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Do type, timing and duration of life course non-employment differentially predict dementia risk? An application of sequence analysis

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Abstract

Periods out of employment may influence dementia, but characterizing lifecourse employment is difficult and prior research is sparse. This study used sequence and cluster analysis to characterize type, timing, and duration of lifecourse work gaps and estimate associations with dementia risk.

Life History Mail Survey supplement to the U.S. Health Retirement Study participants (N = 5,945, 13.6 % of the Health and Retirement Study sample) reported lifecourse employment (full

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CRediT authorship contribution statement

Lucia Pacca: Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **S. Amina Gaye:** Validation. **Willa D. Brenowitz:** Writing – original draft, Conceptualization. **Kaori Fujishiro:** Writing – original draft, Conceptualization. **M. Maria Glymour:** Supervision, Conceptualization. **Amal Harrati:** Supervision, Funding acquisition, Conceptualization. **Anusha M. Vable:** Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Disclaimer

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the National Institute for Occupational Safety and Health, Centers for Disease Control and Prevention.

Ethics approval

Our study, titled “Do type, timing and duration of life course non-employment differentially predict dementia risk? An application of sequence analysis”, uses publicly available and completely anonymized data from the Health and Retirement study, where no identifiable personal information is collected. Therefore, an ethical approval for this study is not required.

time or part time) and reasons and age of work gaps (unemployment, schooling, caregiving, or disability). Our exposure was gender-stratified employment trajectories from age 18–65, characterized using sequence analysis and cluster analysis. Our outcomes were algorithmically defined dementia probability scores and memory scores. We estimated the association between employment trajectories and dementia risk using generalized estimating equations and memory decline using linear mixed effect models, adjusted for age, gender, birthplace, and childhood socioeconomic status.

We identified 11 employment trajectories for women (including predominant work, disability, unemployment, caregiving, retirement) and 10 for men (similar, but no caregiving). Compared to “predominant work”, “disability” and “unemployment” trajectories were associated with higher dementia risk for men and women (e.g., disability among women: OR = 3.62; 95 % CI = 2.25, 5.81). Among women who cared for family, those who did not re-enter the labor force full-time had higher dementia risk (e.g. “family gap, go back part time”: OR = 1.79; 95 % CI = 1.15, 2.79) compared to the predominant work cluster. Women who cared for family and returned to full-time work had similar cognitive outcomes to those in the predominant work cluster. Men who had long spells of part-time work also had elevated dementia risk (e.g. part time earlier: OR = 1.64; 95 % CI = 1.16, 2.57). Finally, women and men with long periods of unreported employment status had higher dementia risk than those in the predominant work trajectory.

Results suggest the type, timing and duration of work gaps are differentially associated with dementia risk. Work gaps due to disability, unemployment or unreported employment status predicted higher dementia risk. Permanently leaving full-time work for caregiving predicted worse cognitive outcomes but temporary caregiving-related work interruptions did not.

1. Introduction

Dementia, a chronic disease of aging characterized by severe cognitive decline and loss of independent function, affects a large and growing number of adults in the United States with wide impact on individuals, families, and the healthcare system (Plassman et al., 2007; Hurd et al., 2013; Brookmeyer et al., 2011). In light of limited treatment options, multifactorial interventions may be needed to reduce population rates of dementia including individual interventions, such as reduction of cardiovascular risk factors and health lifestyle changes, as well as population scale interventions on socio-economic factors such as education and occupation (Evans et al., 1997; Fischer et al., 2009; Galvin, 2017; Livingston et al., 2017, 2020).

Work is the longest-lasting social exposure for many individuals and an important predictor of health. In addition to providing income, work is core to identity, confers social networks, can confer power and autonomy and allows access to social programs and health-promoting resources (Berkman, 2014; Ahonen et al., 2018). Moreover, work, especially when it involves complex tasks and skills, can provide cognitive stimulation and may allow individuals to better cope with later-life cognitive change, as suggested by the cognitive reserve hypothesis (Stern et al., 2019; Opdebeeck et al., 2016; Smart et al., 2014; Andel et al., 2007). This “cognitive reserve” can help individuals maintain cognition function despite

underlying pathologic changes, such through enhancing flexibility and adaptability of brain networks (Stern, 2021).

Theories on how employment intensity (full-time vs. part-time work) may be related to later-life cognition are conflicting. On the one hand, compared to full-time employment, part-time employment may provide a better balance between work and family care (Van Rijswijk et al., 2004; Casey and Grzywacz, 2008; Sparks et al., 1997), a benefit for cognition. On the other hand, part-time workers are generally paid lower wages and offered fewer health and retirement benefits than comparable full-time workers, a potential detriment to cognition. Part-time workers are more likely to have lower job security and to live in families that are poor (Hudson and Kalleberg, 2019). Part-time work, especially among men, has been shown to be associated with less career goal progress, professional ability development, and promotion speed (van Osch and Schaveling, 2020). Financial insecurity, lower quality healthcare and less cognitive stimulation are all factors associated with lower later-life cognitive functioning (Ice et al., 2020; Leist et al., 2013; Hofbauer and Rodriguez, 2021). Research suggests that part-time work may be associated with poorer cognition in men than in women (Bertogg and Leist, 2023). Men are more likely to work part-time for economic reasons (e.g., seasonality or lack of full-time work opportunities) than women, which may result in more stress and financial insecurity (Hudson and Kalleberg, 2019; (Bertogg and Leist, 2023; Ice et al., 2020).

Interruptions to work may have long-term consequences on cognitive functioning, but this relationship may change depending on the reason for work gaps. Periods out of work for education or training may promote cognitive reserve and provide opportunities for career advancement and achieving higher socioeconomic status (SES) (Leist et al., 2013). By contrast, employment gaps without clearly defined or purposeful activities, such as unemployment or illness, may reduce opportunities for cognitively demanding activities or social participation, and reduce financial security, which can have downstream effects on cognitive functioning (Hofbauer and Rodriguez, 2021).

Work is also a highly gendered experience; that is, both paid work and unpaid work (e.g., homemaking, family caregiving) are structured with clearly different social expectations for men and women. A clear indication of such expectation is the fact that men are more likely to hesitate to take parental leave than women (Fujishiro et al., 2021; Olsson et al., 2023). Among women, homemaking and family caregiving can have heterogeneous impacts on health. Parental leave can provide opportunities for social engagement and reduce psychological stress and work-family strain (Heshmati et al., 2023). At the same time, long spells of homemaking may hinder (re-) employment chances and lead to lower SES compared to stable work, which in turn may negatively influence later-life cognitive function (Killewald and Zhuo, 2019; Budig and England, 2001). Findings on retirement are also conflicting. While retirement can result in a reduction in work-related cognitive stimulation, it can also reduce work-related strain, and provide opportunities for cognitively stimulating leisure activities, which prior studies indicate are beneficial for older age cognition (Zulka et al., 2019; Gow et al., 2017). For different types of interruptions to work, the impact on later-life cognitive functioning is likely to depend on the amount of time an individual is out of the labor force, and whether the lack of employment is experienced earlier or later

in life (Ervasti et al., 2017). However, illness, disability, poor health, or early stages of cognitive decline may also contribute to employment gaps or early retirement and could explain associations with late-life cognition (e.g., the healthy worker phenomenon) (Olsson et al., 2023).

Considering previously developed theories and findings, we formulate three testable main hypotheses regarding the association of type, timing and duration of work gaps and later-life cognition.

Type of work gaps.

We hypothesize that types of work gaps will be differentially associated with later-life cognition. This hypothesis is divided into four sub-hypotheses. [H1a] We hypothesize that periods of unemployment and disability, compared to full-time lifecourse employment, will be associated with poorer cognition and faster memory decline in later life. We hypothesize that this association develops through two main mechanisms: 1) decreased cognitive reserve among those with periods of unemployment and disability due to fewer opportunities for developing new skills, fulfilling individual goals and social interactions (Kelly et al., 2017; Corbo et al., 2023; Zijlmans et al., 2022); 2) decreased access to financial resources while being disabled or unemployed, which could cause money-related stress and financial insecurity. Cognitive loads theories posit that the experience of financial hardship consumes cognitive resources, diminishing a person's capacity to perform well on less salient and more complex tasks (Kiely et al., 2019; Mani et al., 1979). [H1b] We hypothesize that periods out of work due to education will be associated with better cognitive outcomes. We hypothesize that this association develops through 1) increased cognitive reserve among those with more education, which can be achieved through learning; 2) access to more financial resources through higher paying jobs, which could reduce money-related stress, leaving room for developing cognitive capabilities (Parisi et al., 2012). [H1c] We hypothesize that retirement will be associated with similar cognition as full-time employment, as the decrease in work-related cognitive stimulation will be compensated by the increase in time for leisure activities. [H1d] Regarding part-time employment and family caregiving, we hypothesize that the association will depend on the timing and duration of these gaps, which will be discussed under H2 and H3 below.

Timing of work gaps.

We hypothesize that, overall, interruptions to work experienced earlier in life will be associated with similar (or better) cognitive outcomes to uninterrupted employment, while interruptions to work experienced later in life will be associated with poorer cognition. Regarding family caregiving, we hypothesize that earlier interruptions to work to care for young children will provide opportunities for social engagement and reduce psychological stress and work-family strain, while later interruptions will hinder labor market re-entry and result into financial instability and less social stimulation. Regarding unemployment and disability, we hypothesize that, when experienced earlier in life and temporarily, these types of gaps will be less detrimental for cognition as it will be easier and faster for younger individuals to recover and return to the labor force.

Duration of work gaps.

We hypothesize that longer duration of work gaps will be overall associated with worse cognition as they will result into prolonged financial hardship and longer periods of decreased cognitive and social stimulation. Similarly, for part-time work, we hypothesize that shorter duration of part-time work will improve cognition by providing a better work-life balance, while longer duration of part-time work will negatively affect cognition.

To test our hypotheses regarding the type, timing and duration of work gaps (summarized in Table A.1, presented in the manuscript's supplement), we examine lifecourse employment and its association with cognition. While there is growing evidence on the importance of lifecourse occupation for cognitive functioning, findings on the direction of the associations between (non-)employment and cognition are mixed, and little research examines changes across the lifecourse. Although in the United States people work from approximately age 18–65, research is often based on self-reports of longest-held occupation or narrow periods of time (Fujishiro et al., 2019; Huang et al., 2020; Sörman et al., 2019), resulting in a loss of information. Moreover, most prior studies on non-employment were not able to differentiate between reasons for being out of the labor force (Kobayashi and Feldman, 2018) or focused on one specific type of work interruption, such as unemployment (Freise et al., 2022) or disability (Rajan et al., 2013). Given the cumulative and dynamic nature of lifecourse employment, it is important to consider type, timing and duration of employment and non-employment simultaneously and evaluate how these different dimensions are associated with later-life cognitive functioning.

We fill existing gaps by evaluating whether lifecourse employment trajectories are associated with dementia risk and memory decline after age 70. We use data from the Health and Retirement Study (HRS) and define employment trajectories between age 18–65 using sequence and cluster analysis, a data-driven approach that reduces thousands of individual employment trajectories into a smaller set of similar trajectory clusters. We identify groups of similar trajectories among men and women based on type, timing and duration of employment and non-employment.

2. Methods

2.1. Data and sample

The HRS is a longitudinal study collecting biennial surveys of US adults 50+ years and their spouses including a rich set of information about health, work and retirement. Our eligible sample included all participants selected for the 2015 or 2017 Life History Mail Survey (LHMS), a supplement of the HRS. The LHMS asked detailed, retrospective questions about participants' whole residential, education, employment and health history. In 2017, participants were asked to report all their previous jobs (up to 10 jobs) with start and end dates and reason (if any) for leaving each job. Detailed questions were also asked on the start and end dates of each attended school. We included participants with at least one cognitive assessment at age 70 years or older between 1998 and 2018. Among 11,761 individuals selected to participate in LHMS, 5,814 participants did not meet our eligibility criteria of at least one cognitive assessment at age 70 or older. In addition, 2 participants who had

missing covariate data, resulting in a final analytic sample of $N = 5,945$. We did not exclude participants with missing information on employment status, since missingness might be informative and associated with more unstable life course employment. Appendix Table A.1 shows differences in main characteristics between included and excluded individuals.

2.2. Exposure

Our exposure was groups of employment trajectories between ages 18–65, characterized using sequence and cluster analysis (Abbott and Forrest, 1986; Billari and Piccarreta, 2005; Liao et al., 2022), which consist of three consecutive steps: 1) characterization of individual employment trajectories; 2) implementation of sequence analysis to quantify differences between trajectories; 3) cluster analysis to group similar trajectories. Consistent with previous studies, which have found employment trajectories to be highly gendered and women's trajectories to be often characterized by inconsistent patterns of full-time work, we conduct sequence and cluster analysis for women and men separately (Bertogg and Leist, 2023; Andres, 2023).

1) Characterization of individual employment trajectories: For each participant, we categorized each year between 18 and 65 as one of the following mutually exclusive occupational “states” (or categories): 1) employed full-time, 2) employed part-time, 3) unemployed, 4) non-employed because of education, 5) non-employed because of family caregiving, 6) non-employed because of disability, 7) non-employed because of retirement, and 8) unreported. If employment information from the LHMS was unreported, we augmented the data whenever possible using the HRS biennial surveys, which asked participants current employment status from the time they were enrolled in the study onwards (typically age 50+), start and end of previous job, and start and end of up to three other jobs held for 5 years or longer. Using HRS biennial surveys allowed us to decrease unreported states from 40.8 % to 24.7 %. We additionally used data from the biennial surveys to validate information from the retrospective LHMS and found a high rate of concordance between the two surveys (see details in the manuscript's supplement). Whenever there was a one-year work gap with unreported reason, we classified that year as unemployment, as unemployment tends to be underreported in surveys (Wahrendorf et al., 2019; Morgenstern and Barrett, 1974). Finally, mothers of children aged 5 or younger who did not report their employment status were classified as non-employed because of family caregiving, which has been previously shown to be the main reason for leaving the workforce among women with young children in the US (Budig, 2003; Johnson et al., 2017). All the remaining years with missing employment status were classified as unreported (17.2 % of total states). Additional assumptions and data cleaning rules are summarized in the Appendix.

2) Sequence analysis to quantify differences between trajectories: We used the optimal matching (OM) (Abbott and Forrest, 1986) method to calculate a dissimilarity measure comparing all the employment trajectories in the data. This approach computes the minimum “cost” required to transform one sequence into another as a combination of two kinds of edit operations: substitution (i.e., changing one state to another state) and insertion-deletions (i.e., inserting or deleting one state to make two sequences equivalent).

We defined substitution costs based on transition frequencies, such that states with more frequent transitions between consecutive time points in our data were assigned lower costs. Insertion-deletion costs were set equal to 1.5, corresponding to 2/3 times the maximum substitution cost (which was equal to 2, consistent with common practice). Choosing a higher insertion-deletion cost than standard practice reduces time distortion and tends to preserve the timing of events (typically, insertion-deletion costs are half the maximum substitution cost as you could think of a substitution as one insertion and one deletion) (Bison, 2009). Among the available methods to calculate dissimilarity measures, we selected Optimal Matching with higher insertion-deletion costs as we are interested in analyzing both timing and duration of employment trajectories, and this method has been shown to capture both dimensions (Studer and Ritschard, 2016). The result of sequence analysis is a distance (or dissimilarity) matrix comparing each employment trajectory with all the other trajectories in the data, where larger numbers represent more dissimilar trajectories.

3) Cluster analysis: We applied cluster analysis based on the distance matrix to group individual-level trajectories into homogeneous clusters. We used agglomerative, hierarchical clustering with a Ward linkage, with the aim of maximizing homogeneity within each cluster and maximizing differences between the clusters (Murtagh and Contreras, 2012). We selected the optimal number of clusters using the Duda-Hart cluster-stopping rules (Clarke et al., 1974; Halpin, 2016) (Figures A.1 and A.2). There are often several cluster solutions that fit the data well; to choose between multiple cluster solutions we additionally considered a) cluster size; we wanted a minimum of 40 observations per cluster to detect meaningful differences between clusters; b) parsimony, prioritizing solutions with fewer clusters for interpretability when possible (Clarke et al., 1974; Halpin, 2016).

2.3. Outcomes

Our outcomes were dementia risk and memory from age 70 onwards. We assessed both baseline memory and rate of memory decline, as previous work has found that socio-economic factors such as education and occupation predicted higher memory levels, but not slower decline (Lenehan et al., 2015; Stern et al., 1999). We included a 5-year “washout period” between the end of our exposure window, age 65, and the outcome assessments to reduce the possibility of reverse causation. We used two longitudinal, continuous scores, previously developed by Wu et al. (2013): algorithmically defined dementia probability scores (ranging from 0 to 1) and memory scores (ranging from -2.20 to 2.19) (Wu et al., 2013). The Wu scores allow the most cognitively impaired individuals, who would typically be excluded due to missing data, to be retained by harmonizing data from self-respondents and proxy respondents (typically spouses) using the Aging, Demographics, and Memory (ADAMS) subsample. The ADAMS subsample includes a complete neuropsychological battery (CERAD Word List Memory Test, delayed recall and recognition and/or Wechsler Memory Scale-Logical Memory) and dementia diagnoses for a subsample of HRS respondents. The Wu approach first builds regression models to predict dementia diagnosis (using logistic regression) and memory scores (using linear regression) in the ADAMS sub-sample, then uses the beta coefficients to impute dementia probability and memory scores for the whole HRS sample. Compared to a dichotomous case status (yes/no), continuous probability scores may be a more appropriate representation of earlier

stages of dementia among individuals with incipient cognitive difficulties but uncertain case status (Wu et al., 2013). We standardized memory scores using the 1998 mean and standard deviation so that every unit change in memory scores corresponds to approximately one standard deviation change in the baseline sample. We included a total of $n = 30,390$ cognitive assessments from 1998 to 2018, and a mean of 5.1 cognitive assessments per individual.

2.4. Confounders

Our confounders were variables that temporally preceded employment trajectories (from ages 18–65) and might be common causes of our exposure and outcome. We included age, race, birthplace (foreign birth, southern US, non-southern US, or not specified), completion of high school (yes/no, based on self-reported degree), and mother's and father's educational attainment (operationalized as years of schooling). We included high school degree to adjust for education that likely preceded the exposure, occupational trajectories from age 18–65 as most people receive post high school education after age 18. High school degree attainment has been previously shown to be associated with both employment and health (Liu et al., 2011). For the AHEAD cohort (people born between 1890 and 1923), whose mother's and father's education were recorded as dichotomized, we used imputed values from previous work (Vable et al., 2017). We imputed missing data as the mean and included missing indicators for missing data on mother's ($N = 484$ missing, 8.1 %) and father's ($N = 759$ missing, 12.8 %) educational attainment, since missing data may be more common among individuals with lower childhood social capital (e.g., individuals whose parent was not present in the household).

2.5. Statistical analyses

We estimated gender-stratified associations between employment trajectory clusters and dementia probability using generalized estimating equations (GEE) to account for repeated measures across individuals, with a logit link and an independence correlation structure. As suggested by Wu et al. and implemented in previous work (Whitlock et al., 2017; Glymour et al., 2012; Wu et al., 2011), the logit link is appropriate in this model given the restricted range of the dementia probability scores (0–1). To account for death or dropout during the study, we used weighted GEE, which estimates inverse probability weights (IPWs) at each time point (Daza et al., 2017). To assess the association between our exposure and age-related memory decline, we used a linear mixed effect model with random intercepts and slopes at participant level modelling memory scores over time. This model allows each individual memory trajectory to deviate from the population average and has been recommended for analyzing health trajectories and previously used to model memory decline (Whitlock et al., 2017; Ghisletta et al., 2015; Landau et al., 2018). The memory decline model included, in addition to the employment trajectories, a time term, reflecting the number of years since study baseline, as well as a multiplicative term for interaction between the employment trajectories and time. The coefficient of the employment trajectories indicates the association between each trajectory and baseline memory, and the coefficient on the interaction term represents the rate of change in memory scores. We included IPWs calculated at each time point. All models adjusted for confounders and the wave in which the outcomes were assessed to account for trends in

dementia prevalence (Farina et al., 2022). Cleaned data was checked against the source data to ensure our data cleaning did not create any unanticipated discrepancies for 0.1 % of the analytic sample (that is, 50 participant trajectories) and a code review was conducted for all analysis code; both the data and code checks were conducted by the second author (Vable et al., 2021). Data cleaning and analyses were conducted in Stata, version 16 (Press, 2019).

2.6. Sensitivity analyses

There are multiple ways to measure dissimilarity between sequences, and the choice is usually made based on which method seems more appropriate for the research question and on the interpretability of the final clusters (Studer and Ritschard, 2016). To assess the robustness of our analysis to a different dissimilarity measure, we conducted a sensitivity analysis using the Dynamic Hamming distance, which has strong timing sensitivity (Lesnard, 2009). This approach uses only substitution costs, which were set to be inversely proportional to the transition rates between states at each time point. In addition, we conducted a sensitivity analysis adding self-reported childhood health status (ranging from “excellent” to “poor”) as a confounder. We used the first reported response between 1996 and 2018. Childhood health status was not used in the main analysis due to the high rate of non-concordance between survey years.

3. Results

3.1. Sequence and cluster analysis

Our 3,540 women participants reported 3,315 unique employment trajectories; among 2,405 men, 1,825 unique employment trajectories were observed. Fig. 1 represents the sequence index plots for women and men separately, visualizing all the individual trajectories in the data. Predominantly full-time employment trajectories were more common among men, while women had more heterogeneous trajectories and longer spells of family caregiving. Applying sequence and cluster analysis, we identified 11 clusters for women and 10 for men based on the Duda-Hart cluster stopping rules, cluster size, and parsimony (see Figures A.1 and A.2).

Trajectory clusters for women (Fig. 2), were: 1) predominantly full-time work (N = 599); 2) disability gap, characterized by disability spells of at least 15 years from midlife to age 65 (N = 166); 3) unemployment gap (N = 62); 4) family gap, followed by full-time work (N = 870); 5) family gap, followed by part-time work (N = 312); 6) career exit due to family (N = 242); 7) family gap, followed by unreported employment information (N = 384); 8) very early retirement (N = 54); 9) full-time employment with retirement at midlife (N = 207); 10) unreported employment information until around age 40 (N = 375); 11) unreported employment information until age 50 or older (N = 269).

Trajectory clusters for men (Fig. 3), were: 1) predominantly full-time work (N = 608); 2) disability at midlife (starting around age 50 or earlier) (N = 65); 3) disability later (starting between age 50 and age 60) (N = 67); 4) full-time work after college (N = 450); 5) part-time work earlier (N = 43); 6) part-time work later (starting around age 50 or later) (N = 159); 7) early retirement (around age 50) (N = 325); 8) retired around age 60 (N =

317); 9) unreported early employment information, followed by full-time work (N = 170); 10) unreported information for most of the trajectory (N = 201).

Summary statistics by cluster are presented in Table 1 (women) and Table 2 (men). Among women, the “early retirement” cluster and the one characterized by long spells of unreported employment had on average, the oldest participants. The “very early retirement” cluster had the highest proportion of White participants (92.6 %), while the disability cluster had the lowest (57.8 %). Women in the “unemployment” cluster had the highest rate of high school completion (89.1 %) and the highest parental education. By contrast, the disability cluster was characterized by the lowest proportion of non-Hispanic White participants (57.8 %), the highest rate of women born in the South (51.2 %), and the lowest rate of high school completion (42.6 %).

Among men, those who started part-time work earlier were the oldest, followed by those with long spells of unreported employment. The “full-time work after college” cluster had the highest proportion of White participants (89.6 %), high school completion (98.0 %) and parental education, and the lowest proportion of men born in the South (26.4 %). Men in the “disability at midlife” cluster had the lowest proportions of White participants (59.8 %) and the highest proportion of men born in non-Southern US (47.6 %). Men in the “unreported until ~30” cluster had the lowest rate of high school completion and the lowest parental education.

3.2. Employment trajectories and cognitive results among women

Fig. 4 displays coefficient plots from GEE and linear mixed effects models estimating the association between employment trajectories and cognitive outcomes in women. Compared to our reference group - predominantly full-time work - women with disability gaps had 3.62 times the odds (95 % CI = 2.25–5.81) of having dementia at 70+ years as well as lower baseline memory ($\beta = -0.37$, 95 % CI = $-0.51, -0.23$), and a faster memory decline. Unemployment gaps were associated with a 3.83 OR (95 % CI = 1.55, 9.45) for dementia probability and faster memory decline ($\beta = -0.11$, 95 % CI = $-0.23, 0.02$), although the memory decline confidence interval included the null. Results on the family caregiving trajectories varied; while women who went back to full time work had similar cognitive outcomes to those who predominantly worked, those who switched to part-time work had higher dementia probability (OR = 1.79, 95 % CI = 1.15, 2.79), similar baseline memory, but faster decline ($\beta = -0.07$, 95 % CI = $-0.12, -0.02$). Women in the “career exit due to family” and “family gap, no reported work” cluster also had higher dementia probability, worse baseline memory (e.g., career exit due to family: $\beta = -0.18$, 95 % CI = $-0.31, -0.06$) and faster decline compared to the predominant work cluster, although memory decline confidence intervals just included the null. Very early retirement was associated with higher dementia probability (OR = 1.75, 95 % CI = 0.95, 3.23) and faster memory decline ($\beta = -0.13$, 95 % CI = $-0.21, -0.05$) than predominant work. By contrast, being retired at midlife was associated with similar cognitive outcomes to predominant work. Finally, compared to predominant work, long spells of unreported employment status were associated with worse dementia probability (e.g., unreported until age 50–60: OR = 2.09, 95 % CI = 1.33, 3.29) and faster memory decline (see Tables 3 and 4).

3.3. Employment trajectories and cognitive results among men

Fig. 5 displays coefficient plots from GEE and linear mixed effects models estimating the association between employment trajectories and cognitive outcomes in men. Compared to the predominantly full-time work cluster, men who became disabled at midlife had higher odds of dementia at 70+ years (OR = 2.32, 95 % CI = 1.30, 4.15) and worse baseline memory ($\beta = -0.28$, 95 % CI: -0.47 , -0.09), while those who became disabled later had similar cognitive outcomes. Men with predominantly full-time work after college had higher baseline memory ($\beta = 0.24$, 95 % CI: 0.15, 0.32), but similar dementia probability and rate of decline to the reference group. Compared to predominantly full-time work, part-time work starting earlier was associated with higher odds of dementia probability (OR = 1.64; 95 % CI = 1.16, 2.57) and faster memory decline, although the memory decline confidence interval included the null. By contrast, part-time work starting later (after age 50) was associated with similar cognitive outcomes. For both retirement clusters (early and later retirement), dementia probability and rate of decline were not significantly different to those in the predominantly work cluster. Finally, men with long spells of unreported employment status had higher dementia probability (e.g., unreported until ~ age 60: OR = 1.89, 95 % CI = 1.45, 2.47) and faster memory decline than the reference group.

3.4. Sensitivity analyses

Results from sensitivity analyses are included in the manuscript's supplement. Sequence analysis results using Dynamic Hamming, compared to Optimal Matching, produced the same number of clusters for women (11 clusters, Fig. A1) and fewer clusters for men (7 clusters, Figure A.2). Despite the different number of clusters for men, the main conclusions from regression analyses estimating the associations between employment trajectories using Dynamic Hamming and cognitive outcomes went in the same direction for women and men as main results and conclusions were unchanged; that is, conclusions regarding disability, caregiving and timing of retirement trajectories were the same as in the main analysis (Tables A.2 and A.3). Another sensitivity analysis additionally adjusting for childhood health (Tables A.4 and A.5) also found similar results to the main analysis and conclusions were unchanged.

4. Discussion

In a large, diverse sample of older adults, we characterized patterns of employment and non-employment from age 18–65 for men and women and evaluated if type, timing and duration of employment gaps were associated with subsequent dementia risk and memory decline. Regarding types of employment gaps, we hypothesized that disability and unemployment would be associated with worse cognition than full-time employment, while education gaps would be associated with better cognition (H1). Regarding timing, we hypothesized that most employment gaps, when experienced later in life, would be associated with worse cognition, while family caregiving earlier in life would be associated with similar or better cognition than full-time work (H2). Finally, regarding duration, we hypothesized that longer duration of work gaps and part-time work would be associated with worse cognition (H3). Using sequence and cluster analysis, we were able to reduce thousands of individual employment trajectories into 11 trajectory groups for women and 10 for men. We

found that some type of employment gaps (disability and unemployment), earlier timing of disability and retirement and longer duration of disability, family caregiving and part-time work predicted worse cognitive functioning later in life compared to predominantly full-time employment.

4.1. Type of employment gaps

Our hypothesis on the type of employment gaps (H1) was confirmed by the association of unemployment and disability gaps with worse cognitive outcomes (H1a), which also confirm and extend results from previous studies (Leist et al., 2013; Emerson et al., 2018). We did not find evidence of association between education gaps and later-life dementia (H1b). Financial insecurity and reduced participation in intellectual, social, and physical activities may link unemployment to dementia risk (Adam et al., 2013; Stern et al., 2019). Stress, which has been previously linked to worse attention performance, learning, and information recall, could also be a mediator between unemployment and dementia (Senft Miller et al., 2022; Sandi, 2013). Unemployment has been shown to be correlated with depression and sleep problems, which may affect cognition (Blanchflower and Bryson, 2021; Jefferis et al., 2011). Similarly, our results on disability may be mediated by the achievement of a lower socio-economic status while being out of the labor force, which in turn may influence later life cognitive function (Stern et al., 2019). We found the association between disability and cognition to be stronger among women than men. Previous research has shown that women with long-term disabilities experienced more pain, fatigue and depressive symptoms than men with similar conditions (Thakral et al., 2019; Leveille et al., 2000). Due to expectations regarding their multiple social roles (e.g. caring for family, household and work responsibilities), women with disabilities may also tend to push themselves harder, which may damage their long-term physical, mental and cognitive health (Lorber, 2000; Werner et al., 2004). Finally, prior to disability, women had on average more unstable employment trajectories than men, which may have contributed to their greater dementia risk. We found that the association of retirement with cognitive outcomes, hypothesized to be similar to full-time employment (H1c), changed based on retirement timing. Finally, consistently with our hypothesis (H1d), the association of family caregiving and part-time work with cognitive outcomes varied by timing and duration of these gaps (discussed below).

4.2. Timing of employment gaps

Regarding timing, our hypothesis that earlier employment gaps would be associated with worse cognition (H2) was confirmed by our results on disability (Adam et al., 2013; Blanchflower and Bryson, 2021; Freise et al., 2022; Jefferis et al., 2011; Sandi, 2013; Senft Miller et al., 2022; Vélez-Coto et al., 2021). Among men, we found that only disability gaps starting at midlife, in contrast to disability at later-life, were associated with worse dementia probability compared to full-time employment. In addition, we found that timing of retirement was differentially associated with cognition: very early retirement among women was associated with worse cognitive outcomes, but both women and men who retired after age 50 had similar cognitive outcomes to those who were employed until age 65. Women in the very early retirement cluster may experience greater financial hardship and lack of cognitive stimulation, similarly to those in the unemployment or disability cluster, which may mediate the relationship between this trajectory and worse cognition.

Because of their atypical retirement age, it is possible that some women in the early retirement cluster called their exit from the labor force due to retirement in later age, while their earlier exit was really due to unemployment, illness or disability. Previous research has shown that people with disabilities may report “retirement” due to social desirability, which may help explain the surprising retirement age in the “very early retirement” cluster (Dwyer and Mitchell, 1999).

4.3. Duration of employment gaps

Our hypothesis on the association of longer duration of employment gaps with worse cognition (H3) was confirmed by our results on disability, family caregiving and part-time work. Regarding disability, we found that, compared to the reference group, longer disability gaps were associated with worse cognitive outcomes than shorter disability gaps. Regarding family caregiving, we found that, among women, longer duration of family caregiving without return to full-time work predicted greater dementia risk, but shorter duration of family caregiving with subsequent return to the labor force did not. These findings are consistent with a recent national study on joint family and work trajectories, which found greater memory decline among consistently non-working mothers compared to working mothers and those who stayed home with children for a limited number of years and then returned to the labor force (Mayeda et al., 2020). In addition, recent evidence on European samples found that homemaking was associated with greater risk of cognitive impairment, mostly mediated by health and socio-economic status, while temporary maternity leave was protective of cognitive impairment (Bertogg and Leist, 2023; Leist et al., 2013). Our results might be due to the difference between caring for young children for a limited time, which can provide opportunities for social engagement and reduce work-family strain, and being a homemaker for a prolonged period of time, which may result in social isolation, less sense of purpose and limited intellectual stimulation (Scharlach, 2001). Returning to work may also provide cognitive enriching experiences or additional income, either of which may benefit long-term brain health. Finally, regarding part-time work, we found that short periods of part-time work were associated with similar dementia risk as full-time work, while prolonged periods of part-time work were associated with worse cognitive outcomes among both men and women. This finding was novel and contrasts results from a recent study (Bertogg and Leist, 2023) showing that part-time employment – as a means of reconciling career and family tasks – is beneficial for cognitive functioning, especially in women. However, previous evidence has focused on European countries, characterized by more robust public social support programs than in the US. A potential explanation may be under-employment and stress experienced by part-time workers in the US, who may have lower income, more unstable jobs, fewer career advancement and skill development opportunities and reduced access to healthcare (Dwyer and Mitchell, 1999).

In addition to our findings on type, timing and duration of employment gaps, we found that the unreported work trajectories among men and women were characterized by higher dementia risk, faster memory decline but similar (or even higher) baseline memory than predominantly work. These results are difficult to interpret and may warrant further investigation. They may be due to a combination of higher employment instability experienced by participants in these clusters and recall bias (as suggested by the fact that

women and men in those clusters were slightly older than the average age). The fact that memory decline (but not baseline memory) was worse for these participants may support the recall bias mechanism, indicating that these participants' cognition may have worsened faster between the first outcome measurement (age 70) and 2017, when the employment questions were asked.

Our study has several strengths. It uses the LHMS supplement to the HRS, which has very detailed employment history questions including the reasons for leaving each job. Very little prior work has been able to differentiate between types of non-employment spells (Kobayashi and Feldman, 2018). Our work considers employment trajectories from age 18–65, a longer period than in most previous studies. Moreover, it uses sequence analysis, a novel approach that characterizes employment trajectories over decades and allows grouping individual sequences into meaningful groups while at the same time preserving heterogeneities. This approach enables capturing differences in timing and duration of lifecourse employment and non-employment. This allowed, for example, identifying more than one disability trajectory (disability at midlife vs. disability later), more than one retirement trajectory (early retirement vs. later retirement), and four different family caregiving trajectories, and explore whether and how these different patterns are associated with cognition.

Our work has some limitations. Our analytic sample had a higher prevalence of White participants (83 %) than the whole HRS sample, since there were more White participants who responded to the LHMS survey and did not drop out or die before age 70, the age of the first outcome assessment for this analysis. Additionally, likely due to employment histories being patterned by race, some clusters had more than 90 % of White participants. In the future, further research should characterize employment trajectories among more racially diverse samples. Although sequence and cluster analysis allowed preserving some heterogeneities, some of the less common trajectories were grouped together with common trajectories instead of as a cluster of their own. For example, among women, trajectories with family caregiving gaps later in life were not common and were grouped together with early life family gaps. Making different analytic choices in terms of substitution and insertion/deletion costs or selecting different clustering approaches could help differentiate these less common trajectories in future research where these trajectories are the focus. Our results are descriptive and should not be interpreted as causal. Selection mechanisms may contribute to some of our findings; in particular, since employment questions are retrospective, it is possible that cognitively impaired individuals have inaccurately or incompletely reported their past trajectories (recall bias). The Life History Mail Survey only asked employment history questions in 2017, when most participants were older than their cognitive outcomes baseline (age 70), and their cognition may have declined with respect to baseline. We obtained some clusters characterized by long spells of unreported employment status, which were difficult to interpret and may be partially due to recall bias. Collecting lifecourse employment data prospectively rather than relying on retrospective reports would increase accuracy and may decrease the possibility of social desirability, e.g. reporting that unemployment or disability as early retirement. Moreover, the relationship between employment and cognition might be bi-directional, since cognitively impaired individuals could be more likely to exit the labor force earlier or for longer (Silvaggi et

al., 2020; Sakata and Okumura, 2017). Several studies have shown that dementia takes years or even decades to develop and suggest that cognition may be affected as early as middle age, which could in turn impact ability to work (Rajan et al., 2015; Cloutier et al., 2015). We were only able to include covariates preceding our trajectories, and we could not adjust for time-varying covariates such as socio-economic characteristics or lifecourse health, which might affect both employment participation and cognitive outcomes. Finally, previous research has shown that self-reported employment data tend to be affected by social desirability, which leads individuals to underreport unemployment or disability (Bühler et al., 2022). Finally, because self-reported employment trajectories may be affected by recall bias and social desirability, matching HRS survey responses with administrative data from the Social Security Administration should be done in the future to validate respondents' employment trajectories.

While our results are associational, they suggest a range of potential policy solutions may improve later life cognitive health. For example, our results on disability gaps suggest that policy initiatives to remove barriers to employment for persons with disabilities, such as labor market activation programs and equality laws may reduce dementia incidence in later-life (Khayat-zadeh-Mahani et al., 2020). Additionally, expanding financial assistance to unemployed workers may also be beneficial for later-life cognitive outcomes. Regarding family caregiving gaps, our research suggests that helping mothers re-enter the labor force may improve women's cognitive outcomes in later life. This can be achieved through several policies, such as childcare subsidies and child benefits, more flexibility of working-time arrangements, and stronger anti-discrimination laws. Finally, findings on part-time work suggest that policies that provide parity for part-time workers in terms of benefits and pay rate may reduce stress and financial insecurity of part-time workers and contribute to better later-life cognition. However, since our results are associational and not causal, more research is needed to determine if these findings are robust to variations in time, place, population and methodological approach.

5. Conclusion

We found that type, timing and duration of employment and non-employment differentially predict dementia risk and cognitive functioning later in life. Our novel application of sequence analysis to lifecourse work trajectories allowed us to make new substantive discoveries and add additional nuance to existing literature regarding the type, timing and duration of employment on subsequent cognitive health for women and men. We found long disability and unemployment gaps were associated with worse cognitive outcomes than predominantly full-time work, especially among women. Family caregiving in women also predicted worse dementia risk, but not when followed by return to full-time work. Part-time employment from early to later age was associated with worse cognitive outcomes among both men and women. Further research repeating these analyses in other data sources, incorporating time-varying confounding, and differentiating cognitively stimulating work are important extensions to further advance research on lifecourse employment trajectories and cognitive health. This line of inquiry needs further attention as work is a long-lasting social exposure, is core to identity, can impact social networks, confers power and autonomy and

allows access to social programs and health-promoting resources (Berkman, 2014; Ahonen et al., 2018).

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data availability

Data will be made available on request.

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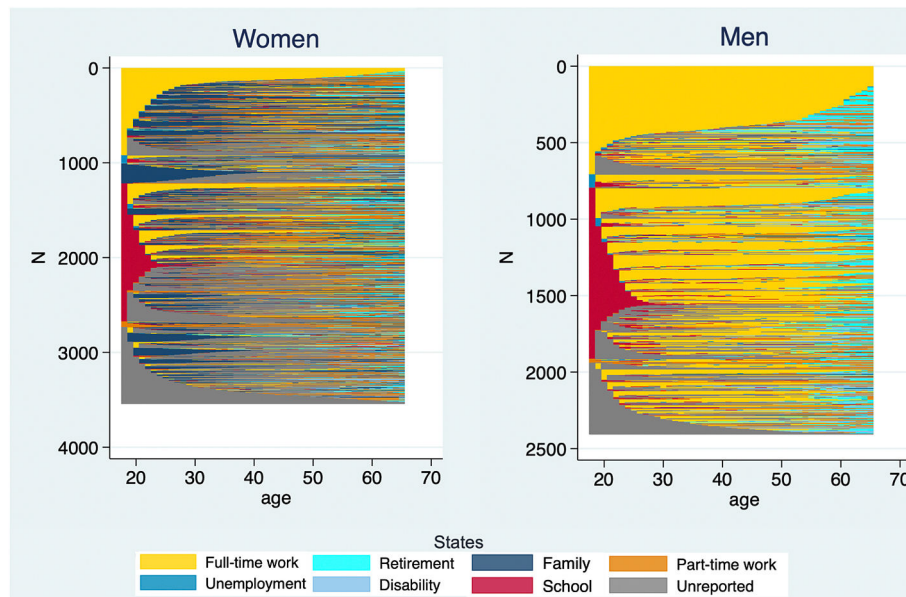


Fig. 1. Sequence index plots for men and women.

Individual-level employment trajectories built from the Life History Mail Survey supplement to the U.S. Health and Retirement Study. Each row on the y-axis represents one individual; each time point on the x axis is one year between age 18–65. Our sample included 3,540 women and 2,405 men. Each year between age 18–65 was characterized as one of the following “states” (or categories): work (full-time or part-time), unemployment, retirement, disability, family caregiving, school or unreported.

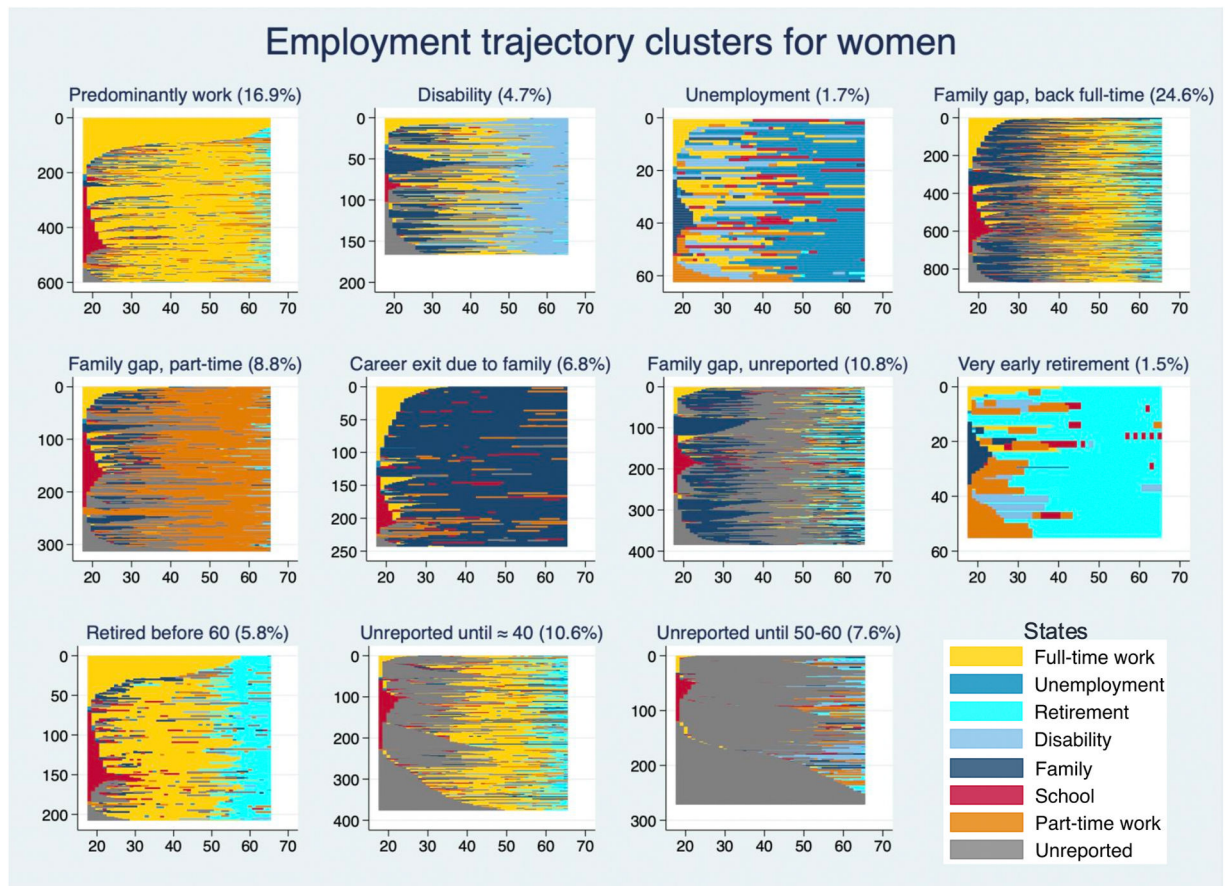


Fig. 2. Employment trajectory clusters obtained with sequence and cluster analysis, women. Sequence index plots for the employment trajectory clusters obtained using sequence and cluster analysis among women ($N = 3,540$). We applied the Optimal Matching algorithm to calculate the dissimilarity between sequences. We then implemented cluster analysis to group sequences based on their similarity. Using Duda-Hart cluster-stopping rules and expert judgment, we identified 11 employment trajectory clusters. Each index plot shows the number of participants on the y-axis and age (18–65) on the x-axis.

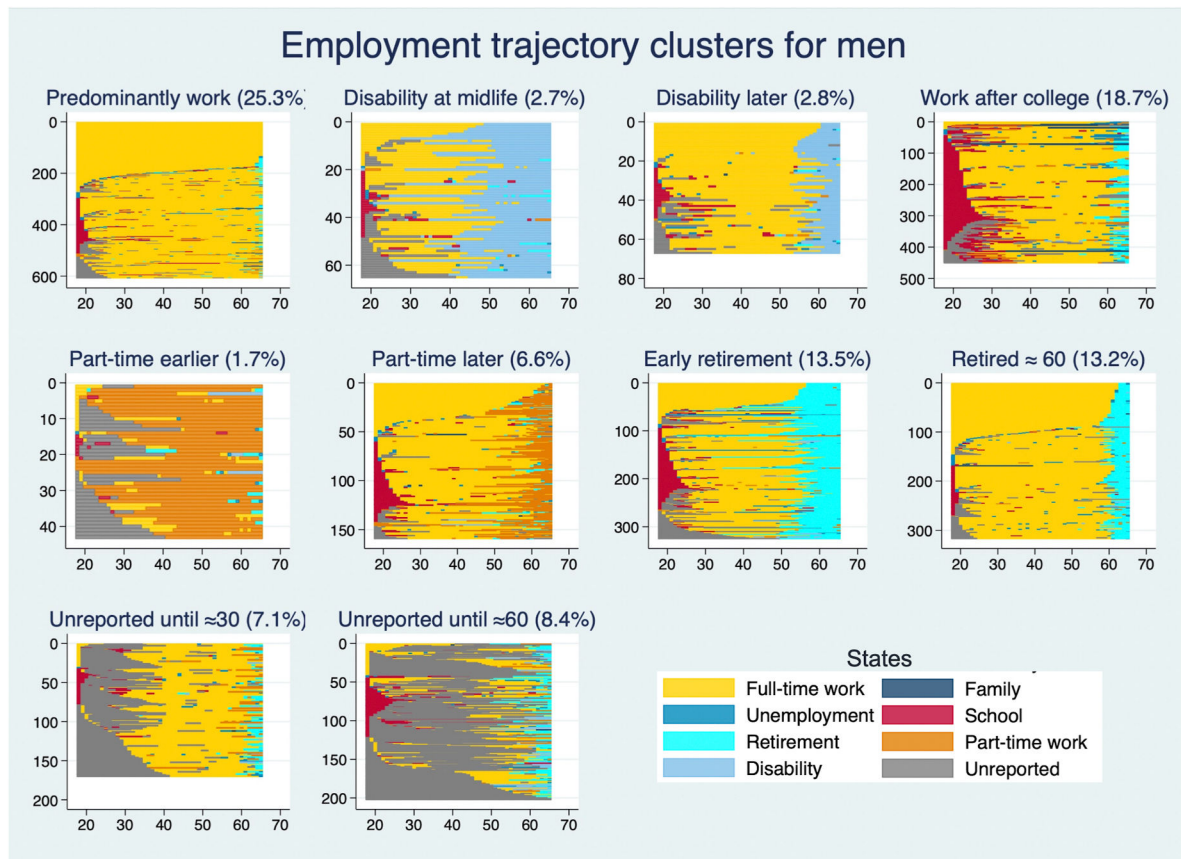


Fig. 3. Employment trajectory clusters obtained with sequence and cluster analysis, men.

Sequence index plots for the employment trajectory clusters obtained using sequence and cluster analysis among men ($N = 2,405$). We applied the Optimal Matching algorithm to calculate the dissimilarity between sequences. We then implemented cluster analysis to group sequences based on their similarity. Using Duda-Hart cluster-stopping rules and expert judgment, we identified 10 employment trajectory clusters. Each index plot shows the number of participants on the y-axis and age (18–65) on the x axis.

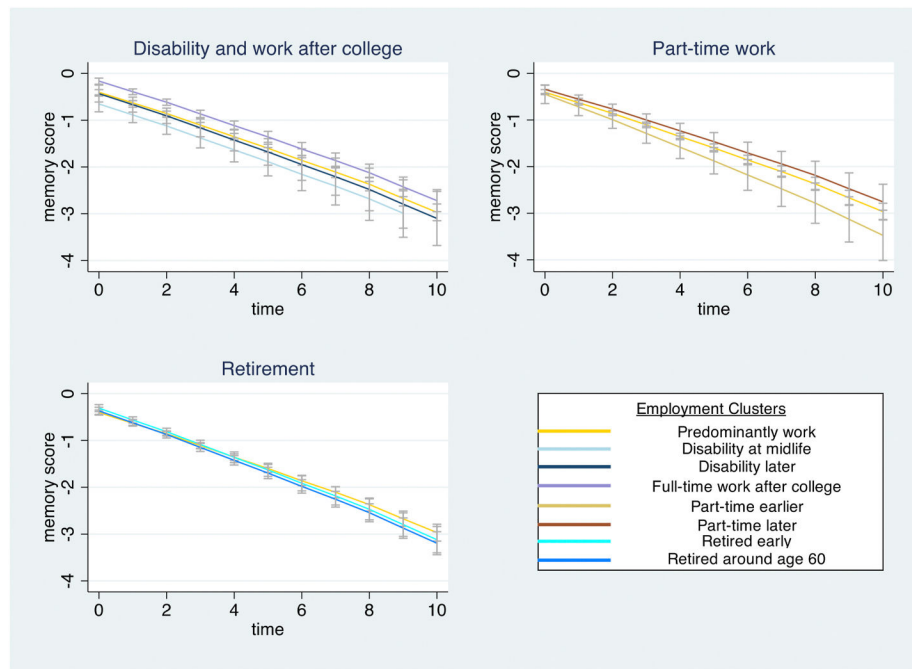


Fig. 4. Predicted memory level and decline by employment cluster, women.

Marginal predictions at the mean of memory scores starting at age 70 for a maximum of 10 time points by employment cluster among women (N = 3,540). We used a linear mixed effect model to estimate the association between employment clusters and memory level/decline. The linear mixed effect model included, in addition to the employment trajectories, a time term, reflecting the number of years since study baseline, and an interaction employment trajectories*time. For each panel, predictions for the employment gaps clusters are compared to the “predominantly work” cluster (reference group). The first time point indicates memory level, while the steepness of the prediction lines indicates rate of decline.

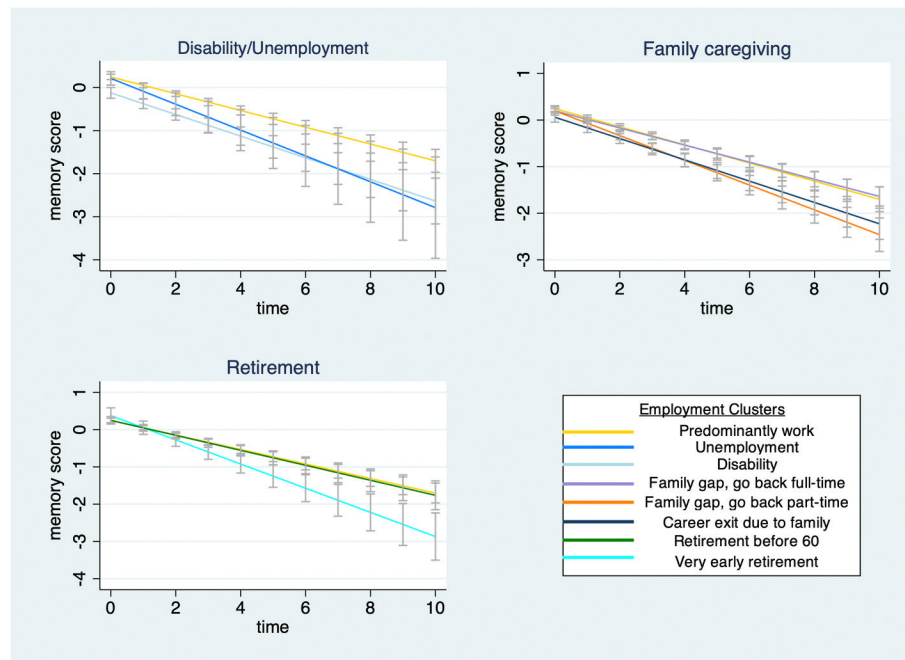


Fig. 5. Predicted memory level and decline by employment cluster, men.

Marginal predictions at the mean of memory scores starting at age 70 for a maximum of 10 time points by employment cluster among men ($N = 2,405$). We used a linear mixed effect model to estimate the association between employment clusters and memory level/decline. The linear mixed effect model included, in addition to the employment trajectories, a time term, reflecting the number of years since study baseline, and an interaction employment trajectories*time. For each panel, predictions for the employment gaps clusters are compared to the “predominantly work” cluster (reference group). The first time point indicated memory level, while the steepness of the prediction lines indicates rate of decline.

Table 1
Baseline sample characteristics by employment trajectory cluster, women (N = 3,540).

Variables	Employment trajectory clusters, women										
	1	2	3	4	5	6	7	8	9	10	11
	N = 599 (16.9 %)	N = 166 (4.7 (%)	N = 62 (1.7 (%)	N = 870 (24.6 %)	N = 312 (8.8 (%)	N = 242 (6.8 (%)	N = 384 (10.8 %)	N = 54 (1.5 (%)	N = 207 (5.8 (%)	N = 375 (10.6 %)	N = 269 (7.6 (%)
Age, mean (sd)	71.2 (1.4)	71.1 (1.2)	71.3 (1.3)	71.1 (0.9)	71.3 (1.6)	71.6 (1.7)	71.3 (1.3)	72.5 (2.9)	71.1 (1.0)	71.6 (1.9)	72.4 (2.7)
Race, N (%)											
White	461 (77.0 %)	96 (57.8 %)	56 (90.3 %)	701 (80.6 %)	253 (81.1 %)	222 (91.7 %)	288 (75.0 %)	50 (92.6 %)	160 (77.3 %)	272 (72.5 %)	187 (69.5 %)
Black	100 (16.7 %)	45 (27.1 %)	2 (3.2 %)	116 (13.3 %)	35 (11.2 %)	8 (3.3 %)	32 (8.3 %)	1 (1.9 %)	40 (19.3 %)	63 (16.8 %)	36 (13.4 %)
Hispanic	25 (4.2 %)	21 (12.7 %)	4 (6.5 %)	41 (4.7 %)	20 (6.4 %)	10 (4.1 %)	58 (15.1 %)	2 (3.7 %)	4 (1.9 %)	31 (8.3 %)	35 (13.0 %)
Other	13 (2.2 %)	4 (2.4 %)	0 (0.0 %)	12 (1.4 %)	4 (1.3 %)	2 (0.8 %)	6 (1.6 %)	1 (1.9 %)	3 (1.4 %)	9 (2.4 %)	11 (4.1 %)
Birth Place, N (%)											
US not south	324 (54.1 %)	60 (36.1 %)	35 (56.5 %)	525 (60.3 %)	191 (61.2 %)	165 (68.2 %)	215 (56.0 %)	34 (63.0 %)	125 (60.4 %)	191 (50.9 %)	132 (48.9 %)
Southern us	229 (38.2 %)	85 (51.2 %)	22 (35.5 %)	292 (33.6 %)	96 (30.8 %)	59 (24.4 %)	119 (31.0 %)	15 (27.8 %)	72 (34.8 %)	134 (35.7 %)	99 (36.7 %)
Immigrant	44 (7.3 %)	19 (11.4 %)	5 (8.1 %)	53 (6.1 %)	25 (8.0 %)	18 (7.4 %)	50 (13.0 %)	4 (7.4 %)	10 (4.8 %)	49 (13.1 %)	39 (14.4 %)
Not specified	2 (0.3 %)	2 (1.2 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	1 (1.9 %)	0 (0.0 %)	1 (0.3 %)	0 (0.0 %)
Mother's education, mean (sd)	10.1 (3.3)	8.4 (3.7)	10.3 (3.2)	10.1 (3.2)	9.8 (3.7)	9.9 (3.2)	8.9 (3.7)	9.2 (2.7)	10.5 (3.4)	9.8 (3.0)	8.2 (3.6)
Father's education, mean (sd)	9.8 (3.6)	8.2 (3.8)	10.4 (2.9)	9.6 (3.4)	9.4 (4.0)	10.0 (3.4)	8.8 (3.7)	9.7 (2.8)	10.1 (3.6)	9.3 (3.4)	8.2 (3.6)
High school, N (%)											
no	71 (11.9 %)	87 (52.4 %)	6 (9.7 %)	165 (19.0 %)	65 (20.8 %)	29 (12.0 %)	129 (33.6 %)	15 (27.8 %)	27 (13.0 %)	81 (21.6 %)	109 (40.4 %)
yes	528 (88.1 %)	79 (47.6 %)	56 (90.3 %)	705 (81.0 %)	247 (79.2 %)	213 (88.0 %)	255 (66.4 %)	39 (72.2 %)	180 (87.0 %)	294 (78.4 %)	161 (59.6 %)
# years in state, mean (sd)											
full-time	40.1 (5.5)	16.1 (12.3)	10.7 (8.5)	26.0 (7.8)	6.2 (7.2)	5.0 (4.2)	9.3 (8.4)	3.7 (6.8)	30.2 (5.9)	23.8 (8.1)	3.3 (4.5)
unemployed	1.0 (2.6)	0.7 (2.2)	22.3 (8.0)	0.6 (1.1)	0.8 (1.8)	0.2 (1.1)	1.0 (1.5)	0.7 (2.8)	0.6 (1.0)	1.1 (2.6)	0.3 (0.8)
retired	1.2 (2.0)	0.5 (1.4)	0.1 (0.6)	2.6 (3.4)	2.3 (4.3)	0.1 (0.9)	3.5 (5.0)	34.4 (8.9)	10.1 (3.7)	2.9 (4.0)	3.1 (5.0)
disabled	0.1 (0.5)	16.0 (8.7)	0.0 (0.0)	0.1 (0.9)	0.8 (2.7)	0.0 (0.1)	0.3 (1.4)	0.0 (0.0)	0.4 (1.9)	0.2 (1.1)	2.8 (6.5)
family	1.2 (2.4)	7.4 (6.9)	5.9 (7.3)	11.9 (6.4)	8.1 (7.2)	38.8 (6.8)	14.1 (7.5)	2.3 (4.9)	1.2 (2.2)	1.3 (3.6)	0.7 (2.5)
education	1.8 (2.5)	0.7 (1.6)	1.8 (2.6)	1.6 (2.4)	1.7 (2.4)	1.5 (2.6)	2.0 (4.6)	1.4 (2.1)	2.5 (3.3)	1.8 (2.9)	1.4 (2.8)
part time	1.4 (3.0)	0.5 (1.5)	4.0 (6.1)	2.5 (4.7)	22.7 (9.5)	1.5 (3.9)	1.3 (2.7)	0.6 (1.8)	0.8 (2.1)	0.9 (2.1)	1.4 (3.5)

Variables	Employment trajectory clusters, women										
	1	2	3	4	5	6	7	8	9	10	11
	N = 599 (16.9 %)	N = 166 (4.7 %)	N = 62 (1.7 %)	N = 870 (24.6 %)	N = 312 (8.8 %)	N = 242 (6.8 %)	N = 384 (10.8 %)	N = 54 (1.5 %)	N = 207 (5.8 %)	N = 375 (10.6 %)	N = 269 (7.6 %)
unreported	1.2 (2.2)	6.2 (6.7)	3.1 (6.6)	2.7 (4.0)	5.5 (7.3)	0.8 (2.1)	16.4 (7.9)	4.9 (5.1)	2.2 (3.4)	16.1 (7.0)	35.1 (8.2)

Baseline sample characteristics for the following clusters: 1) Predominantly full-time work; 2) Disability gap; 3) Unemployment; 4) Family gap, back full-time; 5) Family gap, back part-time; 6) Career exit due to family; 7) Family gap, unreported work; 8) Very early retirement; 9) Retired before 60; 10) Unreported until ~40; 11) Unreported until ~50–60.

Table 2
Baseline sample characteristics by employment trajectory cluster, men (N = 2,405).

Variables	Employment Trajectory Clusters, Men									
	1	2	3	4	5	6	7	8	9	10
	N = 608 (25.3 %)	N = 65 (2.7 %)	N = 67 (2.8 %)	N = 450 (18.7 %)	N = 43 (1.8 %)	N = 159 (6.6 %)	N = 325 (13.5 %)	N = 317 (13.2 %)	N = 170 (7.1 %)	N = 202 (8.4 %)
Age, mean (sd)	71.2 (1.3)	71.2 (1.0)	71.1 (0.9)	71.4 (2.0)	72.1 (3.1)	71.1 (0.9)	71.3 (1.3)	71.3 (1.4)	71.3 (1.3)	71.7 (1.9)
Race, N (%)										
White	481 (79.1 %)	39 (60.0 %)	47 (70.1 %)	403 (89.6 %)	31 (72.1 %)	136 (85.5 %)	266 (81.8 %)	255 (80.4 %)	104 (61.2 %)	126 (62.7 %)
Black	71 (11.7 %)	16 (24.6 %)	12 (17.9 %)	25 (5.6 %)	8 (18.6 %)	12 (7.5 %)	32 (9.8 %)	32 (10.1 %)	36 (21.2 %)	32 (15.9 %)
Hispanic	45 (7.4 %)	9 (13.8 %)	4 (6.0 %)	10 (2.2 %)	3 (7.0 %)	9 (5.7 %)	20 (6.2 %)	21 (6.6 %)	29 (17.1 %)	36 (17.9 %)
Other	11 (1.8 %)	1 (1.5 %)	4 (6.0 %)	12 (2.7 %)	1 (2.3 %)	2 (1.3 %)	7 (2.2 %)	9 (2.8 %)	1 (0.6 %)	7 (3.5 %)
Birth Place, N (%)										
US not south	365 (60.0 %)	26 (40.0 %)	36 (53.7 %)	287 (63.8 %)	21 (48.8 %)	108 (67.9 %)	213 (65.5 %)	183 (57.7 %)	78 (45.9 %)	89 (44.1 %)
Southern us	194 (31.9 %)	34 (52.3 %)	28 (41.8 %)	119 (26.4 %)	18 (41.9 %)	45 (28.3 %)	88 (27.1 %)	118 (37.2 %)	60 (35.3 %)	67 (33.2 %)
Immigrant	47 (7.7 %)	5 (7.7 %)	3 (4.5 %)	42 (9.3 %)	2 (4.7 %)	6 (3.8 %)	23 (7.1 %)	15 (4.7 %)	32 (18.8 %)	45 (22.3 %)
Not specified	2 (0.3 %)	0 (0.0 %)	0 (0.0 %)	2 (0.4 %)	2 (4.7 %)	0 (0.0 %)	1 (0.3 %)	1 (0.3 %)	0 (0.0 %)	1 (0.5 %)
Mother's education, mean (sd)	10.0 (3.2)	8.9 (3.7)	9.3 (3.3)	11.5 (3.3)	8.8 (3.7)	9.9 (3.2)	10.2 (3.1)	9.6 (3.1)	8.6 (3.8)	8.6 (3.6)
Father's education, mean (sd)	9.4 (3.5)	8.4 (4.0)	9.1 (3.0)	11.4 (3.8)	8.2 (4.0)	9.4 (3.5)	9.6 (3.6)	8.9 (3.4)	8.2 (3.6)	8.3 (3.9)
High school, N (%)										
no	119 (19.6 %)	25 (38.5 %)	20 (29.9 %)	9 (2.0 %)	18 (41.9 %)	21 (13.2 %)	48 (14.8 %)	72 (22.7 %)	76 (44.7 %)	81 (40.1 %)
yes	489 (80.4 %)	40 (61.5 %)	47 (70.1 %)	441 (98.0 %)	25 (58.1 %)	138 (86.8 %)	277 (85.2 %)	245 (77.3 %)	94 (55.3 %)	121 (59.9 %)
# years in state, mean (sd)										
full-time	44.5 (3.7)	19.6 (9.7)	33.8 (7.5)	37.9 (5.6)	4.2 (4.6)	34.8 (8.8)	30.6 (8.2)	40.7 (3.1)	30.3 (5.0)	13.7 (9.4)
unemployed	0.5 (1.0)	0.3 (0.5)	0.7 (1.6)	1.0 (2.1)	0.2 (0.5)	0.6 (0.9)	1.7 (6.3)	0.8 (1.0)	0.5 (1.0)	0.7 (1.8)
retired	0.3 (0.7)	0.6 (1.8)	0.3 (0.9)	0.9 (1.5)	0.7 (1.6)	1.0 (2.3)	10.0 (4.6)	4.4 (1.7)	1.0 (1.6)	2.2 (2.8)
disabled	0.0 (0.2)	21.5 (7.4)	7.8 (3.0)	0.1 (0.5)	0.6 (2.5)	0.2 (1.5)	0.2 (1.1)	0.0 (0.3)	0.1 (0.7)	1.0 (3.1)
family	0.1 (0.8)	0.0 (0.0)	0.0 (0.1)	0.4 (3.5)	0.0 (0.0)	0.1 (0.9)	0.0 (0.2)	0.1 (1.2)	0.0 (0.1)	0.0 (0.3)
education	1.0 (2.0)	1.2 (2.0)	1.7 (2.7)	5.7 (3.2)	0.6 (1.2)	2.2 (3.1)	2.3 (2.6)	0.5 (0.8)	1.0 (1.8)	2.2 (4.5)
part time	0.3 (1.1)	0.2 (0.7)	0.2 (0.8)	0.5 (2.0)	32.1 (8.8)	7.9 (6.0)	0.3 (1.4)	0.1 (0.5)	1.1 (2.6)	0.6 (2.0)
unreported	1.4 (2.5)	4.6 (5.6)	3.5 (4.9)	1.5 (2.4)	9.5 (7.6)	1.2 (2.7)	2.9 (5.5)	1.4 (2.5)	14.0 (4.9)	27.5 (10.2)

Baseline sample characteristics for the following clusters: 1) Predominantly full-time work; 2) Disability at midlife; 3) Disability later; 4) Full-time work after college; 5) Part-time work earlier 6) Part-time work later; 7) Early retirement; 8) Retired around age 60; 9) Unreported until ~30; 10) unreported until ~60.

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Association between employment trajectories and cognitive outcomes, women.

Outcome 1: Dementia probability			Outcome 2: Memory Decline	
	Odds Ratio (ci)	Marginal Prediction (ci)	β (ci)	Marginal Prediction (ci)
PREDOMINANTLY WORK (REF.)		0.02 (0.01, 0.03)		0.25 (0.18, 0.31)
DISABILITY GAP	3.62*** (2.25, 5.81)	0.08 (0.05, 0.10)	-0.37*** (-0.51, -0.23)	-0.12 (-0.25, 0.00)
UNEMPLOYMENT GAP	3.83** (1.55, 9.45)	0.08 (0.02, 0.14)	-0.03 (-0.20, 0.13)	0.21 (0.06, 0.37)
FAMILY GAP, GO BACK FULL TIME	1.03 (0.69, 1.55)	0.02 (0.02, 0.03)	-0.05 (-0.12, 0.03)	0.20 (0.15, 0.25)
FAMILY GAP, GO BACK PART TIME	1.79** (1.15, 2.79)	0.04 (0.03, 0.05)	-0.05 (-0.15, 0.06)	0.20 (0.11, 0.29)
CAREER EXIT DUE TO FAMILY	1.71* (1.06, 2.76)	0.04 (0.03, 0.05)	-0.18** (-0.31, -0.06)	0.06 (-0.05, 0.17)
FAMILY GAP, NO REPORTED WORK	1.82** (1.18, 2.81)	0.04 (0.03, 0.05)	-0.13** (-0.22, -0.04)	0.11 (0.04, 0.19)
RETIRED VERY EARLY	1.75 (0.95, 3.23)	0.04 (0.02, 0.06)	0.13 (-0.09, 0.35)	0.37 (0.16, 0.58)
RETIRED AT MIDLIFE	1.02 (0.60, 1.73)	0.02 (0.01, 0.03)	0 (-0.11, 0.12)	0.25 (0.15, 0.35)
UNREPORTED UNTIL $\approx$ 40	1.71* (1.11, 2.63)	0.04 (0.03, 0.05)	0.04 (-0.06, 0.14)	0.28 (0.20, 0.36)
UNREPORTED UNTIL 50-60	2.09** (1.33, 3.29)	0.05 (0.03, 0.06)	0.15 (-0.01, 0.32)	0.40 (0.24, 0.56)
time			-0.19*** (-0.22, -0.16)	
PREDOMINANTLY WORK (REF.)*time			0 (0.00, 0.00)	
DISABILITY GAP*time			-0.06 (-0.12, 0.01)	
UNEMPLOYMENT GAP*time			-0.11 (-0.23, 0.02)	
FAMILY GAP, GO BACK FULL TIME*time			0.01 (-0.02, 0.04)	
FAMILY GAP, GO BACK PART TIME*time			-0.07** (-0.12, -0.02)	
CAREER EXIT DUE TO FAMILY*time			-0.03 (-0.08, 0.01)	
FAMILY GAP, NO REPORTED WORK*time			-0.03 (-0.07, 0.01)	
RETIRED VERY EARLY*time			-0.13** (-0.21, -0.05)	
RETIRED AT MIDLIFE*time			-0.01 (-0.06, 0.04)	
UNREPORTED UNTIL $\approx$ 40*time			-0.10*** (-0.14, -0.06)	
UNREPORTED UNTIL 50-60*time			-0.17*** (-0.21, -0.12)	
N groups (obs)	3540 (18,318)		3540 (18,318)	

Odds ratios, β coefficients and marginal predictions at the mean for the association between employment trajectory clusters from age 18–65 and cognitive outcomes at age 70+ compared to “predominantly work” (reference group) among women. We used generalized estimating equations with logit link for dementia probability, and a linear mixed effect model for memory decline. The linear mixed effect model included, in addition to the employment trajectories, a time term, reflecting the number of years since study baseline, and an interaction employment trajectories*time indicating the difference in rate of decline between the reference group and the other clusters. All the models included inverse probability weights and adjusted for age, race, birthplace, completion of high school, and mother's and father's education.

Table 4
Association between employment trajectories and cognitive outcomes, men.

	Outcome 1: Dementia probability		Outcome 2: Memory Decline	
	OR (ci)	Marginal Prediction (ci)	β (ci)	Marginal Prediction (ci)
PREDOMINANTLY WORK		0.03 (0.03, 0.04)		-0.40 (-0.46, -0.35)
DISABILITY AT MIDLIFE	2.32** (1.30, 4.15)	0.07 (0.03, 0.11)	-0.25** (-0.43, -0.07)	-0.65 (-0.82, -0.49)
DISABILITY LATER	1.18 (0.70, 1.99)	0.04 (0.02, 0.05)	-0.03 (-0.22, 0.16)	-0.43 (-0.61, -0.25)
WORK AFTER COLLEGE	0.95 (0.74, 1.22)	0.03 (0.02, 0.04)	0.24*** (0.15, 0.32)	-0.16 (-0.23, -0.10)
PART-TIME EARLIER	1.64* (1.01, 2.67)	0.05 (0.03, 0.07)	-0.04 (-0.25, 0.16)	-0.45 (-0.65, -0.25)
PART-TIME LATER	1.01 (0.73, 1.42)	0.03 (0.02, 0.04)	0.06 (-0.04, 0.16)	-0.34 (-0.43, -0.25)
EARLY RETIREMENT	1.23 (0.94, 1.61)	0.04 (0.03, 0.05)	0.09* (0.00, 0.19)	-0.31 (-0.38, -0.24)
RETIRED $\approx$ 60	1.22 (0.95, 1.56)	0.04 (0.03, 0.04)	0.04 (-0.06, 0.13)	-0.37 (-0.44, -0.29)
UNREPORTED UNTIL $\approx$ 30	1.96*** (1.36, 2.83)	0.06 (0.04, 0.08)	0.04 (-0.08, 0.17)	-0.36 (-0.47, -0.25)
UNREPORTED UNTIL $\approx$ 60	1.89*** (1.45, 2.47)	0.06 (0.05, 0.07)	0.02 (-0.10, 0.14)	-0.38 (-0.49, -0.28)
time			-0.24*** (-0.26, -0.22)	
PREDOMINANTLY WORK*time			0 (0.00-0.00)	
DISABILITY AT MIDLIFE*time			-0.01 (-0.07-0.05)	
DISABILITY LATER*time			-0.01 (-0.08-0.06)	
WORK AFTER COLLEGE*time			0 (-0.03-0.03)	
PART-TIME EARLIER*time			-0.05 (-0.11-0.02)	
PART-TIME LATER*time			0.02 (-0.03-0.06)	
EARLY RETIREMENT*time			-0.02 (-0.06-0.01)	
RETIRED $\approx$ 60*time			-0.03 (-0.06-0.01)	
UNREPORTED UNTIL $\approx$ 30*time			-0.07** (-0.11, -0.03)	
UNREPORTED UNTIL $\approx$ 60*time			-0.07*** (-0.10, -0.03)	
N groups (obs)	2405 (12076)		2405 (12076)	

Odds ratios, β coefficients and marginal predictions at the mean for the association between employment trajectory clusters from age 18–65 and cognitive outcomes at age 70+ compared to “predominantly work” (reference group) among men. We used generalized estimating equations with logit link for dementia probability, and a linear mixed effect model for memory decline. The linear mixed effect model included, in addition to the employment trajectories, a time term, reflecting the number of years since study baseline, and an interaction employment trajectories*time indicating the difference in the rate of decline between the reference group and the other clusters. All the models included inverse probability weights and adjusted for age, race, birthplace, completion of high school, and mother’s and father’s education.