of the patterns were characterized. The goal of this chapter is to investigate how these patterns of productive engagement are related to two outcomes: cognitive functioning and self-rated health.

4.1.1 Literature Review

Working. Research has consistently documented a number of outcomes related to the productive engagement of older adults. Wickrama et al. (2013) found positive associations between full-time work status and subsequent measures of health: immediate memory, physical disability, and depressive symptoms. Research has also linked paid work with happiness when there is a sense of control over the retirement process (Calvo et al., 2009), less depressive symptoms among non-continuously retired men (J. E. Kim & Moen, 2002), increased cognitive capacities (Fisher et al., 2017), slower mental health decline (Hao, 2008), and meaning through generativity (Mor-Barak, 1995). It is important to note that older adults who reap the benefits of extended employment may represent a select group of workers in good health status with a higher propensity of continued working (Li & Sung, 1999). Indeed, the benefits of self-employment may be privileged to those with a higher baseline of social and financial security nets (Halvorsen, 2021). Older workers with negative poor self-rated health and symptomatic depression are also more likely to exit the labor force early (Rice et al., 2011). One line of research on the relationship between employment and well-being has focused on "deaths of despair" or deaths due to drugs, alcohol, and suicide. Case & Deaton (2020) found that lower unemployment rates is associated with lower rates of deaths of despair; and rural places often have little work or employees who are underpaid. Using nationally representative, cross-sectional survey data from 2010-2016, Graham and Pinto (2021) found that older adults above age 54 who were out of the workforce had higher life satisfaction than those who were unemployed or in the labor force; however, those who were out of the workforce had higher levels of pain and more poor health days than those who were in the labor force.

Volunteering. There is mounting evidence for the physical, cognitive, and psychosocial benefits of volunteering for older adults. Experience Corps, a high-intensity program in which volunteers 60 years and older are paired with elementary school students at least 15 hours a week to improve student outcomes, is the only randomized controlled trial on the benefits of volunteering in later life (Rebok et al., 2011). Compared with the control group, Experience Corps participants have demonstrated increased physical activity, strength, walking speed, generativity, and cognitive functioning (Brydges et al., 2021). Using a matched comparison group, Hong & Morrow-Howell (2010) also found fewer depressive symptoms and functional limitations among Experience Corps participants. Longitudinal and cross-sectional studies of the benefits of volunteering have generated strong evidence for reduced depressive symptoms (Huo et al., 2020), increased positive affect and life satisfaction (Huo & Kim, 2021), reduced mortality (S. J. Lee et al., 2011), and higher self-esteem (Okun & Michel, 2006). In a critical review of the current evidence, Anderson et al. (2014) note that studies have identified individual differences in psychosocial benefits, such as different outcomes depending on gender or baseline health conditions, as well as nonlinear relationships between the number of volunteer hours and psychosocial outcomes.

Caregiving. A review of the literature on rural caregiving found mixed evidence on urban/rural differences in mental and physical health outcomes for caregivers; a higher likelihood for rural caregivers to use informal supports than those in more urban areas, in part due to limited access to formal health services; and a positive association between caregiver burden and depression among rural caregivers (Goins et al., 2009). Research on African American caregivers with chronic health issues in a rural community found that their quality of care reflected a sense of obligation, responsibility, and commitment to family roots, and their chronic illness did not negatively affect their ability to care for their grandchildren (Woods, 2021). Studies on caregiver satisfaction after institutional placement is mixed; however, in their study of family caregivers, Tornatore and Grant (2004) found that rural caregivers were more satisfied with nursing home care than those in urban facilities. They hypothesized that close social relationships in rural communities render staff interactions less impersonal and cited the higher turnover rates of urban facilities. Multiple systematic reviews and meta-analyses have established an association between informal caregiving and caregiver health, including evidence from a set of quasi-experimental studies that suggest a causal pathway between caregiving and negative mental and physical health outcomes (Bom et al., 2019). Caregiving strain not only has an effect on caregiving responsibilities and the quality of care, but may also lead to challenges with balancing family and employment (Navaie-Waliser et al., 2002). Beyond the physical and mental outcomes of caregiving, the financial burden of caregiving is also well documented, especially if caregivers forgo paid work to provide care or incur high debt for caregiving expenses (Girgis et al., 2013). In contrast to these negative findings, some studies have documented better health outcomes for subgroups and when comparing caregivers with non-caregivers (Bertrand et al., 2012). Life satisfaction, for example, is one of the positive rewards of caregiving that some caregivers experience, and the effect may be more salient for adult children compared to spousal caregivers (Raschick & Ingersoll-Dayton, 2004).

4.1.2 Conceptual Framework

A gap in the current literature is that the outcomes of productive engagement have not been related to lifecourse patterns of activity engagement. The NIA Health Disparities Research Framework proposes a multidimensional approach to studying health disparities across the lifecourse, focusing on environmental, sociocultural, behavioral, and biological levels of analysis, as well as fundamental factors, such as gender, age, and race. This framework provides a comprehensive set of factors that are related to health disparities in the hopes of broadening the search for modifiable targets for intervention (Hill et al., 2015, pp. 247–248). In the environmental dimension, the framework posits that differential residential arrangements could bias subgroups to environments with fewer opportunities and greater risks. Scholars have noted that the decline of manufacturing jobs in rural and suburban areas is associated with lower well-being (Graham & Pinto, 2021; Scutchfield & Keck, 2017). Hogue et al. (2015) also observed that the physical remoteness of some rural places may create a barrier for access to information, education, health care, and communication. Another level of analysis is the sociocultural dimension, such as group norms, beliefs, and values. An example is the role of community religiosity, which in rural America plays a vital role in providing social support and promoting positive health behaviors (Holt et al., 2009; Wuthnow, 2018). Religiosity is also connected to increased opportunities for volunteering (Forbes & Zampelli, 2014) and the development of public health infrastructures, which has, in turn, affected rates of mortality (Blanchard et al., 2008).

One promising line of research suggests that productive engagement may be related to rural-urban health disparities (Vogelsang, 2016). This hypothesis is supported by the strong evidence base between engagement in activities such as working, volunteering, and caregiving and multiple health outcomes. Research using the Health and Retirement Study (HRS) has linked the mental and social demands of working with higher levels of cognitive functioning (Y. J. Lee et al., 2022); volunteering with lower risk of cognitive impairment (Infurna et al., 2016); and grandparent caregiving with higher cognitive functioning.(Sneed & Schulz, 2019). However, this literature is complicated by the fact that caregiving activities may have either a protective or harmful effect, depending on the context in which it occurs (Bertrand et al., 2012). Moreover, several studies employ cross-sectional data or examine engagement in an individual activity only. These limitations present a critical need to study how engagement in multiple activities across the life course affects rural-urban health disparities.

4.2 Methods

4.2.1 Data

To investigate the outcomes of lifecourse patterns of productive engagement, this study used the nationally representative Health and Retirement Study (HRS), which is sponsored by the NIA (grant number NIA U01AG009740) and is conducted by the University of Michigan. This study is part of a larger study that analyzed the effects of lifecourse patterns of engagement between 2008-2010, which used the following HRS datasets: (a) the RAND HRS Longitudinal File 2020 (V3) (HRS, 2023c), (b) the Cross-Wave Census Region/Division and Mobility File (Final V9.0) (HRS, 2023d), and (c) the 2008, 2010, 2012, 2014, 2016, and 2018 RAND HRS Fat Files (HRS, 2017, 2021a, 2021b, 2022, 2023a, 2023b). This present study drew upon additional sociodemographic variables from the RAND HRS Longitudinal File 2020 (V3) and the Langa-Weir Classifications (Crimmins et al., 2011; Langa et al., 2023). The study sample used a complete case analysis of respondents who completed every biennial survey between 2008 to 2018, because it remains unclear how to handle missing data in sequence analysis (Piccarreta &

Studer, 2019) (n = 8,023), not in a nursing home in any of the waves to focus on community-dwelling adults (n = 7,738), had no missing geographical data and did not change geographical regions (n = 6,741), and were between ages 51-60 in 2008 (n = 2,027). The final sample size contained 1,992 respondents with 11,952 observations. Bivariate comparisons between the present study sample and a larger sample including respondents who later dropped out due to attrition or death revealed that the present study sample tended to have better self-rated health, more full-time working individuals, and a higher total cognitive functioning score at the 2008 baseline wave (Table 3).

4.2.2 Variables

The dependent variables are (1) self-rated health in 2018, a common proxy for general health (ordinal scale; ranges from 1-5), and (2) total cognitive functioning in 2018 (ranges from 0-27 points). This study uses total cognitive functioning as a continuous measure; however, the Langa-Weir Classifications can be used to interpret the score: Normal (12-27); Cognitively Impaired but not Demented (CIND) (7-11); and Demented (0-6) (Langa et al., 2023, p. 3). Higher scores on both measures indicate better health and better cognitive functioning, respectively.

The independent variable is lifecourse patterns of productive engagement (LPPEs), a nominal variable constructed in a previous study (Chapter 2) using multichannel sequence analysis followed by partitioning around medoids (PAM) clustering. LPPEs summarize 10-year sequences of working (full-time, part-time, not working), volunteering (more than 50 hours, 50 hours or less, no volunteering), and caregiving (caring for a spouse, grandchild, or parent and not a caregiver) states from 2008-2018. An eight-cluster solution was optimal, therefore this variable was coded from 1-8. Additionally, The publicly available HRS files contains three collapsed

RUCC codes (the full codes are only available under special agreement): “Urban” areas are defined as counties in metro areas of 1 million population or more; “suburban” areas are counties in metro areas of 250,000 to 1 million population; and “ex-urban” areas consist of counties in metro areas of fewer than 250,000 population and non-metro counties. In this study, “rural” is defined as “ex-urban,” even though it is an imperfect measure of rurality and consists of both small metro counties and non-metro counties (Sun et al., 2022). The reference category is “urban” or a collapsed variable using codes 1-2.

The covariates included the following baseline 2008 variables: Gender (1 = Male, 2 = Female), age, education (ranging from 0 to 17 years), marital status (dichotomized to 1 = Married, 2 = Not Married), race (1 = White/Caucasian, 2 = Black/African American, 3 = Other), religious preference (dichotomized to 0 = No Religious Preference, 1 = Has Religious Preference [Protestant, Catholic, Jewish, and Other]), income (logged), and number of diagnosed health problems (ranging from 0-8, including high blood pressure, diabetes, cancer, lung, heart condition, stroke, psychiatric, arthritis), self-rated health (1-5; higher scores indicate better health), and total cognitive functioning (ranges from 0-27 points; higher scores indicate better cognitive functioning).

4.2.3 Analytical Strategy

Similar to the analytical procedure in Chapter 3, missingness in the dataset was inspected prior to the statistical modeling. There were 3.87% missing data in the study variables, resulting in a loss of 77 out of 1,992 cases if listwise deletion were used. Little’s MCAR test was conducted using the R package *naniar* (Tierney & Cook, 2023), and the null hypothesis of a MCAR mechanism in the data was rejected, $\chi^2(95) = 124.84$, $p = .022$. Further, longitudinal cohorts such as those in the HRS are likely to suffer from non-random attrition due to unobservable characteristics (Kapteyn et al., 2006). To address the possibility of a Missing at Random (MAR) mechanism, multivariate imputation by chained equations (MICE) was used to minimize bias due to missing data. Based on the rule of thumb that the number of imputations should be equal or greater than the percentage of incomplete cases (White et al., 2011), 20 multiply imputed datasets were created via chained equations using the R package *mice* (Buuren & Groothuis-Oudshoorn, 2011). Missing values were imputed using predictive mean modeling for continuous variables, proportional odds model for ordinal variables, and logistic regression for dichotomous variables. Trace plots were inspected for each imputed variable to look for adequate mixing and convergence around a stable mean (Enders, 2022).

To determine the outcomes of LPPEs, two regression models were fitted on the multiply imputed dataset, regressing cognitive functioning and self-rated health, respectively, on the LPPEs, baseline covariates, and two-way interactions between the LPPE clusters and rural/urban. Only baseline covariates were included in the models, because including covariates occurring at a later wave would attempt to account for past events in the LPPEs using future predictors, a problem known as anticipatory analysis (Hoem & Kreyenfeld, 2006; Studer et al., 2018). The results were pooled using Rubin's (1976) rule. To test if the models were significant against null models and also against each other, pooled likelihood ratio tests were conducted using pooled χ^2 statistics (D_2) (Meng & Rubin, 1992), obtained from the R package *mitml* (Grund et al., 2023). To assess model performance, the Akaike information criterion (AIC) and McFadden's pseudo R^2 were calculated for each imputed model using the R package *performance* (Lüdecke et al., 2021), and their respective means across the imputations were calculated.

HRS sample weights were not incorporated in the regression models, because "it is not generally clear how to apply weights to more complicated estimands such as regression coefficients" (Gelman, 2007, p. 163). Furthermore, HRS does not recommend base-year weighting when "the attrition propensity is correlated with the propensity to experience the event of interest" (HRS, n.d., p. 2). Because the participants who dropped out of the study tended to be less healthy than the participants who remained throughout the study observation window, there is likely a non-zero association with the attrition propensity and the outcomes of interest. This is a limitation that may result in oversampled individuals in the HRS—Blacks, Hispanics, and Florida residents—being over-emphasized in the results (Fisher & Ryan, 2018, p. 2). Additional R packages that were used included *tidyverse* (Wickham et al., 2019) for importing data and data cleaning. All analyses were conducted in R version 4.3.2 (R Core Team, 2023). This study was deemed exempt by the Washington University in St. Louis Human Research Protection Office (#202210130).

4.3 Results

Table 10 presents the results of the regression analysis predicting cognitive functioning. Three clusters that feature a volunteering-related pattern were found to be positively associated with higher cognitive functioning in 2018: 3. Increasing High-Intensity Volunteering ($\beta = .94$, SD = .27, $p < .001$), 5. Decreasing Full-Time Working & Low-Intensity Volunteering ($\beta = .73$, SD = .28, $p = .0099$), and 7. Decreasing Full-Time Working & High-Intensity Volunteering ($\beta = 1.2$, SD = .35, $p < .001$), compared with the reference cluster 1. Steady Limited Productive Engagement, all other things being equal.

Table 11 presents the results of the ordinal logistic regression model predicting self-rated health. Using the Brant (1990) test for parallel regression assumption in the *brant* R package (Schlegel & Steenbergen, 2020), the assumption of parallel regression assumption could not be rejected. Both multinomial and ordinal logistic regression models were fitted, and the ordinal logistic regression had a better fit (i.e., lower AIC), therefore the results of the ordinal logistic regression is reported. Two clusters were significantly related to self-rated health: First, the odds of having excellent self-rated health compared to lower self-rated health (i.e., the combined levels Very Good, Good, Fair, and Poor) was 1.4 (SE = .16, p = .04) for respondents in "5. Decreasing Full-Time & Low-Intensity Volunteering," compared to the reference cluster of steady limited productive engagement. Second, the odds of having excellent self-rated health compared to lower self-rated health was 0.66 (SE = .18, p = .02) for respondents in "6. Steady Caregiving & Decreasing Volunteering and Working," compared to the reference cluster of steady limited productive engagement. Two-way interactions between the LPPE clusters and rural/urban were not significant, therefore they were removed from both models.

4.4 Discussion

This study contributes to the productive engagement literature by demonstrating a positive association between working and volunteering activities with health outcomes in later life (e.g., Hao, 2008). Specifically, this study found that ten-year patterns of working and volunteering were both positively related to cognitive functioning and self-rated health, compared to patterns in which individuals were not working, volunteering, or caregiving. In general, patterns involving both working and volunteering were positively related to cognitive functioning and self-rated health, and a caregiving-only pattern was associated with worse self-rated health. This study also did not find any significant associations by geography.

The absence of any rural effect in this paper's models suggests that rural health policy aiming to narrow rural-health disparities should also focus on the social determinants of health that are able to explain the rural-urban differentials. Lower education, for example, is associated with poorer health, which points to the need for community-wide educational initiatives to improve health. Ideally, efforts to increase individual capital and community-level resources should be implemented concurrently.

This study had several limitations. First, the rural/urban indicator used in this study did not account for regional differences among rural communities. The demographics of rural communities in the South, for example, are very different from communities in the Southwest. Rural-urban disparities also depend on place-based characteristics such as area-level socioeconomic status (Cohen et al., 2018, p. 301). Incorporating these additional factors will better account for the heterogeneity of rural-urban status.

Chapter 5: Conclusion and Implications

5.1 Dissertation Overview

Using a three-paper model, this dissertation investigated ten-year patterns of working, volunteering, and caregiving activities in a nationally representative sample of older adults; associations between the patterns and sociodemographic antecedents; and associations between the patterns and the outcomes self-rated health and cognitive functioning. The first paper drew upon lifecourse sociology to focus on ten-year sequences of working, volunteering, and caregiving activities by two groups, ages 51-60 in 2008 and ages 61-70 in 2008. The second paper drew upon productive engagement frameworks to investigate the antecedents of the patterns discovered among the ages 51-60 group. The third paper drew upon the NIA Health Disparities Research Framework to study how the patterns of productive engagement were related to two longstanding rural-urban health disparities, self-rated health and cognitive functioning. The major findings included: (1) rural participants are less likely than urban participants to belong to the patterns of both 'increasing high-intensity volunteering' and 'decreasing part-time working,' compared to the reference pattern of 'steady limited productive engagement'; (2) patterns of productive engagement vary by age groups in both quantity and complexity; and (3) patterns involving simultaneous working and volunteering engagement are related to improved cognitive functioning and self-rated health; and (4) the pattern of 'steady caregiving and decreasing volunteering and working' is related to lower self-rated health.

5.2 Practice and Policy Implications

There are several practice and policy implications from this research. First, the rural-urban differential between patterns of volunteering and part-time work suggest a need to increase structural opportunities for engagement in rural communities. One barrier to volunteering for rural older adults is access to transportation, whether through driving or public transportation (S. J. Lee et al., 2011). Levasseur et al. (2020) found that social participation was significantly associated with the availability of public transportation and paratransit, both of which tend to be in short supply in rural communities. The Village model and the Naturally Occurring Retirement Community (NORC) model may address this challenge, as they emphasize mutual assistance among members, such as providing transportation for one another (Greenfield, 2016, p. 657). Age-friendly rural initiatives also include volunteer transportation programs that may minimize the rural-urban gap in access to engagement opportunities (Huffman-Oh, 2021). In addition to transportation, another barrier for rural older adults is related to the nature of their work: More rural than urban older adults are engaged in lower-skilled jobs that are less likely to have comprehensive employment benefits (Henning-Smith et al., 2023, p. 677). Older adults living in rural areas who want to engage in part-time work may not have the same level of benefits and support as urban older adults. For example, part-time workers are far less likely to have paid sick leave (Bureau of Labor Statistics, 2014, as cited in Romich, 2015, p. e1). It is important to note some caveats associated with this recommendation. Increasing volunteering and part-time working opportunities may not be applicable to all rural communities. Some rural older adults may already be engaging in higher levels of volunteering than urban older adults (Davies et al., 2018) or prefer informal helping behaviors over formal volunteering (Steblay, 1987, as cited in Paarlberg et al., 2022, p. 107). Furthermore, it is unclear under what circumstances part-time working among older adults may lead to health and well-being benefits; this is still an area of active research (Mas & Pallais, 2020; Wallace, 2003).

Second, the variations in patterns of productive engagement by age groups suggest the need for programs and policies to be adaptive to the age-related or biological effects of engagement in later life—assuming that the differences are not solely due to birth cohort. In general, it was found that the younger age group engaged mainly in patterns of working, while the older cohort engaged mainly in patterns of volunteering and caregiving. A less intuitive finding was the trend from more complex and numerous patterns of engagement in the younger age group to less complex and fewer patterns of engagement in the older age group. In other words, the older age group engaged in more similar patterns of engagement, while the younger age group engaged in more diverse patterns. One consequence of this difference is that the average duration of patterns of engagement in the younger age group was shorter than the average duration for the older age group. Programs catering to a younger age group will have to contend with a more dynamic group of individuals, with more frequent transitions to short-term activity engagement; in contrast, programs targeting an older age group may need to consider models that are supportive of a single mode of engagement across a longer duration. Fewer opportunities for the relatively older group could explain these findings. But, it is also possible, according to the theory of socioemotional selectivity, that the losses in activity complexity are due to "proactive processes," such as selecting more familiar social networks that bring greater emotional fulfillment (Carstensen et al., 1999, p. 173).

Third, programs and policies should continue to inform, support, and develop patterns of engagement involving both working and volunteering. In particular, this study found that the greatest improvements in cognitive functioning were for high-intensity volunteers who were decreasing full-time working, followed by low-intensity volunteers who were decreasing full-time working, and lastly, respondents with increasing high-intensity volunteering. While cross-validation is needed to verify these patterns, these results suggest that both the timing of working (and retirement) transitions and the intensity of volunteering matter with respect to improving cognition. This has important implications for the dosage of working and volunteering that are ideal for older adults and the timing of facilitating volunteering opportunities to complement or serve as a transition from full-time employment. Unlike the aforementioned finding, this recommendation is not particular to rural or urban geography, as there were no statistically significant rural-urban differences after controlling for sociodemographic variables.

Finally, the finding that steady caregiving and decreasing volunteering and working engagement is negatively associated with better self-rated health suggests the need for increased caregiver supports. A key point in this analysis is that this cluster of participants did not represent all caregivers in the sample. Caregivers who were simultaneously engaged in working or volunteering were accounted for in other clusters that did not have the same negative associations with self-rated health. Thus, individuals who are engaged in continuous caregiving may be particularly vulnerable and require supports such as paid family and medical leave or cash assistance (Morrow-Howell, Gonzales, & Matz-Costa, 2016). In their review of practices, interventions, and policies to support rural caregivers, Talley et al. (2011) described systems to support rural caregivers as often fragmented and lacking in integration. At the local level, there have been some successes with coalition building, where concerned community groups focus on various aspects of caregiving. Buckwalter and Davis (2011) found that linking local Area Agencies on Aging with the mental health system was perceived as one of the most effective ways to provide mental health services to rural caregivers. Recently, the Recognize, Assist, Include, Support and Engage (RAISE) Family Caregivers Act was signed into law in 2018 and will develop a national family caregiving strategy to identify and integrate promising practices. A preliminary report identified flexible transportation, telecommunications, and broadband access as gaps in service delivery for rural caregivers (RAISE Act Family Caregiving Advisory

Council, 2021). Interventions for rural dementia caregivers include education interventions using both written and an interactive voice response (IVR) information system to provide support and a toll-free interactive voice response information system for Alzheimer disease education (as cited in Innes et al., 2011).

5.3 Research Implications

There is a need to increase longitudinal research in the productive engagement field, focus on rural populations and health disparities, investigate multiple activities simultaneously, and further disentangle age, period, and cohort effects. Building on this research, my future plan consists of further work on the measurement of patterns of productive activities, the causal relationships of those patterns, and policy analysis on issues that are germane to the productive aging perspective.

First, more work needs to be done on the measurement of lifecourse patterns of productive engagement. As discussed in this dissertation, there are many ways of operationalizing productive activities, such as the degree of care that constitutes a caregiver. Depending on how the activities are defined, there could be a difference in how the activities are correlated with one another or grouped into separate clusters. Measuring additional types of activities, such as through time use data, may also shed light on what participants in the most dominant pattern for both age groups—non-engagement in the traditional tripartite vision of productive aging (working, volunteering, and caregiving)—are doing. Further tests also need to be done on the appropriate distance metric for determining the distances between different activities and the appropriate algorithm for assigning cluster memberships to individuals. There is also a limit to how much information can be contained within discrete sequences. For example, it is not possible to categorize every aspect of the continuum that is work, as well as factor in whether the working activity is voluntary or non-voluntary. Similarly, it may also be important to distinguish between part-time work in later life that is of a precarious nature versus those that are volitional. The measurement of productive engagement is also dependent upon the age, period, and birth cohort of the sample at hand. In this study, it was not possible to tease apart age effects and cohort effects when examining the two age groups, 51-60 and 61-70, in Paper 1. For example, the lack of complexity in the patterns in the older age group could be due to either the preferences of an older birth cohort or biological changes due to age. Age-period-cohort (APC) models, such as a random effects model or a fixed effects model, would be useful in overcoming these difficulties (Lin et al., 2012). Finally, operationalizing rural-urban as a binary variable is admittedly a crude representation of rural America and is prone to the ecological fallacy. A more sophisticated approach would be to test the same model against several different measures of rurality, such as using population density, distance to nearest metropolitan area, or Rural-Urban Commuting Area (RUCA) measures (e.g., Cohen et al., 2018). Ultimately, the goal of refining these measurements is to formulate patterns of engagement that accurately represent individual life courses, while maintaining a level of parsimony that would render the patterns amenable for further analysis.

Second, the focus of this dissertation was primarily associational, because the use of ten-year-long sequences makes it difficult to generate inferences about outcomes when there are time-varying confounders. One of the solutions to this perennial problem in sequence analysis is the use of Markovian models (MM) that permit the inclusion of “a hidden or latent variable that can be time-constant or time-varying” (Liao et al., 2022b, p. 11). Other innovations include the Sequence Analysis Multistate Model (Studer et al., 2018) or combining sequence analysis with propensity score matching. Applying these approaches will be a key next step in establishing causal pathways between patterns of productive engagement and modifiable antecedents or health and well-being outcomes.

Third and finally, my goal is to expand this research into applied policy analysis questions. Given that a main finding of this dissertation is that rural older adults may have fewer opportunities for volunteering and part-time working, as well as limited pathways to realize these opportunities across the life course (i.e., complexity), research is needed to assess current and future policies that aim to encourage inclusion into these roles, evaluate policy supports for sustaining these roles, and test if the policies truly generate the desired intervention effect. Alternatively, if rural older adults are less likely to be in these traditionally productive roles due to a difference in preferences, then it will be necessary for public policy to target their preferred modes of engagement. Ideally, future policy analysis will build upon the two preceding goals of measurement and causal analysis, such as using a structural equation modeling approach.

5.4 Conclusions

Scholarly interest in rural America has not only waned but given over to the direst of affections—the "graying" of rural America, the "brain drain" of rural youth, the imminent threat of the "silver tsunami." Also, the rising rates of hospital closures (B. G. Kaufman et al., 2016), the increased risks for social isolation and loneliness (Henning-Smith, 2020), and, most recently, the devastating impacts wrought by the COVID-19 pandemic (J. T. Mueller et al., 2021). A critically overlooked aspect of these pressing needs—if abstracted of their alarmism—is that the more than 10 million older adults in rural America represent a tremendous capacity for productive engagement. As Marc Freedman (2012) wrote, older adults are "our great national repository of generativity." Robert Wuthnow (2018) in *The Left Behind* and Robert D. Putnam (2000) in *Bowling Alone*, also remind us that many rural Americans are actively engaged in their communities and in some areas even more productively involved than city-dwelling older adults. Volunteer associations, for instance, have been found to be more prevalent in smaller versus larger communities (Wuthnow, 2018). These observations are encouraging in shifting attention away from a deficit perspective, but more work is needed to unravel the diverse modes of engagement in rural America. Both intra- and inter-regional research will be needed to fully comprehend the opportunities and challenges for a productively engaged rural population. This dissertation advanced the notion of lifecourse patterns of productive engagement, which can be used to model patterns of engagement across time, place, and age groups. These patterns were found to vary significantly between rural and urban places, and patterns involving simultaneous working and volunteering activities were predictive of better cognitive functioning and self-rated health.

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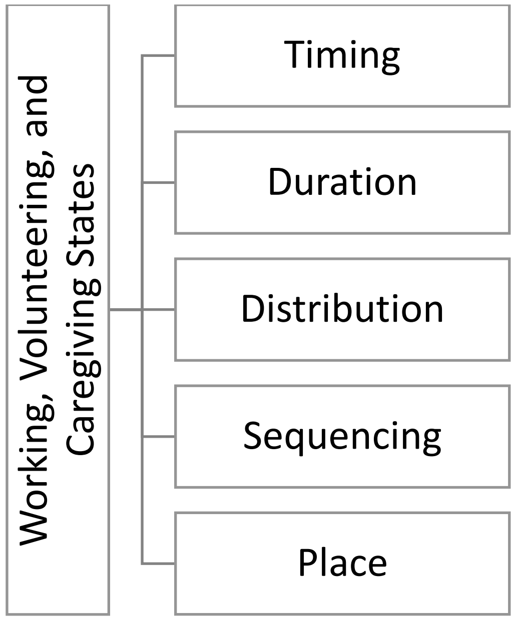
Figure 1

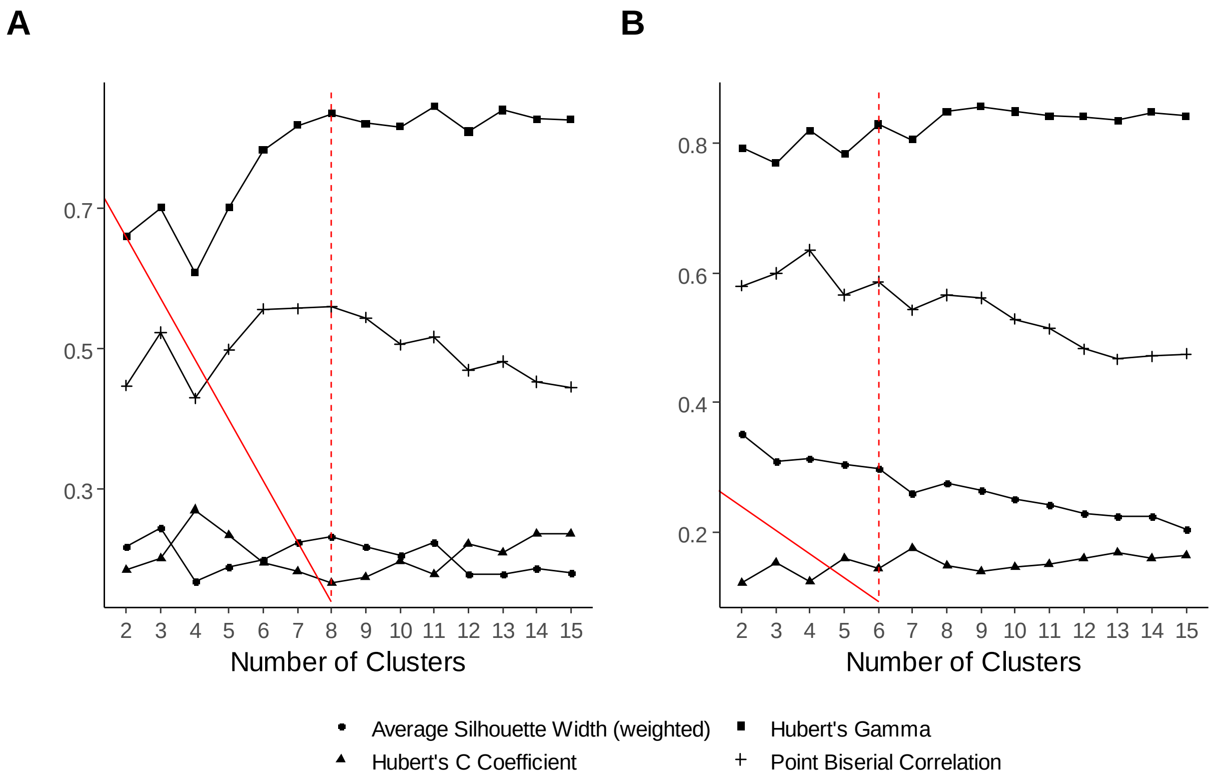
Conceptual Model of Lifecourse Patterns of Productive Engagement



Note. The sequence characteristics—states, timing, duration, distribution, and sequencing—are drawn from Studer & Ritschard (2016, p. 483).

Figure 2

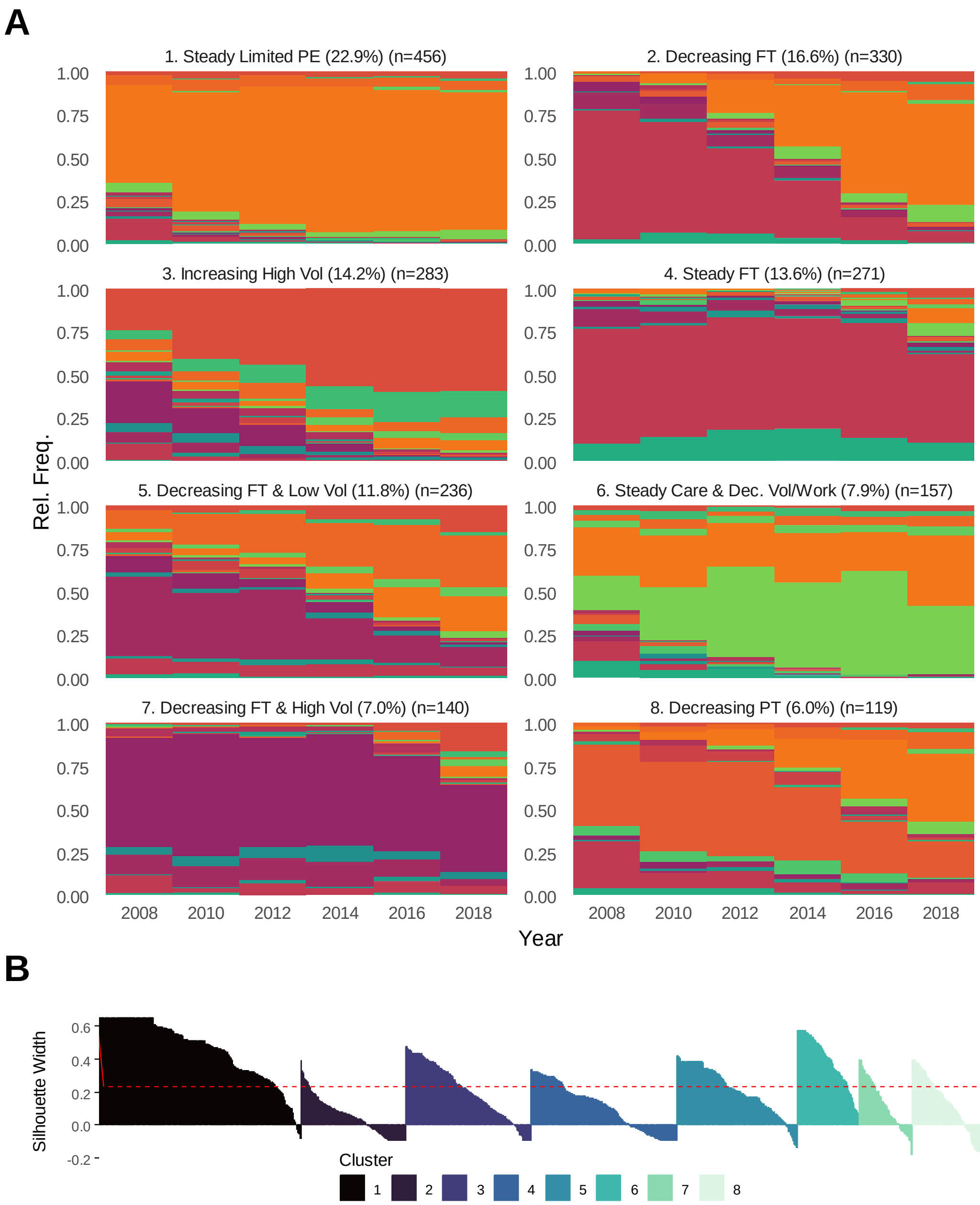
Cluster Quality Indicators Using Partitioning Around Medoids (PAM) Clustering



Note. *A*, Clusters of older adults ages 51-60 in 2008. *B*, Clusters of older adults ages 61-70 in 2008. The red dotted lines indicate the chosen stopping values.

Figure 3

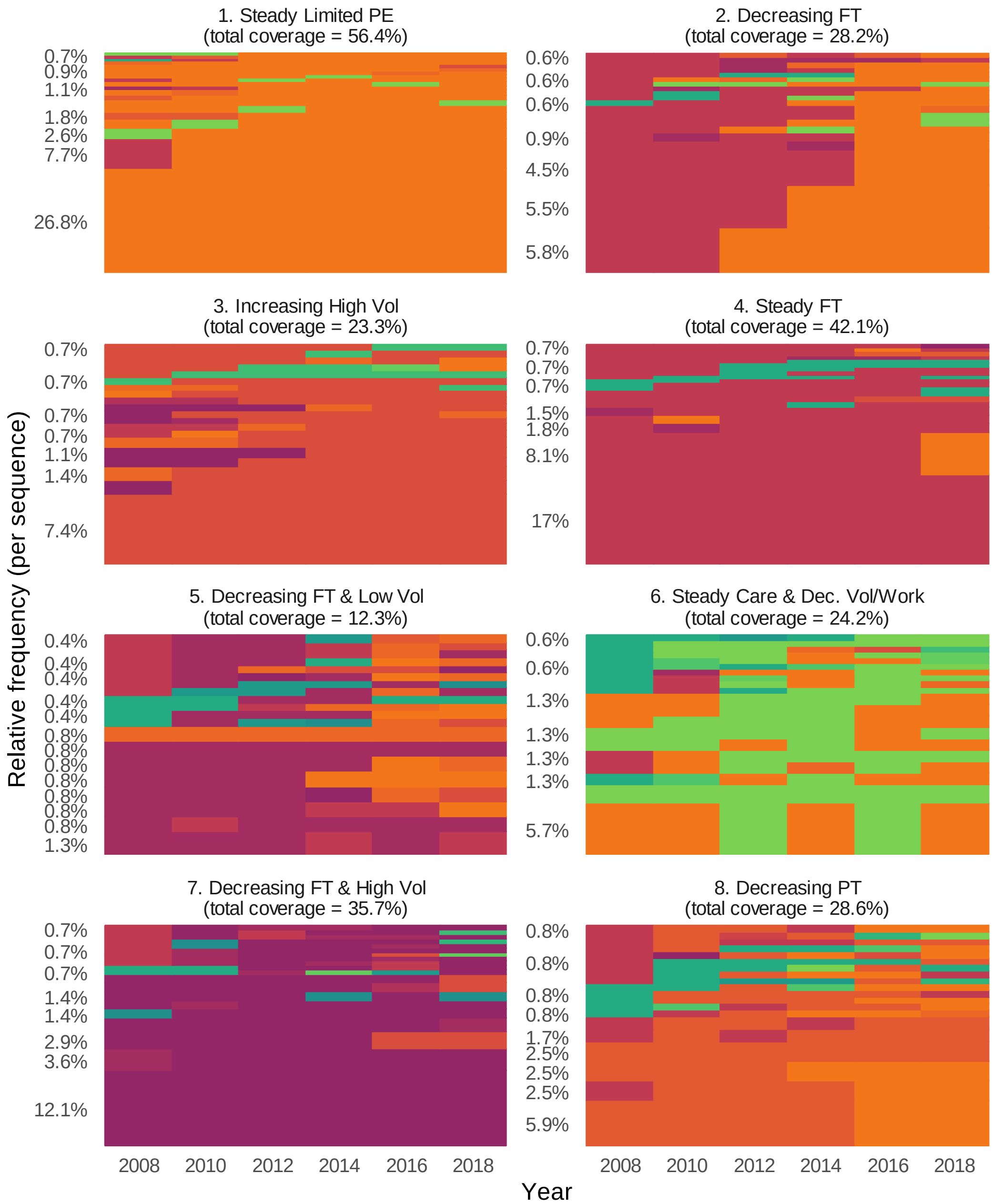
State Distribution Plots of Older Adults Ages 51-60 in 2008



Note. N = 1992. *A*, PE = Productive engagement in working, caregiving, and volunteering; FT = Full-time work; PT = Part-time work; Care = Caregiving; Vol = Volunteering; Dec. = Decreasing. Green colors represent caregiving; red colors denote non-caregiving; darker reds and darker greens denote multi-activity and higher intensity engagement; *B*, Silhouette plot for the eight-cluster solution.

Figure 4

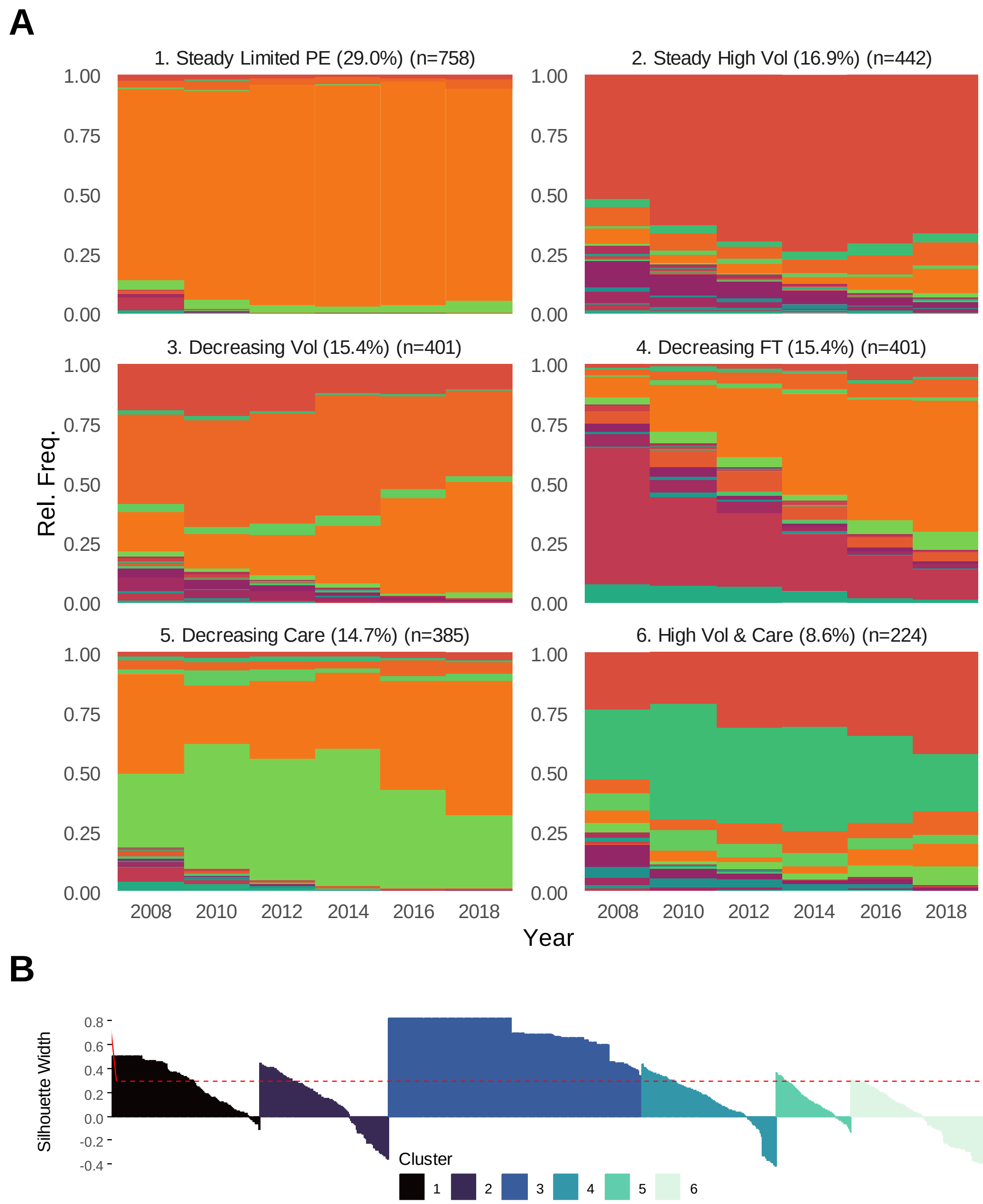
Sequence Frequency Plots of Older Adults Ages 51-60 in 2008



Note. The 20 most frequent sequences are plotted for each cluster (overlapping y-axis labels are removed). Sequence heights are displayed proportional to their frequencies. PE = Productive engagement in working, caregiving, and volunteering; FT = Full-time work; PT = Part-time work; Care = Caregiving; Low = Low-intensity; High = High-intensity; Vol = Volunteering; Dec. = Decreasing; green colors represent caregiving; red colors denote non-caregiving; darker reds and darker greens denote multi-activity and higher intensity engagement.

Figure 5

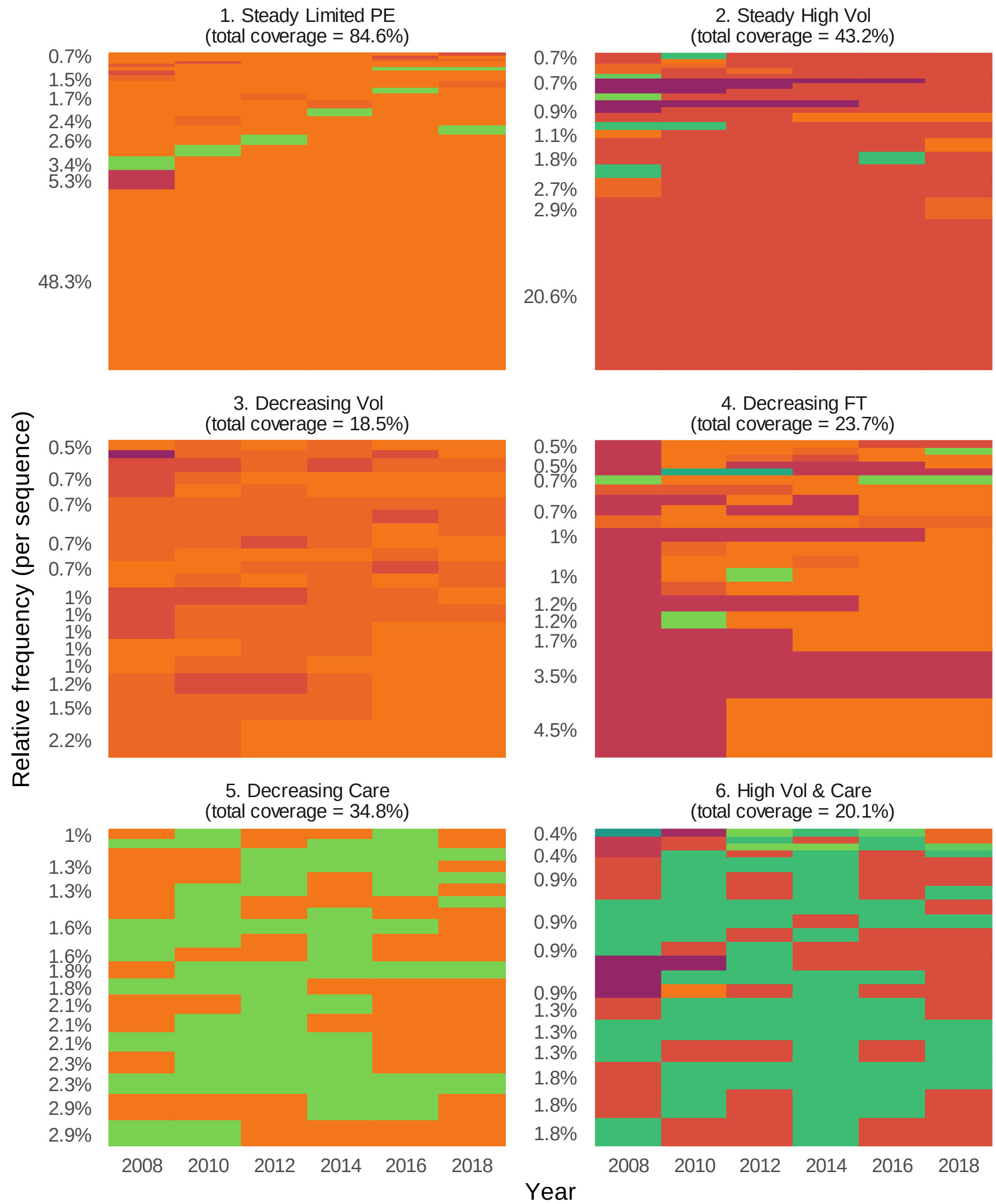
State Distribution Plots of Older Adults Ages 61-70 in 2008



Note. N = 2,611. *A*, PE = Productive engagement in working, caregiving, and volunteering; FT = Full-time work; PT = Part-time work; Care = Caregiving; High = High-intensity; Vol = Volunteering; green colors represent caregiving; red colors denote non-caregiving; darker reds and darker greens denote multi-activity and higher intensity engagement; *B*, Silhouette plot for the six-cluster solution.

Figure 6

Sequence Frequency Plots of Older Adults Ages 61-70 in 2008



Note. The 20 most frequent sequences are plotted for each cluster (overlapping y-axis labels are removed). Sequence heights are displayed proportional to their frequencies. PE = Productive engagement in working, caregiving, and volunteering; FT = Full-time work; PT = Part-time work; Care = Caregiving; Vol = Volunteering; green colors represent caregiving; red colors denote non-caregiving; darker reds and darker greens denote multi-activity and higher intensity engagement.

Table 1

Description of Paper 1 Scheme 1 Sample, Older Adults Ages 51-60 in 2008

Year	Type	Variable	Rural	Urban	Statistics[a]
2008	Working	Employed Full-Time	53.00%	61.10%	F(3.62, 202.49) = 2.57, p = 0.045*
		Employed Part-Time	12.20%	9.20%	
		Not Employed	34.80%	29.70%	
	Volunteering	> 50 hours in the past 12 months	19.50%	23.70%	F(2.76, 154.83) = 1.24, p = 0.30
		≤ 50 hours in the past 12 months	20.10%	19.50%	
		Non-Volunteer	60.40%	56.80%	
	Caregiving	Caregiver	14.80%	12.60%	F(2, 111.78) = 2.51, p = 0.086
		Non-Caregiver	85.20%	87.40%	
2010	Working	Employed Full-Time	45.20%	50.00%	F(3.75, 209.82) = 2.13, p = 0.083
		Employed Part-Time	7.30%	10.40%	
		Not Employed	47.50%	39.60%	
	Volunteering	> 50 hours in the past 12 months	21.60%	25.70%	F(3.16, 177.06) = 0.57, p = 0.64
		≤ 50 hours in the past 12 months	18.20%	19.40%	
		Non-Volunteer	60.20%	54.90%	
	Caregiving	Caregiver	21.70%	15.10%	F(1.96, 109.98) = 4.21, p = 0.018*
		Non-Caregiver	78.30%	84.90%	
2012	Working	Employed Full-Time	39.30%	43.00%	F(3.54, 198.04) = 1.72, p = 0.15
		Employed Part-Time	8.90%	8.90%	
		Not Employed	51.80%	48.10%	
	Volunteering	> 50 hours in the past 12 months	19.50%	23.30%	F(2.92, 163.39) = 0.98, p = 0.40
		≤ 50 hours in the past 12 months	20.50%	19.90%	
		Non-Volunteer	60.00%	56.80%	
	Caregiving	Caregiver	22.80%	17.60%	F(1.92, 107.35) = 1.81, p = 0.17
		Non-Caregiver	77.20%	82.40%	

Table 1 (continued)

Year	Type	Variable	Rural	Urban	Statistics[a]
2014	Working	Employed Full-Time	32.00%	34.10%	F(3.36, 188.23) = 0.99, p = 0.41
		Employed Part-Time	6.50%	7.00%	
		Not Employed	61.60%	58.90%	
	Volunteering	> 50 hours in the past 12 months	20.20%	26.00%	F(2.82, 158.18) = 1.38, p = 0.25
		≤ 50 hours in the past 12 months	17.20%	16.30%	
		Non-Volunteer	62.60%	57.70%	
	Caregiving	Caregiver	19.00%	19.40%	F(1.95, 108.97) = 0.46, p = 0.63
		Non-Caregiver	81.00%	80.60%	
2016	Working	Employed Full-Time	22.00%	25.00%	F(3.4, 190.32) = 1.56, p = 0.20
		Employed Part-Time	3.90%	6.00%	
		Not Employed	74.10%	69.00%	
	Volunteering	> 50 hours in the past 12 months	20.40%	26.10%	F(3.18, 177.98) = 1.57, p = 0.20
		≤ 50 hours in the past 12 months	16.30%	15.10%	
		Non-Volunteer	63.30%	58.80%	
	Caregiving	Caregiver	20.70%	19.70%	F(1.92, 107.76) = 0.83, p = 0.43
		Non-Caregiver	79.30%	80.30%	
2018	Working	Employed Full-Time	15.60%	18.50%	F(3.02, 169.27) = 1.08, p = 0.36
		Employed Part-Time	2.20%	3.40%	
		Not Employed	82.10%	78.10%	
	Volunteering	> 50 hours in the past 12 months	21.70%	26.20%	F(3.43, 191.89) = 0.85, p = 0.48
		≤ 50 hours in the past 12 months	18.00%	15.00%	
		Non-Volunteer	60.30%	58.80%	
	Caregiving	Caregiver	21.00%	18.90%	F(1.9, 106.63) = 0.33, p = 0.71
		Non-Caregiver	79.00%	81.10%	

Note. *N* = 1,992 (Rural = 548, Urban = 1444). Proportions weighted using the baseline HRS 2008 person-level analysis weights.

[a] Chi-square test with Rao-Scott second-order correction and converted to *F* statistic

*$p < .05$

Table 2

Description of Paper 1 Scheme 2 Sample, Older Adults Ages 61-70 in 2008

Year	Activity	Variable	Rural	Urban	Statistics[a]
2008	Working	Employed Full-Time	24.60%	29.70%	F(3.32, 172.6) = 1.05, p = 0.38
		Employed Part-Time	4.70%	5.30%	
		Not Employed	70.80%	64.90%	
	Volunteering	> 50 hours in the past 12 months	25.20%	24.10%	F(2.53, 131.75) = 0.28, p = 0.81
		≤ 50 hours in the past 12 months	17.50%	15.80%	
		Non-Volunteer	57.30%	60.10%	
	Caregiving	Caregiver	18.20%	17.30%	F(1.67, 86.61) = 1.9, p = 0.16
		Non-Caregiver	81.80%	82.70%	
2010	Working	Employed Full-Time	16.30%	18.90%	F(3.7, 192.41) = 0.88, p = 0.47
		Employed Part-Time	3.80%	4.30%	
		Not Employed	79.90%	76.80%	
	Volunteering	> 50 hours in the past 12 months	25.50%	28.30%	F(2.98, 155.07) = 1.05, p = 0.37
		≤ 50 hours in the past 12 months	19.90%	15.60%	
		Non-Volunteer	54.50%	56.00%	
	Caregiving	Caregiver	22.50%	24.60%	F(1.99, 103.31) = 1.64, p = 0.2
		Non-Caregiver	77.50%	75.40%	
2012	Working	Employed Full-Time	11.10%	14.40%	F(3.34, 173.81) = 1.08, p = 0.36
		Employed Part-Time	4.20%	3.20%	
		Not Employed	84.70%	82.40%	
	Volunteering	> 50 hours in the past 12 months	24.60%	27.40%	F(2.94, 153.06) = 2.86, p = 0.040*
		≤ 50 hours in the past 12 months	20.40%	13.90%	
		Non-Volunteer	55.00%	58.70%	
	Caregiving	Caregiver	22.60%	19.50%	F(1.99, 103.58) = 0.93, p = 0.40
		Non-Caregiver	77.40%	80.50%	

Table 2 (continued)

Year	Activity	Variable	Rural	Urban	Statistics[a]
2014	Working	Employed Full-Time	8.40%	9.70%	F(3.5, 181.97) = 0.7, p = 0.58
		Employed Part-Time	1.90%	2.90%	
		Not Employed	89.70%	87.40%	
	Volunteering	> 50 hours in the past 12 months	27.00%	25.80%	F(3.3, 171.66) = 0.77, p = 0.53
		≤ 50 hours in the past 12 months	16.60%	14.90%	
		Non-Volunteer	56.50%	59.20%	
	Caregiving	Caregiver	22.20%	19.60%	F(1.96, 101.7) = 0.77, p = 0.46
		Non-Caregiver	77.80%	80.40%	
2016	Working	Employed Full-Time	5.00%	7.00%	F(3.87, 201.24) = 1.95, p = 0.11
		Employed Part-Time	1.20%	2.00%	
		Not Employed	93.80%	91.00%	
	Volunteering	> 50 hours in the past 12 months	24.70%	26.00%	F(2.89, 150.1) = 1.6, p = 0.19
		≤ 50 hours in the past 12 months	16.10%	12.30%	
		Non-Volunteer	59.10%	61.80%	
	Caregiving	Caregiver	17.40%	15.50%	F(1.97, 102.39) = 0.49, p = 0.61
		Non-Caregiver	82.60%	84.50%	
2018	Working	Employed Full-Time	3.80%	5.40%	F(3.27, 169.85) = 1.42, p = 0.24
		Employed Part-Time	1.00%	1.40%	
		Not Employed	95.10%	93.30%	
	Volunteering	> 50 hours in the past 12 months	24.50%	23.50%	F(3.15, 163.81) = 0.66, p = 0.59
		≤ 50 hours in the past 12 months	14.90%	12.40%	
		Non-Volunteer	60.60%	64.10%	
	Caregiving	Caregiver	14.40%	13.80%	F(1.9, 98.75) = 2.1, p = 0.13
		Non-Caregiver	85.60%	86.20%	

Note. N = 2,611 (Rural = 757, Urban = 1,854). Proportions weighted using the baseline HRS 2008 person-level analysis weights.

[a] Chi-square test with Rao-Scott second-order correction and converted to F statistic

*$p < .05$

Table 3

Comparison of Incomplete and Complete Observations for Paper 1 Scheme 1

	Incomplete Observations	**Complete Observations (Scheme 1)**	**p**
n	3195	1992	
Female (ref: Male) (n (%))	1912 (59.8)	1238 (62.1)	.10
Married (ref: Not Married) (n (%))	2180 (68.3)	1408 (70.7)	.066
Race (n (%))			.80
White/Caucasian	2366 (74.1)	1483 (74.4)	
Black/African American	523 (16.4)	313 (15.7)	
Other	306 (9.6)	196 (9.8)	
Has Religious Preference (ref: No Religious Preference) (n (%))	2805 (88.1)	1753 (88.3)	.86
Rural (ref: Urban) (n (%))	871 (27.3)	548 (27.5)	.87
Self-Rated Health (n (%))			.015*
Poor	253 (7.9)	112 (5.6)	
Fair	582 (18.2)	342 (17.2)	
Good	937 (29.3)	601 (30.2)	
Very Good	1018 (31.9)	659 (33.1)	
Excellent	404 (12.6)	278 (14.0)	
Working (n (%))			.033*
Full-Time	1772 (55.5)	1159 (58.2)	
Part-Time	325 (10.2)	218 (10.9)	
Not Working	1098 (34.4)	615 (30.9)	
Volunteering (n (%))			.15
Non-Volunteer	2010 (63.0)	1203 (60.4)	
Low-Intensity Volunteer	544 (17.1)	369 (18.5)	
High-Intensity Volunteer	634 (19.9)	420 (21.1)	
Caregiving (n (%)) (ref: Not Caregiving)	2775 (86.9)	1727 (86.7)	.84
Age (mean (SD))	56.57 (2.39)	56.56 (2.39)	.94
Years of Education (mean (SD))	13.18 (3.12)	13.24 (3.21)	.45
Income (logged) (mean (SD))	10.73 (1.71)	10.78 (1.68)	.30
Number of Diagnosed Health Problems (mean (SD))	1.58 (1.37)	1.54 (1.31)	.25
Total Cognitive Functioning (mean (SD))	16.64 (4.23)	16.95 (4.13)	.011†

Note. Both samples consisted of community-dwelling older adults ages 51-60 who completed the survey in 2008 and who did not change their urban/rural residence during the 2008-2018 observation. The “Incomplete Observations” sample included respondents who dropped out of the survey between 2008-2018 due to attrition or death, while the “Complete Observations” (Scheme 1) sample contained respondents who completed all biennial surveys between 2008-2018. All of the compared variables were taken from the baseline 2008 wave.

* $p < .05$, Chi-square test of independence

† $p < .05$, Two sample unpaired *t*-test

Table 4

Comparison of Incomplete and Complete Observations for Paper 1 Scheme 2

	Incomplete Observations	**Complete Observations (Scheme 2)**	**p**
n	4636	2611	
Female (ref: Male) (n (%))	2689 (58.0)	1579 (60.5)	.042*
Married (ref: Not Married) (n (%))	3154 (68.0)	1803 (69.1)	.38
Race (n (%))			.79
White/Caucasian	3724 (80.3)	2115 (81.0)	
Black/African American	706 (15.2)	386 (14.8)	
Other	205 (4.4)	110 (4.2)	
Has Religious Preference (ref: No Religious Preference) (n (%))	4338 (93.9)	2454 (94.3)	.47
Rural (ref: Urban) (n (%))	1453 (31.3)	757 (29.0)	.040*
Self-Rated Health (n (%))			< .001*
Poor	365 (7.9)	109 (4.2)	
Fair	843 (18.2)	404 (15.5)	
Good	1566 (33.8)	909 (34.8)	
Very Good	1415 (30.5)	902 (34.6)	
Excellent	443 (9.6)	286 (11.0)	
Working (n (%))			.14
Full-Time	997 (21.5)	611 (23.4)	
Part-Time	210 (4.5)	124 (4.7)	
Not Working	3429 (74.0)	1876 (71.8)	
Volunteering (n (%))			<.001*
Non-Volunteer	2978 (64.4)	1531 (58.6)	
Low-Intensity Volunteer	674 (14.6)	428 (16.4)	
High-Intensity Volunteer	970 (21.0)	652 (25.0)	
Caregiving (n (%)) (ref: Not Caregiving)	3860 (83.4)	2146 (82.2)	0.205
Age (mean (SD))	66.03 (2.84)	65.87 (2.83)	.017†
Years of Education (mean (SD))	12.61 (3.06)	12.87 (3.00)	.0010†
Income (logged) (mean (SD))	10.64 (1.21)	10.73 (1.14)	.0020†
Number of Diagnosed Health Problems (mean (SD))	2.19 (1.42)	2.03 (1.31)	< .001†
Total Cognitive Functioning (mean (SD))	15.91 (4.19)	16.38 (3.94)	< .001†

* $p < .05$, Chi-square test of independence
† $p < .05$, Two sample unpaired *t*-test

Table 5

Mean Values of Sequence Indicators by Sample Scheme, Cluster, and Geography

		Complexity		Mean Duration		Transitions		Visited States	
Scheme	**Cluster**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Scheme 1 Ages 51-60 in 2008	1	0.23	0.25	3.20	3.07	1.56	1.69	2.07	2.20
	2	0.46	0.45	1.73	1.76	2.87	2.80	3.31	3.28
	3	0.43	0.42	2.10	2.03	2.79	2.69	3.21	3.13
	4	0.35	0.30	2.41	2.71	2.28	2.02	2.75	2.45†
	5	0.51	0.50	1.57	1.60	3.31	3.28	3.69	3.60
	6	0.48	0.47	1.53	1.64	3.40	3.24	3.17	3.24
	7	0.37	0.37	2.28	2.30	2.43	2.46	2.83	2.75
	8	0.53	0.46†	1.63	1.78	3.38	2.96	3.86	3.31*
	All	0.39	0.38	2.23	2.23	2.56	2.50	2.95	2.90
Scheme 2 Ages 61-70 in 2008	1	0.12	0.13	4.30	4.04†	0.80	0.90	1.54	1.60
	2	0.29	0.27	2.86	2.89	1.91	1.77	2.36	2.34
	3	0.45	0.46	1.67	1.59	3.00	3.18	3.10	3.11
	4	0.45	0.44	1.89	1.82	2.87	2.80	3.28	3.16
	5	0.42	0.40	1.78	1.83	2.88	2.79	2.80	2.71
	6	0.51	0.49	1.42	1.56	3.61	3.35	3.31	3.36
	All	0.33	0.32	2.66	2.59	2.19	2.18	2.52	2.51

Note. Scheme 1 clusters are named as: (1) Steady limited productive engagement, (2) Decreasing full-time working, (3) Increasing high-intensity volunteering, (4) Steady full-time working, (5) Decreasing full-time working and low-intensity volunteering, (6) Steady caregiving and decreasing volunteering and working, (7) Decreasing full-time working and high-intensity volunteering, and (8) Decreasing part-time working. Scheme 2 clusters are named as: (1) Steady limited productive engagement, (2) Steady high-intensity volunteering, (3) Decreasing volunteering, (4) Decreasing full-time working, (5) Decreasing caregiving, and (6) High-intensity volunteering and caregiving.

* $p < .05$, Two samples unpaired t-test between rural and urban

† $p < .10$, Two samples unpaired t-test between rural and urban

Table 6

Description of Paper 2 Sample, Older Adults Ages 51-60 in 2008

	Lifecourse Patterns of Productive Engagement, 2008-2018 Scheme 1: Older Adults Ages 51-60 in 2008			
	1. Steady Limited PE	**2. Decreasing FT**	**3. Increasing High Vol**	**4. Steady FT**
n	456	330	283	271
Categorical Predictors in 2008 (count, %)	309 (67.8)	173 (52.4)	190 (67.1)	144 (53.1)
Female (ref: Male)	263 (57.7)	214 (64.8)	225 (79.8)	193 (71.2)
Married (ref: Not Married)				
Race	304 (66.7)	247 (74.8)	217 (76.7)	205 (75.6)
White/Caucasian	98 (21.5)	49 (14.8)	49 (17.3)	32 (11.8)
Black/African American	54 (11.8)	34 (10.3)	17 (6.0)	34 (12.5)
Other	400 (88.3)	269 (81.8)	262 (93.2)	229 (84.5)
Has Religious Preference (ref: No Religious Preference)	138 (30.3)	86 (26.1)	72 (25.4)	69 (25.5)
Rural (ref: Urban)	309 (67.8)	173 (52.4)	190 (67.1)	144 (53.1)
Continuous Predictors in 2008 (mean (SD))				
Age	56.90 (2.28)	56.55 (2.43)	57.14 (2.24)	55.70 (2.28)
Years of Education	11.83 (3.52)	13.26 (3.15)	14.50 (2.50)	13.23 (3.04)
Income (logged)	9.95 (2.11)	10.92 (1.89)	11.05 (1.55)	11.17 (0.75)
Number of Diagnosed Health Problems	2.07 (1.48)	1.45 (1.24)	1.41 (1.21)	1.14 (1.08)

Table 6 (continued)

	Lifecourse Patterns of Productive Engagement, 2008-2018 Scheme 1: Older Adults Ages 51-60 in 2008			
	5. Decreasing FT & Low Vol	**6. Steady Care & Decreasing Vol/Work**	**7. Decreasing FT & High Vol**	**8. Decreasing PT**
n	236	157	140	119
Categorical Predictors in 2008 (count, %)	139 (58.9)	108 (68.8)	77 (55.0)	98 (82.4)
Female (ref: Male)	178 (75.4)	128 (81.5)	118 (84.3)	89 (74.8)
Married (ref: Not Married)				
Race	187 (79.2)	121 (77.1)	109 (77.9)	93 (78.2)
White/Caucasian	35 (14.8)	20 (12.7)	21 (15.0)	9 (7.6)
Black/African American	14 (5.9)	16 (10.2)	10 (7.1)	17 (14.3)
Other	220 (93.2)	147 (93.6)	130 (92.9)	96 (80.7)
Has Religious Preference (ref: No Religious Preference)	71 (30.1)	48 (30.6)	35 (25.0)	29 (24.4)
Rural (ref: Urban)	139 (58.9)	108 (68.8)	77 (55.0)	98 (82.4)
Continuous Predictors in 2008 (mean (SD))				
Age	56.62 (2.33)	56.88 (2.61)	55.77 (2.48)	56.34 (2.27)
Years of Education	14.08 (2.43)	12.62 (3.20)	15.28 (1.93)	12.45 (3.73)
Income (logged)	11.13 (1.32)	10.58 (1.33)	11.37 (1.44)	10.86 (1.13)
Number of Diagnosed Health Problems	1.49 (1.23)	1.81 (1.33)	1.03 (1.05)	1.27 (1.17)

Note. *N* = 1,992. PE = Productive engagement in working, caregiving, and volunteering; FT = Full-time work; PT = Part-time work; Care = Caregiving; Vol = Volunteering.

Table 7

Results from Multinomial Logistic Regression Model 1

	Lifecourse Patterns of Productive Engagement, 2008-2018 Scheme 1: Older Adults Ages 51-60 in 2008						
	2. Decreasing FT	**3. Increasing High Vol**	**4. Steady FT**	**5. Decreasing FT & Low Vol**	**6. Steady Care & Decreasing Vol/Work**	**7. Decreasing FT & High Vol**	**8. Decreasing PT**
(Intercept)	0.80 (0.075)*	0.78 (0.099)*	0.63 (0.14)*	0.62 (0.082)*	0.35 (0.11)*	0.35 (0.22)*	0.29 (0.073)*
Rural	0.77 (0.11)*	0.62 (0.12)*	0.74 (0.18)	0.82 (0.15)	1.05 (0.21)	0.68 (0.22)	0.61 (0.26)

Note. Model was weighted using baseline 2008 person-level analysis weights (HRS, 2023c). Coefficients are relative risk ratios. Standard errors of regression coefficients in parentheses. “Rural” is defined as Beale Rural-Urban Continuum Codes (RUCC) 3-9 (ref: RUCC 1-2). Reference category for the outcome is “1. Steady Limited Productive Engagement.”

[*] $p < .05$, difference between the column cluster and the reference cluster “1. Steady Limited Productive Engagement.”

Table 8

Results from Multinomial Logistic Regression Model 2

	Lifecourse Patterns of Productive Engagement, 2008-2018 Scheme 1: Older Adults Ages 51-60 in 2008						
	2. Decreasing FT	**3. Increasing High Vol**	**4. Steady FT**	**5. Decreasing FT & Low Vol**	**6. Steady Care & Decreasing Vol/Work**	**7. Decreasing FT & High Vol**	**8. Decreasing PT**
(Intercept)	0.11 (2.1)	0.00 (2.9)*	1945.70 (0.89)*	0.53 (1.9)	0.00 (3.2)*	0.07 (1.4)	11.04 (2.5)
Female	0.58 (0.063)*	1.33 (0.13)*	0.69 (0.082)*	0.83 (0.084)*	1.26 (0.12)	0.70 (0.19)	3.16 (0.048)*
Age	0.98 (0.038)	1.03 (0.048)	0.79 (0.017)*	0.91 (0.037)*	1.10 (0.054)	0.86 (0.052)*	0.89 (0.048)*
Education	1.06 (0.015)*	1.33 (0.013)*	1.09 (0.023)*	1.21 (0.022)*	1.06 (0.015)*	1.62 (0.040)*	1.00 (0.023)
Married	0.71 (0.095)*	2.41 (0.17)*	0.99 (0.15)	1.33 (0.18)	3.11 (0.17)*	2.10 (0.24)*	1.70 (0.11)*
Race: Black	0.79 (0.16)	1.17 (0.15)	0.77 (0.087)*	0.89 (0.21)	0.63 (0.38)	1.01 (0.22)	0.31 (0.57)*
Race: Other	1.11 (0.19)	0.70 (0.25)	1.20 (0.28)	1.11 (0.26)	1.01 (0.18)	1.11 (0.23)	1.01 (0.26)
Religious	0.84 (0.13)	1.96 (0.11)*	0.84 (0.11)	1.71 (0.082)*	2.44 (0.30)*	2.06 (0.59)	0.52 (0.19)*
Income	1.38 (0.030)*	1.17 (0.027)*	1.59 (0.067)*	1.28 (0.022)*	1.06 (0.011)*	1.29 (0.19)	1.33 (0.015)*
Health Problems	0.81 (0.034)*	0.79 (0.064)*	0.72 (0.070)*	0.84 (0.049)*	0.98 (0.050)	0.62 (0.10)*	0.69 (0.20)
Rural	0.81 (0.11)	0.64 (0.12)*	0.84 (0.20)	0.86 (0.14)	0.97 (0.19)	0.84 (0.18)	0.62 (0.22)*

Note. Model weighted using baseline 2008 person-level analysis weights (HRS, 2023c). Coefficients are relative risk ratios. Standard errors of regression coefficients in parentheses. “Rural” is defined as Beale Rural-Urban Continuum codes (RUCC) 3-9 (ref: RUCC 1-2). Reference category for the outcome is “1. Steady Limited Productive Engagement.”
[*] $p < .05$, difference between the column cluster and the reference cluster “1. Steady Limited Productive Engagement.”

Table 9

Description of Paper 3 Sample, Older Adults Ages 51-60 in 2008

	Lifecourse Patterns of Productive Engagement Scheme 1: Older Adults Ages 51-60 in 2008								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**p**
n	456	330	283	271	236	157	140	119	
Age (mean (SD))	56.90 (2.28)	56.55 (2.43)	57.14 (2.24)	55.70 (2.28)	56.62 (2.33)	56.88 (2.61)	55.77 (2.48)	56.34 (2.27)	*
Education (mean (SD))	11.83 (3.52)	13.26 (3.15)	14.50 (2.50)	13.23 (3.04)	14.08 (2.43)	12.62 (3.20)	15.28 (1.93)	12.45 (3.73)	*
Income (mean (SD))	9.95 (2.11)	10.92 (1.89)	11.05 (1.55)	11.17 (0.75)	11.13 (1.32)	10.58 (1.33)	11.37 (1.44)	10.86 (1.13)	*
Number of Diagnosed Health Conditions (mean (SD))	2.07 (1.48)	1.45 (1.24)	1.41 (1.21)	1.14 (1.08)	1.49 (1.23)	1.81 (1.33)	1.03 (1.05)	1.27 (1.17)	*
Total Cognitive Functioning in 2008 (mean (SD))	15.37 (4.42)	17.23 (4.03)	18.21 (3.42)	17.39 (3.93)	17.41 (3.84)	16.14 (4.19)	18.61 (3.36)	16.44 (4.42)	*
Self-Rated Health in 2008 (mean (SD))	2.77 (1.16)	3.37 (1.02)	3.64 (0.94)	3.61 (0.92)	3.43 (0.96)	3.06 (1.17)	3.83 (0.84)	3.47 (1.13)	*
Female (ref: Male) (n (%))	309 (67.8)	173 (52.4)	190 (67.1)	144 (53.1)	139 (58.9)	108 (68.8)	77 (55.0)	98 (82.4)	*
Married (ref: Not Married) (n (%))	263 (57.7)	214 (64.8)	225 (79.8)	193 (71.2)	178 (75.4)	128 (81.5)	118 (84.3)	89 (74.8)	*
Race (n (%))									*
White/Caucasian	304 (66.7)	247 (74.8)	217 (76.7)	205 (75.6)	187 (79.2)	121 (77.1)	109 (77.9)	93 (78.2)	
Black/African American	98 (21.5)	49 (14.8)	49 (17.3)	32 (11.8)	35 (14.8)	20 (12.7)	21 (15.0)	9 (7.6)	
Other	54 (11.8)	34 (10.3)	17 (6.0)	34 (12.5)	14 (5.9)	16 (10.2)	10 (7.1)	17 (14.3)	
Has Religious Preference (ref: No Religious Preference) (n (%))	400 (88.3)	269 (81.8)	262 (93.2)	229 (84.5)	220 (93.2)	147 (93.6)	130 (92.9)	96 (80.7)	*

Table 7 (continued)

	Lifecourse Patterns of Productive Engagement Scheme 1: Older Adults Ages 51-60 in 2008								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**p**
Rural (ref: Urban) (n (%))	223 (48.9)	171 (51.8)	146 (51.6)	140 (51.7)	120 (50.8)	64 (40.8)	71 (50.7)	68 (57.1)	
Total Cognitive Functioning in 2018 (mean (SD))	14.84 (4.77)	16.43 (4.14)	17.87 (3.62)	16.67 (3.65)	17.17 (3.63)	15.43 (4.18)	18.49 (3.27)	16.08 (4.64)	*
Self-Rated Health in 2018 (n (%))									*
1	54 (11.8)	22 (6.7)	5 (1.8)	3 (1.1)	7 (3.0)	18 (11.5)	2 (1.4)	5 (4.2)	
2	126 (27.6)	53 (16.1)	36 (12.7)	32 (11.8)	34 (14.4)	42 (26.8)	9 (6.4)	24 (20.2)	
3	158 (34.6)	118 (35.8)	81 (28.6)	103 (38.0)	80 (33.9)	49 (31.2)	44 (31.4)	32 (26.9)	
4	94 (20.6)	108 (32.7)	141 (49.8)	106 (39.1)	85 (36.0)	39 (24.8)	62 (44.3)	41 (34.5)	
5	24 (5.3)	29 (8.8)	20 (7.1)	27 (10.0)	30 (12.7)	9 (5.7)	23 (16.4)	17 (14.3)	

Note. Scheme 1 clusters are named as: (1) Steady limited productive engagement, (2) Decreasing full-time working, (3) Increasing high-intensity volunteering, (4) Steady full-time work, (5) Decreasing full-time working and low-intensity volunteering, (6) Steady caregiving and decreasing volunteering and working, (7) Decreasing full-time working and high-intensity volunteering, and (8) Decreasing part-time working. Scheme 2 clusters are named as: (1) Steady limited productive engagement, (2) Steady high-intensity volunteering, (3) Decreasing volunteering, (4) Decreasing full-time working, (5) Decreasing caregiving, and (6) High-intensity volunteering and caregiving.

* $p < .05$, Chi-square test of independence or Fisher's exact test (for self-rated health)

Table 10

Multiple Linear Regression Model Predicting Cognitive Functioning in 2018

	Estimate	SD	t	p
(Intercept)	6.6	2.0	3.3	< .001*
Lifecourse Patterns of Productive Engagement				
(ref: 1. Steady Limited Productive Engagement)				
2. Decreasing Full-Time Working	0.35	0.26	1.4	0.18
3. Increasing High-Intensity Volunteering	0.94	0.27	3.5	< .001*
4. Steady Full-Time Working	0.47	0.28	1.7	0.092
5. Decreasing Full-Time Working & Low-Intensity Volunteering	0.73	0.28	2.6	0.0099*
6. Steady Caregiving & Decreasing Volunteering and Working	-0.22	0.32	-0.68	0.5
7. Decreasing Full-Time Working & High-Intensity Volunteering	1.2	0.35	3.5	< .001*
8. Decreasing Part-Time Working	0.21	0.36	0.59	0.56
Rural (ref: Urban)	0.05	0.17	0.29	0.77
Female (ref: Male)	0.69	0.16	4.2	< .001*
Age (years)	-0.015	0.033	-0.46	0.65
Years of Education	0.23	0.029	8	< .001*
Married (ref: Not Married)	0.26	0.18	1.4	0.15
Race (ref: White/Caucasian)				
Black/African American	-1.4	0.23	-6.4	< .001*
Other Race	-1.1	0.28	-4	< .001*
Has Religious Preference (ref: No Religious Preference)	0.0081	0.24	0.033	0.97
Income (logged)	0.02	0.053	0.39	0.7
Number of Diagnosed Health Problems	-0.15	0.062	-2.4	0.016*
Cognitive Functioning in 2008	0.41	0.022	18	< .001*
AIC	10510.41			
R^2	.38			

* $p < .05$

Table 11

Ordinal Logistic Regression Model Predicting Self-Rated Health in 2018

	Estimate	**SE**	**t**	**p**
Lifecourse Patterns of Productive Engagement				
(ref: 1. Steady Limited Productive Engagement)				
2. Decreasing Full-Time Working	1.07	0.14	0.5	.62
3. Increasing High-Intensity Volunteering	1.19	0.15	1.14	.26
4. Steady Full-Time Working	1.26	0.15	1.52	.13
5. Decreasing Full-Time Working & Low-Intensity Volunteering	1.4	0.16	2.09	.04*
6. Steady Caregiving & Decreasing Volunteering and Working	0.66	0.18	-2.27	.02*
7. Decreasing Full-Time Working & High-Intensity Volunteering	1.36	0.2	1.54	.12
8. Decreasing Part-Time Working	1.11	0.2	0.52	.6
Rural (ref: Urban)	0.96	0.1	-0.42	.68
Female (ref: Male)	1.48	0.09	4.3	<.001*
Age (years)	0.99	0.02	-0.41	.68
Years of Education	1.08	0.02	4.7	<.001*
Married (ref: Not Married)	1.3	0.1	2.53	.01*
Race (ref: White/Caucasian)				
Black/African American	0.72	0.12	-2.64	.01*
Other Race	0.73	0.15	-2.07	.04*
Has Religious Preference (ref: No Religious Preference)	1.08	0.14	0.54	.59
Income (logged)	1.06	0.03	1.84	.07
Number of Diagnosed Health Problems	0.81	0.04	-5.34	<.001*
Self-Rated Health in 2008 (ref: Poor)				
Fair	2.91	0.22	4.91	<.001*
Good	9.11	0.22	9.92	<.001*
Very Good	32.85	0.24	14.74	<.001*
Excellent	132.97	0.27	18.08	<.001*
Intercepts:				
Poor|Fair	1.08	1.11	0.07	.94
Fair|Good	9.75	1.11	2.05	.04*
Good|Very Good	92.13	1.12	4.05	<.001*
Very Good|Excellent	1515.56	1.12	6.54	<.001*
AIC	4545.47			
R^2	.47			

Note. Coefficients are odds ratios. Standard errors (SE) of regression coefficients in parentheses.
$^{*}p < .05$