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From Snapshots to Movies: The Association Between Retirement Sequences and Aging Trajectories in Limitations to Perform Activities of Daily Living

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Abstract

Objective: This study analyzes the dynamic association between retirement sequences and activities of daily living (ADLs) trajectories between ages 60 and 70.

Method: Retirement sequences previously established for 7,880 older Americans from the Health and Retirement Study were used in hierarchical linear and propensity score full matching models, analyzing their association with ADL trajectories.

Results: Sequences of partial retirement from full- or part-time jobs showed higher baseline and slower decline in ADL than sequences characterized by early labor force disengagement.

Discussion: The conventional model in which people completely retire from a full-time job at normative ages and the widely promoted new conventional model of late retirement are both associated with better functioning than early labor force disengagement. But unconventional models, where older adults keep partially engaged with the labor force are also significantly

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The study is exempt from ethics approval by the institutional review board. Health and Retirement Study (HRS) data are publicly available to any registered user from the Institute for Social Research at University of Michigan. Collection and production of HRS data comply with the requirements of the University of Michigan's Institutional Review Board. Ignacio Madero-Cabib is also affiliated to Pontifical Catholic University of Chile.

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associated with better functioning. These findings call attention to more research on potential avenues to simultaneously promote productive engagement and health later in life.

Keywords

ADLs; functioning; retirement; policy; epidemiology

An aging population poses big challenges to the prosperity and well-being of modern societies. These challenges require new evidence to stimulate novel policy solutions to simultaneously promote productive and healthy aging (Bloom et al., 2015; Staudinger, Finkelstein, Calvo, & Sivaramakrishnan, 2016). In this context, a growing body of literature has been investigating the association between labor force status and transitions with the functional ability to perform activities of daily living (ADLs) later in life (Bowen, Noack, & Staudinger, 2010; Dhaval, Rashad, & Spasojevic, 2008; Jokela et al., 2010; Stenholm et al., 2014). For example, controlling for baseline disability, findings suggest that the *unemployed* show worse levels of functional ability than those in paid work—this is true during unemployment spells as well as afterwards (Von Bonsdorff, Kuh, Von Bonsdorff, & Cooper, 2016). Findings on the association between *retirement* and functional ability are more mixed. Using data from the Health and Retirement Study (HRS) in the United States, Stenholm et al. (2014) argued that retirement has a negative effect over functional ability when compared with those who remain in a full-time job, among those aged 65 years or older, after controlling for sociodemographic factors and baseline health status. In contrast, Hessel (2016) documented beneficial effects of retirement on activity limitations across gender and educational levels among 12 Western European countries. However, other studies find that retirement is linked with neither improvement nor deterioration of functional ability (van der Heide, van Rijn, Robroek, Burdorf, & Proper, 2013).

Most of these studies analyze labor force patterns near retirement as a snapshot of a certain labor force status at a given point in time or a snapshot of a transition from one status to another (Calvo, Sarkisian, & Tamborini, 2013; Iparraguirre, 2014). In the present study, we depart from this snapshot approach to focus on "retirement sequences," as defined by Calvo, Madero-Cabib, and Staudinger (2018). These retirement sequences encompass a series of chronologically ordered labor force states and transitions between the ages of 60 to 61 and 70 to 71 years and do not necessarily start with full-time employment and end with complete retirement. Specifically, Calvo et al. (2018) identified six types of retirement sequences: *early* (most individuals are completely retired at age 62 or before), *ambiguous* (the majority moves from out of the labor force to retirement), *complete* (most people are completely retired from a full-time job at age 66), *late* (working in full-time jobs until age 66 or above), *partial* (most individuals move from full-time job to partial retirement at age 66), and *compact* (partial retirement from part-time job). *Early* and *ambiguous* sequences can be characterized as showing weaker attachment to the labor force, *complete* and *late* as conventional models often discussed in academic and policy debates, and *partial* and *compact* as unconventional models that have received relatively less attention.

The purpose of the current study was to examine the longitudinal association between 10-year retirement sequences and trajectories of functional ability during later life, measured as the absence of limitations to perform ADLs. Our results showed that after adjusting for sociodemographic variables (e.g., gender and race/ethnicity), as well as socioeconomic and health disadvantages accumulated earlier in life (e.g., parental education and allostatic load), individuals both in the *early* and *ambiguous* sequences showed lower baseline and steeper declines in functional ability, relative to individuals in the *complete, late, partial,* and *compact* sequences. We discuss the importance of using dynamic approaches to inform novel policy solutions that may contribute to promoting optimal functional ability through the late stages of life. Current policy debates have been narrowly focused on late retirement, overlooking other possibilities of remaining partially engaged in the labor force that may also be beneficial for productive and healthy aging in societies with unprecedented change in demographic structures.

Background

To our knowledge, no other studies have yet explored the association between retirement sequences and functional ability. Therefore, in this section, we review related literature discussing theoretical mechanisms and empirical findings about labor force patterns and its association with functional ability in old age. Next, we combine this evidence with a dynamic framework and formulate testable predictions about the relationship between retirement sequences and ADL trajectories.

Labor Force Patterns and Functional Ability in Old Age

Extant literature describes several mechanisms that might explain the association between labor force patterns and trajectories of functional ability, paying particular attention to *self-selection,* as well as to specific labor force *statuses* (e.g., work, retirement, unemployment) and characteristics of *transitions* (e.g., timing, speed) that describe these patterns.

Studies across all of adulthood have emphasized self-selection by documenting that poor functional ability, together with unstable employment histories, increases the probability of experiencing involuntary job loss, which in turn may accelerate early retirement (Flippen & Tienda, 2000). In contrast, studies among older adults suggest that the relationship between labor force patterns and functional ability may not be entirely due to self-selection. There are a limited number of studies that have addressed the relationship between unemployment and functional ability among older adults. For instance, there is evidence—using HRS data—for negative effects of involuntary job loss on physical functioning, measured as using a 15-item index of self-reported performance of ADLs and mobility tasks (Gallo, Bradley, Siegel, & Kasl, 2000). Consistently, it was found that intermittent unemployment throughout life had detrimental effects on physical functioning—as measured by a subscale of physical functioning obtained from the Short Form 36 (SF-36) health survey questionnaire—later in life for the British cohort born in 1946, after adjusting for socioeconomic position, health status, and lifestyle factors (Von Bonsdorff et al., 2016).

A larger body of literature emphasizes the role of broader productive and social activities (Adams, Leibbrandt, & Moon, 2011; Luoh & Herzog, 2002). Beneficial activities may be informal or formal, physical or mental. Although these activities differ in type, previous studies have consistently documented that productive activities in old age—including volunteer or paid work, particularly after retirement—help maintain functional ability in later life primarily due to the physical exercise associated with leaving the house on a regular basis (Menec, 2003). In the same vein, Luoh and Herzog (2002) found that engaging in paid or volunteer work at old age is positively associated with functional ability, protecting against subsequent poor health and death.

The association between retirement and functional ability, however, is complex. In a systematic literature review, van der Heide et al. (2013) concluded that there is ambiguous evidence about the effects of retirement on functional ability. Whereas some studies show no association between retirement and functional ability (Gayman, Pai, Kail, & Taylor, 2013), others document a significant association, which is more often deemed as detrimental (Dhaval et al., 2008; Jokela et al., 2010; Mein, Martikainen, Hemingway, Stansfeld, & Marmot, 2003) than beneficial (Hessel, 2016) to functional ability. For example, Stenholm et al. (2014) found that the decline in functional ability was linear and had a steeper negative slope for individuals who retired compared with those who kept working full-time. Following a standard practice in the literature (which we also used in our study), Stenholm et al. (2014) examined age-related trajectories testing for the linearity of the aging effect by measuring age and age squared to determine whether the rate of functional decline increases or decreases as subjects age. For example, aging from 70 to 75 years may have a more negative effect on functioning than moving from 60 to 65 years of age. Including an age squared parameter allowed them to test for a nonlinear association. Stenholm et al. (2014) also tested for differences in the rates of decline by including interactions of both age and its squared term with a grouping variable indicating retirement status (in our study the grouping variable is retirement sequence rather than retirement status). These interaction terms tested whether the observed effects of age—linear and quadratic—varied across different groups, making the model less constrained and more flexible. In our study, there is no strong theoretical or empirical reason to constrain functioning trajectories to be linear and with similar slopes for all retirement sequences; thus, we adopted a similarly flexible approach to model the complex association between retirement sequences and functioning.

The relationship between retirement and functional ability has also been documented to vary depending on the specific characteristics of the retirement transition, including timing and speed. Studies on retirement timing suggest that early transitions into retirement are associated with more shortterm detrimental health effects than transitions that happen later (Calvo et al., 2013). Regarding the speed of retirement, it is important to consider whether individuals completely retire all at once or maintain some kind of part-time work after retirement. Different forms of gradual retirement, including bridge-jobs, give older adults the opportunity to remain engaged in productive activities and through maintaining financial means, improve quality of life overall (Cahill, Giandrea, & Quinn, 2006; Calvo, Haverstick, & Sass, 2009). Gradual retirement and postretirement employment/activity may allow individuals to maintain continuity in terms of physical and social environments, thus potentially protecting levels of functional ability (Stowe & Cooney, 2015).

In addition to emphasizing self-selection and the characteristics of labor force status and transition between these statuses, extant literature suggests that there may be common causes earlier in life that explain the association between labor force patterns and functional ability in old age. For example, job characteristics in midlife may have a long-term effect on functional ability later in life (Nilsen, Agahi, & Kareholt, 2016). This indicates the importance of adjusting for life-course antecedents when addressing the relationship between labor force patterns and functional ability in old age (Luo & Waite, 2005; Lyu & Burr, 2016).

Retirement Sequences: From Snapshots to Movies

By and large, the literature reviewed above examines the association between labor force patterns and functional ability in old age by looking at snapshots in specific moments of time (Iparraguirre, 2014). However, we are not interested in observing the association of a specific labor force status or transition with functional ability, but rather on the association between specific types of retirement sequences with functional ability. To our knowledge, no study has yet addressed the association between retirement sequences and functional ability in old age. By moving from snapshots to movies, we analyze the dynamic association between retirement sequences and functional ability. We argue that together with the initial or final labor force status and specific transitions in between, it is also the *type* of retirement sequence that individuals follow that can improve our understanding of functional ability in later life.

We anticipated a series of associations between following a particular type of retirement sequence and trajectories in functional ability between the ages of 60 and 70. As defined in the introduction, and further developed in the "Method" section, we considered six types of retirement sequences that were identified in a previous study by Calvo et al. (2018): *early* (retirement by or before age 62), *ambiguous* (moving from out of the labor force to retirement), *complete* (conventional retirement around age 66), *late* (retirement typically after age 66), *partial* (partial retirement around age 66), and *compact* (partial retirement from part-time job).

Although underlying mechanisms may differ, we expected that individuals with lower functional ability would self-select into the *early* and *ambiguous* sequences as previous studies have shown that low levels of functional ability are associated with early retirement and absence from the labor force. Hence, we predicted that individuals following the *early* and *ambiguous* sequences would show lower levels of functional ability at the beginning (intercept) of their 10-year trajectory in functional ability. We also predicted a steeper decline (slope) in functioning trajectories for individuals in the *early* sequence, given that many retired before normative ages probably due to health reasons and lack of employment opportunities, as well as for individuals in the *ambiguous* sequence due to the high concentration of out of the labor force and unemployment statuses. We further anticipated for *partial* and *compact* sequences to have a slower decline in functioning trajectories compared with *complete* and *early* sequences due to the gradual nature of the transitions that are characteristic of these retirement sequences. We expected these associations to hold even after adjusting—through control variables and propensity score full matching—for life-course antecedents that may be a common cause of both retirement sequences and trajectories in functional ability. Finally, we explored for heterogeneous associations between retirement sequences and trajectories in functional ability.

Method

Study Population

The HRS is a longitudinal panel survey, including biannual observations for a nationally representative sample of older Americans and their spouses. For the current study, we analyzed 11 waves, from 1992 to 2012, focusing on the initial HRS cohort of 9,752 individuals born between 1931 and 1941. Within this time window of 11 HRS waves, we restricted the observations to those individuals who were continuously observed between the ages of 60 to 61 and 70 to 71 years (i.e., covering six assessments per individual). We conducted a single stochastic imputation for missing values on 17.94% of all data points (Allison, 2002). We selected the age range from 60 to 70 because this was the longest time span available for all individuals observed between 1992 and 2012 (for more details see Table 1 in Calvo et al., 2018). The imputation model included all variables in our model and supplementary demographic, socioeconomic, and health variables. The final balanced panel data set included 7,880 individuals observed six times between the ages of 60 and 70 over a 10-year period between 1992 and 2012 (i.e., 47,280 observations). Although the odds of being in the final sample relative to the initial HRS cohort were relatively higher for older individuals, females, and individuals with better health, selectivity effects by other sociodemographics and health variables were overall fairly small (see appendix Figure A1). Furthermore, we included all these variables as covariates in our fully adjusted models.

Measures

Functional ability.—Functional ability was measured by counting the lack of limitations to perform 10 ADLs: walking across a room, getting dressed, taking a bath, eating, getting in/out bed, walking one block, sitting for 2 hr, getting up from a chair, picking up a dime from the table, and reaching the arms above the shoulders. The sum score tolerated up to one missing indicator and ranged from 0 to 10, with higher values indicating better functional ability.

Retirement sequences.—We measured retirement sequences based on an indicator developed by Calvo et al. (2018). Using sequence and cluster analysis for the same data we used in the present study, the authors identified six types of retirement sequences: *early,* where most individuals were retired by the age of 62 (n = 2,889); *ambiguous,* characterized by people who were out of the labor force and moved to formal retirement (n = 865); *complete,* including mostly people who followed a traditional career, completely retiring at age 66 from full-time jobs (n = 1,446); *late,* where individuals usually delayed retirement to keep working in a full-time job until age 66 (n = 920); *partial,* composed mainly of people who started their sequence with a full-time job and retired at age 66 (n = 1,224); and *compact,* including mostly individuals who started their career with part-time jobs and ended it in partial retirement (n = 536).

Covariates.—To adjust for self-selection, confounding, and omitted variable bias, we included a wide range of covariates in our models. Because socioeconomic status (SES) is known to be a strong predictor of physical functioning in general (Marmot, Shipley, Brunner, & Hemingway, 2001; Yang, Konttinen, Martikainen, & Silventoinen, 2018) and

ADLs in particular (Freedman, Martin, Schoeni, & Cornman, 2008; Jagger, Matthews, Melzer, Matthews, & Brayne, 2007; Lee, Xu, & Lee, 2014; Taylor & Lynch, 2004), we included three measures of SES as covariates: educational level (less than 12 years of education, 12 years, and more than 12 years), household total wealth measured in 2010 constant US$1,000, and type of occupation for the job with longest tenure (white-, pink-, and blue-collar worker, as well as never worked). Although we originally included individual-level wealth, it was not statistically significant and did not add to the variance explained by our model and thus was dropped from the final models. Sociodemographic covariates for gender and race/ethnicity (White non-Hispanic, Black non-Hispanic, Other non-Hispanic, and Hispanic) were also included in the models, together with health-related covariates for self-reported health (5-point scale ranging from *poor* to *excellent*), depressive symptomatology based on a count of eight depressive symptoms from a reduced version of the Center for Epidemiological Studies–Depression (CES-D) scale, body mass index (BMI) categories (underweight, normal, overweight, and obese), number of chronic diseases at ages 60 to 61 (ranging from 0 to 8), and lifestyle indicators of drinking (abstainer, soft, moderate, and heavy) and smoking habits (ever, current, never).

As retirement sequences and functional ability in old age are also known to be codetermined by earlier life-course antecedents (Lyu & Burr, 2016), we included two additional covariates: childhood SES, measured as years of education of the highest educated parent (Luo & Waite, 2005), and cumulative stress exposure, measured as an allostatic load index averaging the *z* scores of the following biomarkers and physical measures: C-reactive protein, glycated hemoglobin, high-density lipoprotein cholesterol, total cholesterol, BMI, waist circumference, systolic blood pressure, and diastolic blood pressure (Delpierre et al., 2016; Stephan, Sutin, Luchetti, & Terracciano, 2016).

Statistical Analyses

Age-related trajectories in functional ability were estimated using hierarchical linear models (HLMs) for longitudinal data, also known as mixed-effects regressions (Raudenbush & Bryk, 2002; Snijders, 1996). This technique allows for the modeling of intercepts and slopes in a nested data structure of repeated measurements within individuals, incorporating both time-varying and time-invariant covariates. We estimated sequential models. Model 1 was a null model used to calculate the percentage of unexplained variance in functional ability. Next, we replicated this model including only the effect of age to test for nonlinearity and identify the form of the trajectories in functional ability (results available from the authors upon request). We tested linear, quadratic, and cubic forms for the age-related effect, obtaining significant results for the linear and quadratic form. Model 2 allowed baseline levels (intercepts) in functional ability to vary across retirement sequences by adding a set of dummies that captured the main effects of following the *early, ambiguous, late, partial,* or *compact* sequence, as opposed to following the *complete* sequence. Model 2 tested whether the effect of age—both in magnitude and in shape—was the same or different across retirement sequences. This model allowed both slopes and shapes in functioning trajectories to vary across retirement sequences by adding interaction terms between the sequences and both age and its squared term. Finally, Model 3 was fully adjusted by sociodemographics and life-course antecedents.

To further address self-selection by observed characteristics, we conducted additional analyses. First, we analyzed the effect of the retirement sequences over functional ability based on a full matching procedure using propensity score (Hansen, 2004; Rosenbaum, 2002). This matching procedure is a variant of propensity score matching that creates a matched sample composed of blocks of individuals, where one treated individual is matched with one or more controls (or vice versa), making these individuals comparable in all observed characteristics, while avoiding decreases in sample size. We used all covariates described above to create balanced samples at a baseline of treated and control individuals for all possible pairs of sequences. This allowed us to estimate average treatment effects (ATE) by comparing treated individuals and controls with equivalent features in their observed covariates at ages 60 to 61, but who followed different retirement sequences. As the full matching procedure creates blocks of individuals, where one treated individual is matched with one or more controls (or vice versa), the ATE was estimated using a hierarchical regression model with weights that corrected for the number of treated and control individuals in each block. Second, based on the marginal effects obtained from Model 3, we explored for heterogeneous associations between retirement sequences and functioning across class (i.e., wealth, education, and occupation), gender, and race/ethnicity. For example, some individuals may choose an *early* sequence due to their good socioeconomic position, making the effect of an *early* sequence over functional ability different for those who are better off when compared with those who are in a more disadvantaged position.

Results

Table 1 presents descriptive statistics at the baseline by retirement sequence. Overall, the *early* and *ambiguous* sequences are characterized by disadvantages in functional ability and most covariates, providing preliminary evidence in favor of a self-selection effect. That is, individuals who are worse off tend to follow *early* and *ambiguous* sequences.

Table 2 presents results from the HLMs. The ICC calculated from Model 1 suggests that 50.4% of variation in functional ability is between individuals. Model 2 includes retirement sequences and the interaction terms between each sequence and both age and age squared, which allows modeling the baseline level (intercept), as well as rate and shape of decline (slope) of trajectories in functional ability. Model 3 presents similar analyses but is adjusted for sociodemographic covariates and life-course antecedents.

We found consistent results in Models 2 and 3 (highlighted in grey), suggesting that individuals in the *early* and *ambiguous* sequences have a lower baseline level (intercept) and steeper nonlinear declines (slope) of functional ability, relative to individuals in the *complete* retirement sequence. Postestimation tests suggest that the *early* and *ambiguous* sequences show a similar disadvantage with respect to the *late, partial,* and *compact* sequences. Specifically, individuals in both the *early* sequence (many of whom were forced to retire due to ill health or lack of employment) and in the *ambiguous* sequence (which concentrates disabled) lose more functional ability later in the trajectory over and above the fact that their baseline level is lower relative to individuals in the other sequences.

Figure 1 illustrates the results presented in Model 3. Relative to individuals in the *complete, late, partial,* and *compact* retirement sequences, individuals in the *ambiguous* and *early* sequences show a lower level of functional ability at baseline and then follow an inverted curvilinear trajectory that begins relatively flat and then plummets.

Covariates in Table 2 had largely expected effects. Gender and education are significantly associated with functional ability. Women and individuals who have less years of education show worse functional ability. Race and wealth are not significantly associated with functional ability. As expected, self-reported health is positively associated with functional ability, whereas depressive symptomatology and number of chronic diseases have the opposite association. Higher BMI is negatively associated with functional ability. Abstainers have lower levels of functional ability when compared with those who drink moderately, following a J-shaped curve that has been widely debated in previous literature (Connor, 2006). With respect to occupation, functional ability is lower among those who have never worked and those in blue- and pink-collar activities when compared with those who are or were engaged mainly in white-collar activities. Finally, with respect to life-course antecedents, low parental education is associated with worse functional ability, while allostatic load shows no significant association.

The bottom of Table 2 reports fit statistics and variance components for the three nested models. Akaike information criterion (AIC), Bayesian information criterion (BIC), and log-likelihood suggest that model fit improved significantly with each model. At the same time, residual variance decreased across models, and variance explained at the individual level (Level 2) increased when considering covariates. Model 3 explains 48.6% of total variance between individuals. With regard to within-individual variance, Model 3 explains 19.8% of variation in functional ability when compared with the null model.

To further address self-selection by observed characteristics, we conducted additional analyses based on propensity score full matching including balanced samples of treated and control individuals that followed each pair of sequences (see appendix Table A1 for pre- and postmatching balance in all covariates). This allowed us to compare treated and control individuals with equivalent features in their observed covariates at ages 60 to 61, but who followed different retirement sequences, estimating the average effect of moving from one sequence to another.

Table 3 reports the six most relevant comparisons: individuals in the *complete, late, partial,* and *compact* sequences are matched with controls in the *early* sequence, and individuals in the *partial* and *compact* sequences are matched with controls in the *complete* sequence (see appendix Table A2 for results comparing other retirement sequences). For each comparison, we report linear and nonlinear age coefficients, ATE, and interaction terms for the ATE and age coefficients. ATEs represent the average difference in functional ability for treated individuals and controls in each fully matched sample. Using the partial-complete model as an example, we observe similar baseline functional ability levels at ages 60 to 61 (ATE = −0.01; $p = .755$), followed by a linear age-related decline for individuals in the *complete* sequence (age = −0.05, $p < .001$; age^2 = 0.00, $p = .752$) and a slower linear age-related decline for individuals in the *partial* sequence (ATE × Age = 0.04, $p < .001$; ATE × Age^2 = −0.00, $p = .243$).

Figure 2 illustrates ATEs by plotting differences in predicted values of functional ability for treated individuals and controls in each fully matched sample. As the upper Panels A to D illustrate, individuals who follow an *early* sequence have worse functional ability at the beginning and throughout their trajectories, relative to individuals who follow a *complete, late, partial,* and *compact* retirement sequence. This disadvantage for individuals in the *early* sequence is similar to that observed for individuals who followed an *ambiguous* sequence (see appendix Table A2). Panel E shows that individuals who followed a *partial* retirement sequence do not differ in their baseline functional ability levels from individuals who followed a *complete* sequence, though the latter show a steeper age-related decline. Panel F suggests that functional ability in the *compact* and *complete* sequences are similar.

Finally, we explored whether the association between sequences and ADLs varied across social groups (see appendix Figures A2 to A6). Our results remained by and large the same, with the *early* and *ambiguous* sequences having the most detrimental effects on ADLs across class, gender, and race/ethnicity. If anything, we find that the detrimental marginal effects for the *early* and *ambiguous* sequences might be even stronger for individuals with parents with less than 8 years of education than individuals with more educated parents, as well as for Blacks than Whites. The *ambiguous* sequence might also be more detrimental for Others than Whites.

Discussion

We used a nationally representative longitudinal sample of older Americans, observed between ages 60 to 61 and 70 to 71 years, to assess the association between retirement sequences and trajectories of functional ability in old age over time. We conducted our analyses measuring functional ability as the absence of limitations to perform ADLs.

Previous literature has addressed the association between labor force participation and functional ability in old age by assessing labor force status or transition as a snapshot (Calvo et al., 2013; Iparraguirre, 2014). We contribute to the extant literature by focusing on retirement movies rather than snapshots, that is, we used six previously established types of retirement sequences that describe longitudinal successions of labor force statuses and transitions between the ages of 60 and 70. Our results suggest that the association between retirement sequences and trajectories of functional ability is only partly explained by self-selection and common causes experienced earlier in the life-course. In addition to self-selection and life-course antecedents, characteristics of the retirement sequence itself, such as the prevalence of statuses and the timing and speed of transitions throughout the sequence, seem to be an important factor to consider in the study of the relationship between retirement sequences and trajectories in functional ability in old age.

As expected, we found that individuals following dissimilar retirement sequences differ in their baseline levels of functional ability, showing evidence in favor of a self-selection effect (Flippen & Tienda, 2000). Beyond these baseline differences (as assessed using longitudinal

HLM and propensity full score matching), individuals following dissimilar retirement sequences also differ in the trajectories of their functional ability across a 10-year time window. Different retirement sequences were linked with different slopes of the ADL trajectories. Self-selection is unlikely to be the only explanatory mechanism, given that slopes were different even after adjusting the models for a number of variables (including clinical indicators for the diagnoses of chronic diseases and subclinical health markers such as allostatic load, self-reported health, other indicators that measure health status even before a disease may develop, and life-course antecedents such as parental education).

Functional ability for individuals in the *complete* sequence, those who completely retire from a full-time job around legal retirement age, is very similar to the trajectories of functional ability for individuals who follow a *compact* sequence characterized by partial retirement from a part-time employment. Individuals in the *late* and *partial* sequence, characterized by delayed and partial retirements from full-time jobs, respectively, together with individuals in the *complete* and *compact* sequences, experience more favorable functional ability trajectories than individuals who follow a sequence characterized by *early* retirement, as well as individuals who follow an *ambiguous* sequence characterized by being out of the labor force for reasons other than retirement, such as unemployment, disability, or housemaking. Individuals in the *early* and *ambiguous* retirement sequences begin with a disadvantage in functional ability, which tends to aggravate further as they approach their 70s. These results are consistent with the argument that retiring at younger ages or being out of the labor force accelerates age-related decline in functional decline, most likely because of decreased physical activity (Dhaval et al., 2008; Jokela et al., 2010; Mein et al., 2003; Menec, 2003; Stenholm et al., 2014). Departing from a snapshot approach, however, our results call attention to the potential benefits of retirement sequences where older adults keep partially engaged with the labor force.

Our findings are not without limitations. First, causality could go in both directions (Hessel, 2016). Adjusting for sociodemographics and life-course antecedents—including childhood SES and an allostatic load score of cumulative stress exposure—as well as estimating the results with propensity score full matching suggests that it is plausible to conclude that there are effects that go from retirement sequences to functional ability. For example, as previous literature has documented, job setting characteristics in later midlife may have an effect over functional ability even 20 years later (Nilsen et al., 2016). However, individuals may of course choose to follow retirement sequences based on their preexisting functional ability levels. Furthermore, functional ability is a multidimensional concept that may be measured in several ways (Clouston et al., 2013). We only focus on ADLs because it is a widely used indicator in the literature. Future research should assess how these observed differences may vary across countries and cohorts, as well as how they could be related to other meaningful health outcomes, such as cognitive functioning, different chronic conditions, and mortality.

Despite limitations and areas for future research, our results have important practical implications. The magnitude of the associations that we observed between retirement sequences and functional trajectories are quite considerable. As an illustration, the difference in the functional ability intercept between the *early* and both *compact* and *partial* sequences is more than two times bigger than the average difference observed between individuals who have less than 12 years of education and individuals with 12 years of education throughout the functional ability trajectory.

Our findings also have policy salience. In a context with an unprecedented demographic structure like the one we have today and with a rapidly increasing number of individuals living into older ages, policy solutions are required to simultaneously promote productive and healthy aging, with functional ability levels that allow older adults to enjoy longer lives and a better quality of life. Today, numerous studies suggest that early retirement can have detrimental health effects (Calvo et al., 2013; Dhaval et al., 2008; Jokela et al., 2010; Mein et al., 2003; Menec, 2003; Stenholm et al., 2014), but exclusively promoting later retirement sequences as a new conventional policy prescription might prove insufficient to face the challenges of an aging population. Thus, policy innovation is not an option, but a must.

Considering retirement sequences, rather than a single transition, suggests that it could be beneficial to develop more and different ways of being productively engaged in the labor force and beyond to progress into later life with better functional ability. As can be expected, the old conventional model, where people completely retired at expected ages from full-time jobs (*complete* sequence) and the new conventional model of continued employment promoted by scholars and policy makers (*late* sequence) are both associated with better functional ability, relative to showing weaker attachment to the labor force (*early* and *ambiguous* sequences). Interestingly, alternative unconventional models (*partial* and *compact* sequences) are also associated with better functional ability. These unconventional models entail combinations of part-time jobs and partial retirement, which may be considered as new ways of active engagement in productive activities that could help to protect functional ability in old age.

In sum, the unprecedented demographic structure we live in today requires novel solutions for promoting productive and healthy aging. Our study contributes to these potential solutions with new evidence resulting from a dynamic approach, which helps outline some promising alternatives to the current policy debate that has narrowly focused on delaying retirement and promoting continued employment into later life.

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Appendix

Table A1.

Pre- and Postmatching Standardized Differences Between Treated and Control Groups for Each Comparison.

	Complete-early		Late-early		Partial-early		Compact-early		Partial-complete	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Gender	−0.22***	−0.01	−0.39***	−0.01	−0.26***	−0.02	0.47***	−0.02	−0.04	0.02
Race	0.06	0.00	0.11**	0.00	−0.12***	0.00	−0.02	0.00	−0.17***	0.00
Education	0.11***	−0.01	0.17***	−0.02	0.33***	0.00	0.14**	0.02	0.22***	0.00
Household wealth	−0.05	−0.03	0.05	0.02	0.13***	0.00	0.16***	0.02	0.18***	0.03
Self-reported health	0.31***	−0.01	0.47***	0.00	0.44***	−0.02	0.36***	0.03	0.14***	0.01
Depressive symptoms	−0.23***	−0.03	−0.23***	0.00	−0.33***	−0.02	−0.21***	0.01	−0.12**	0.00
Chronic diseases	−0.14***	0.00	−0.15***	−0.03	−0.28***	0.01	−0.13**	0.00	−0.14***	0.02
BMI	−0.02	0.00	−0.04	0.01	−0.05	−0.01	−0.16***	−0.03	−0.02	−0.02
Drinking condition	0.04	−0.02	0.01	0.01	0.16***	0.00	−0.10*	0.00	0.12**	0.00
Smoking condition	0.01	−0.01	−0.03	0.00	−0.12***	0.00	−0.16**	0.02	−0.13***	0.03
Occupation	−0.03	0.01	−0.10**	0.02	−0.24***	−0.02	−0.15**	−0.01	−0.21***	−0.03
Parental education	0.03	−0.02	0.05	−0.01	0.19***	0.01	0.05	0.02	0.16***	0.01
Allostatic load	−0.01	−0.01	−0.02	0.03	−0.09**	0.01	−0.16***	−0.02	−0.09*	0.00

	Compact-complete		Ambiguous-complete		Late-complete		Ambiguous-early		Ambiguous-late	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Gender	0.71***	0.00	1.21***	−0.01	−0.17***	−0.01	0.88***	0.00	1.56***	−0.03
Race	−0.07	−0.03	0.22***	−0.04	0.05	0.02	0.3***	−0.01	0.17***	0.00
Education	0.03	0.00	−0.51***	−0.02	0.06	0.01	−0.4***	−0.05	−0.57***	−0.03
Household wealth	0.19***	0.00	0.01	0.02	0.09*	0.02	−0.04	0.00	−0.08	0.01
Self-reported health	0.07	−0.03	−0.46***	−0.02	0.18***	−0.01	−0.13***	0.02	−0.62***	−0.04
Depressive symptoms	0.02	0.02	0.42***	0.00	0.00	0.02	0.18***	0.02	0.41***	0.01
Chronic diseases	0.01	0.03	0.14**	0.02	−0.01	0.01	−0.01	−0.03	0.14**	0.01
BMI	−0.15**	0.00	0.01	0.03	−0.02	−0.01	−0.01	−0.03	0.03	0.00
Drinking condition	−0.14**	−0.01	−0.44***	0.00	−0.03	0.03	−0.39***	−0.04	−0.43***	−0.01
Smoking condition	−0.16**	−0.01	−0.19***	0.01	−0.03	0.01	−0.19***	0.00	−0.16***	0.02
Occupation	−0.12*	0.01	−0.44***	0.01	−0.07	0.00	−0.48***	0.08*	−0.37***	−0.01

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	Complete-early		Late-early		Partial-early		Compact-early		Partial-complete	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Parental education	0.03	0.01	−0.3***	0.04	0.03	0.01	−0.27***	0.00	−0.32***	−0.02
Allostatic load	−0.15**	−0.02	−0.06	0.00	−0.01	−0.01	−0.06	−0.02	−0.04	−0.01

	Ambiguous-partial		Ambiguous-compact		Partial-late		Compact-late		Partial-compact	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Gender	1.30***	−0.04	0.54***	−0.08	0.13**	−0.02	0.92***	0.01	−0.76***	0.02
Race	0.4***	0.00	0.28***	0.04	−0.22***	−0.01	−0.12*	0.03	−0.09	0.01
Education	−0.76***	−0.05	−0.55***	−0.03	0.16***	0.02	−0.03	−0.01	0.19***	0.03
Household wealth	−0.17***	−0.02	−0.17**	0.01	0.07	0.01	0.09	0.00	−0.03	−0.01
Self-reported health	−0.6***	−0.05	−0.5***	−0.11*	−0.04	0.02	−0.10	−0.01	0.07	0.03
Depressive symptoms	0.54***	0.01	0.38***	−0.02	−0.12**	−0.01	0.02	0.03	−0.14**	−0.02
Chronic diseases	0.28***	0.03	0.12*	0.02	−0.12**	−0.01	0.02	0.05	−0.15**	−0.05
BMI	0.04	−0.02	0.15**	−0.01	−0.01	−0.02	−0.13*	0.04	0.12*	0.00
Drinking condition	−0.59***	−0.03	−0.33***	0.02	0.15***	0.00	−0.11*	−0.03	0.27***	0.03
Smoking condition	−0.07	−0.03	−0.03	0.00	−0.1*	0.00	−0.12*	−0.01	0.04	−0.03
Occupation	−0.25***	0.03	−0.33***	0.02	−0.14**	−0.02	−0.05	0.00	−0.10	−0.01
Parental education	−0.47***	−0.02	−0.32***	−0.03	0.13**	0.03	0.00	−0.04	0.14**	−0.02
Allostatic load	0.03	0.02	0.09	0.00	−0.07	−0.01	−0.14*	0.01	0.07	−0.01

Note. Nonsignificant postmatching coefficients with magnitude close to zero suggest that the full matching procedure was successful, reaching a balanced sample of blocks. BMI = body mass index.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table A2.

ATE of Retirement Sequences on Functional Ability.

	Complete-early	Late-early	Partial-early	Compact-early	Partial-complete
Age	0.02 (0.01)**	0.02 (0.01)**	0.02 (0.01)**	0.02 (0.01)**	−0.05 (0.01)***
Age^2	−0.01 (0.00)***	−0.01 (0.00)***	−0.00 (0.00)***	−0.01 (0.00)***	0.00 (0.00)
ATE	0.62 (0.05)***	0.69 (0.05)***	0.60 (0.05)***	0.58 (0.06)***	−0.01 (0.04)
ATE × Age	−0.08 (0.02)***	−0.02 (0.02)	−0.02 (0.02)	−0.04 (0.03)	0.04 (0.02)***
ATE × Age^2	0.01 (0.00)***	0.00 (0.00)	0.00 (0.00)*	0.00 (0.00)	−0.00 (0.00)

	Complete-early	Late-early	Partial-early	Compact-early	Partial-complete
Observations	26,010	22,854	24,678	20,550	16,020
Individuals	4,335	3,809	4,113	3,425	2,670
Blocks	1,620	1,130	1,410	774	1,100

	Compact-complete	Ambiguous-complete	Late-complete	Ambiguous-early	Ambiguous-late
Age	−0.05 (0.01) ***	−0.08 (0.03) **	−0.05 (0.01) ***	0.02 (0.01)	−0.07 (0.07)
Age^2	0.00 (0.00)	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00) ***	0.00 (0.01)
ATE	−0.03 (0.06)	−1.09 (0.18) ***	0.11 (0.05) **	−0.36 (0.14) ***	−1.01 (0.12) ***
ATE × Age	0.03 (0.03)	0.25 (0.12) **	0.01 (0.02)	0.10 (0.09)	0.08 (0.08)
ATE × Age^2	−0.00 (0.00)	−0.02 (0.01) *	0.00 (0.00)	−0.01 (0.01)	−0.01 (0.01)
Observations	11,892	13,866	14,196	22,524	10,710
Individuals	1,982	2,311	2,366	3,754	1,785
Blocks	625	606	943	934	416

	Ambiguous-partial	Ambiguous-compact	Partial-late	Compact-late	Partial-compact
Age	−0.02 (0.02)	−0.06 (0.03) *	−0.01 (0.01)	−0.01 (0.01)	−0.03 (0.02)
Age^2	0.00 (0.00)	0.00 (0.00)	−0.00 (0.00) *	−0.00 (0.00) *	−0.00 (0.00)
ATE	−0.90 (0.10) ***	−0.88 (0.09) ***	−0.08 (0.05) *	−0.12 (0.07) *	0.00 (0.06)
ATE × Age	0.07 (0.05)	0.09 (0.04) **	−0.00 (0.02)	−0.00 (0.03)	0.02 (0.02)
ATE × Age^2	−0.01 (0.00) *	−0.01 (0.00) **	0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
Observations	12,534	8,406	12,864	8,736	10,560
Individuals	2,089	1,401	2,144	1,456	1,760
Blocks	519	462	871	491	561

Note. As the full matching procedure creates blocks of individuals, where one treated individual is matched with one or more controls (or vice versa), the ATE is estimated using a hierarchical regression model with weights that correct for the number of treated and control individuals in each block. Intercepts and random components are omitted. ATE = average treatment effect.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

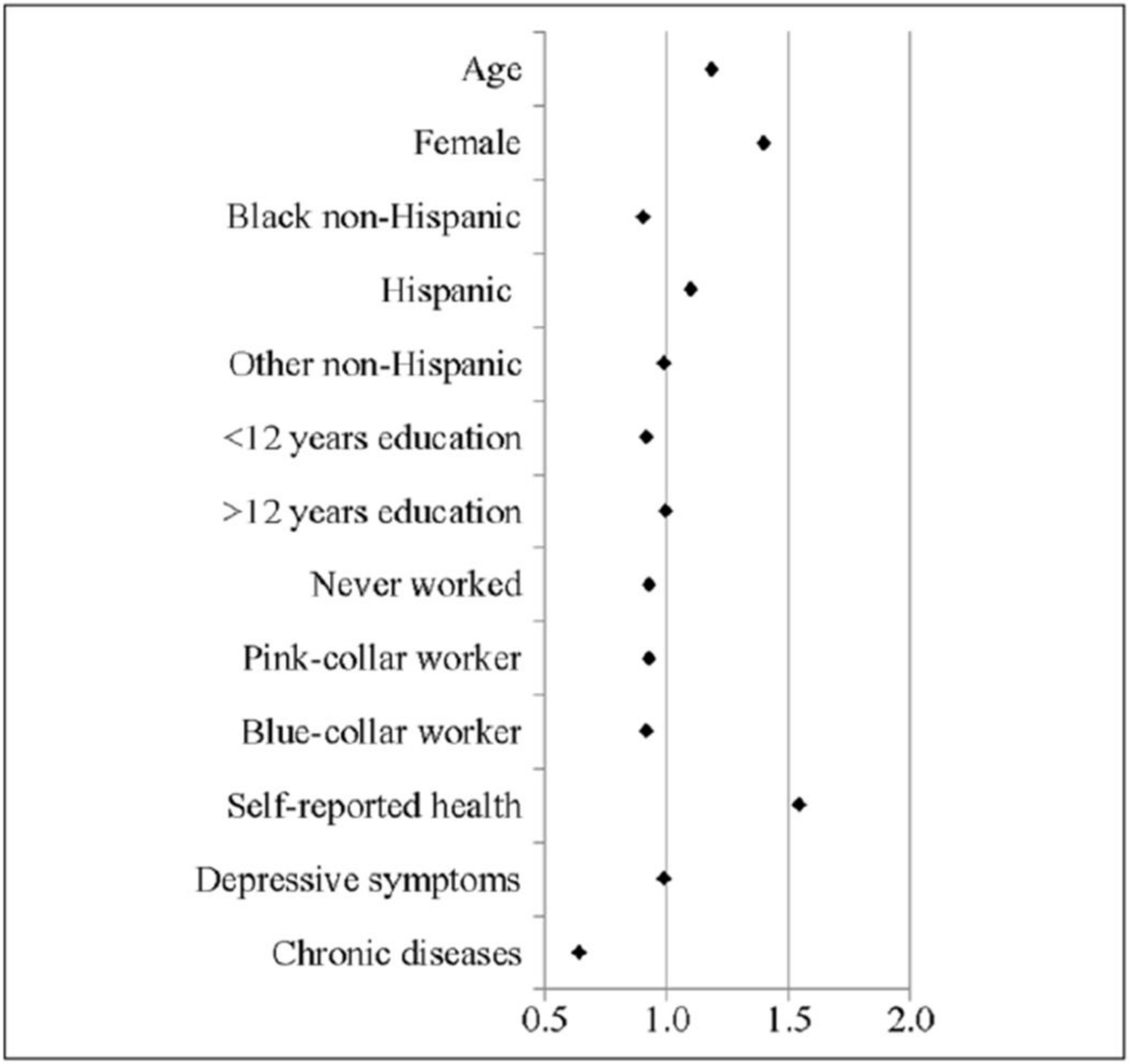

Figure A1.
Logistic regression results for sample selectivity (N = 9,752).
Note. Standardized odds ratios reported. Reference categories are White non-Hispanic, 12 years of education, and white-collar worker.

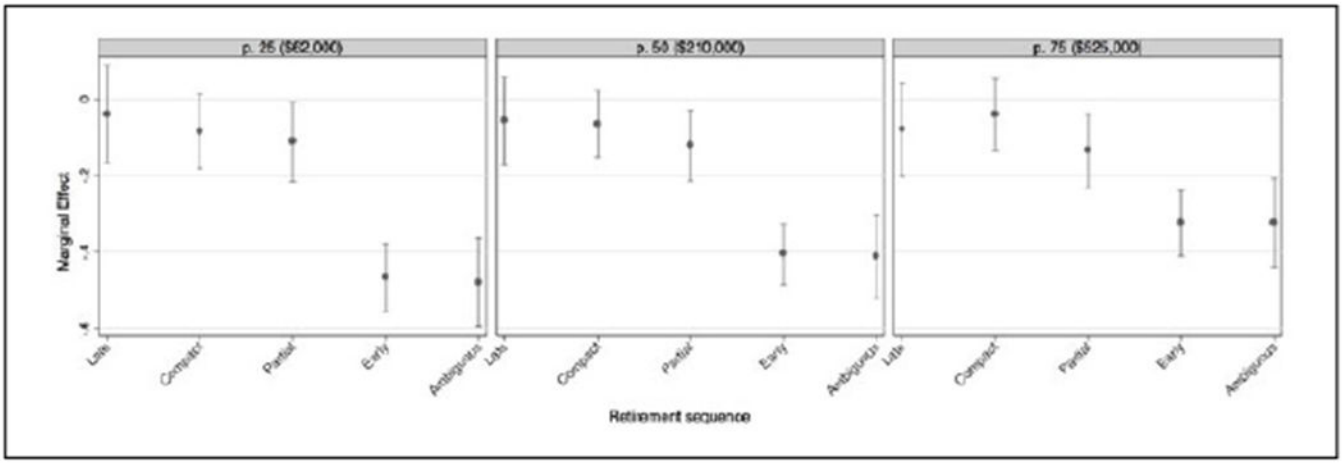

Figure A2.
Marginal effects of retirement sequences on functional ability by level of total wealth (percentiles 25, 50, and 75).
Note. The 95% confidence intervals are illustrated with brackets. “Complete” is the reference category.

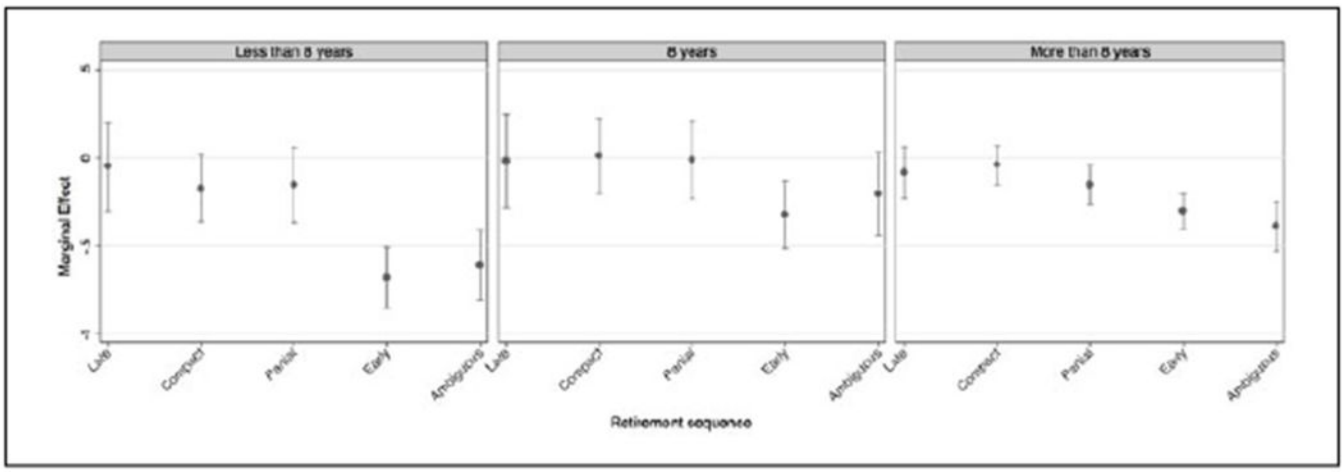

Figure A3.
Marginal effects of retirement sequences on functional ability by level of parental education.
Note. The 95% confidence intervals are illustrated with brackets. “Complete” is the reference category.

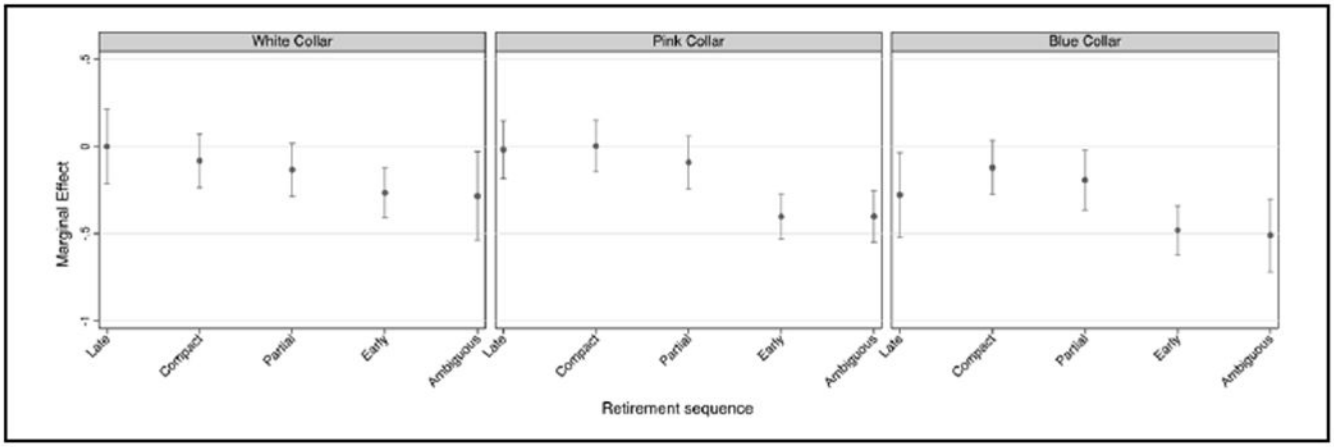

Figure A4.
Marginal effects of retirement sequences on functional ability by type of occupation.
Note. The 95% confidence intervals are illustrated with brackets. “Complete” is the reference category.

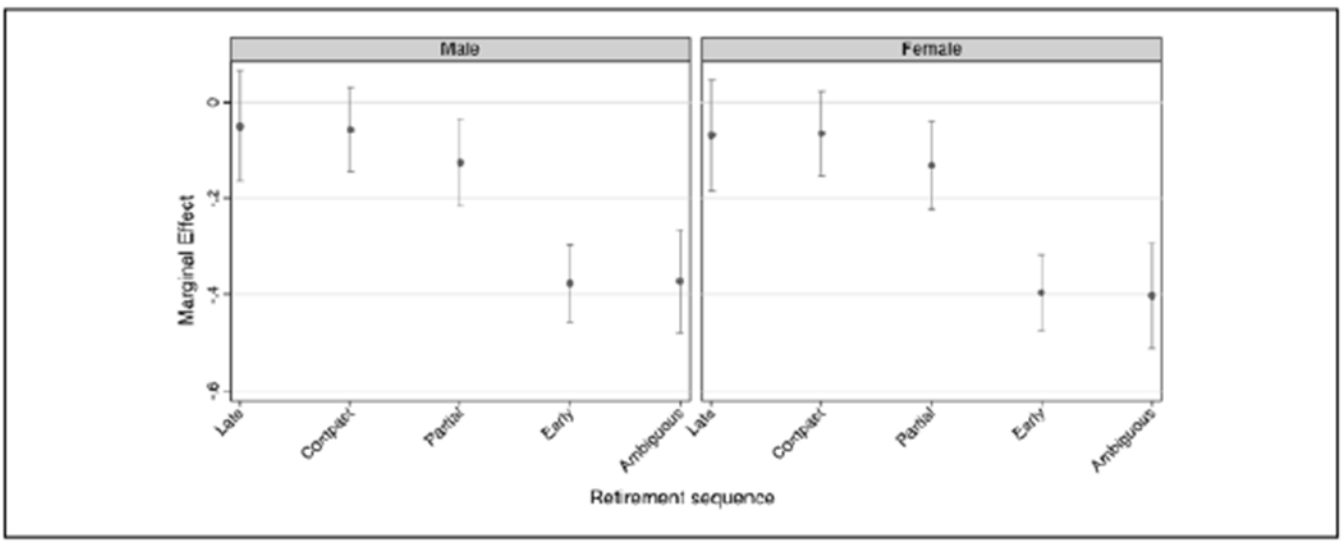

Figure A5.
Marginal effects of retirement sequences on functional ability by gender.
Note. The 95% confidence intervals are illustrated with brackets. “Complete” is the reference category.

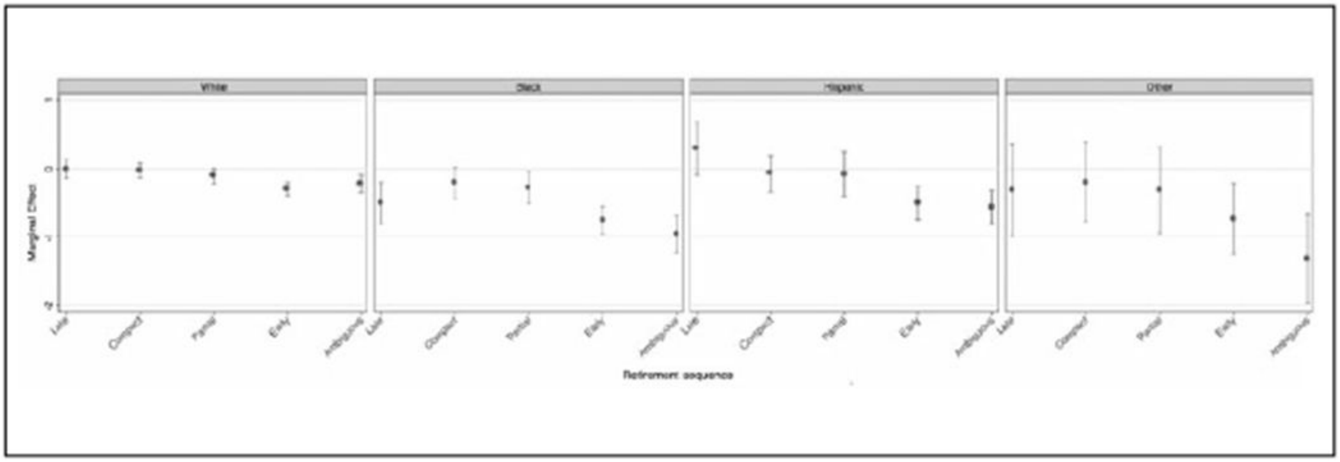

Figure A6.

Marginal effects of retirement sequences on functional ability by race/ethnicity.

Note. The 95% confidence intervals are illustrated with brackets. “Complete” is the reference category.

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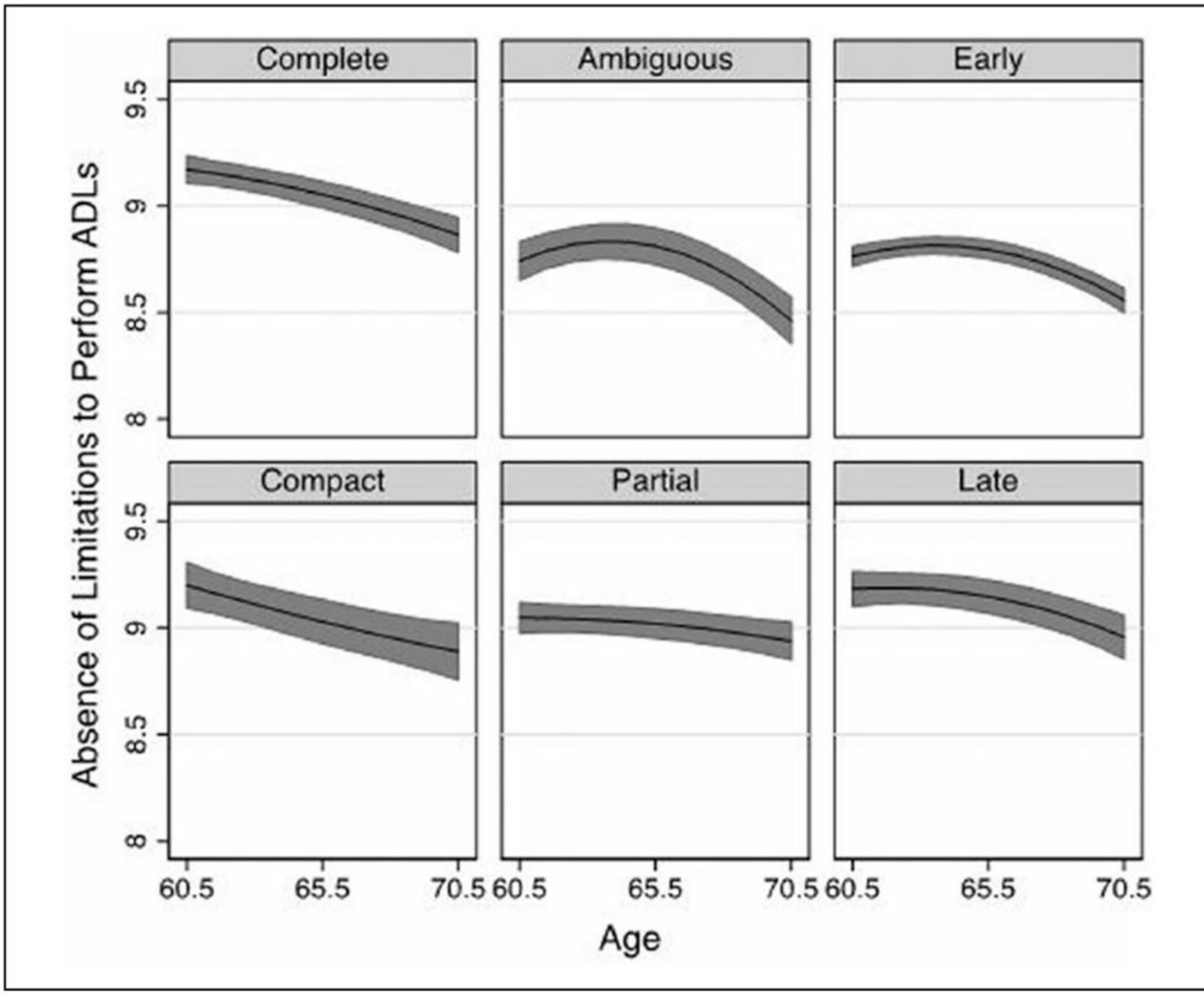

Figure 1.

Adjusted functioning trajectories by type of retirement sequence.

Note. Predicted values are calculated using the coefficients in Model 3 and setting all covariates at their mean. Shaded regions represent 95% confidence intervals around predicted values. ADLs = activities of daily living.

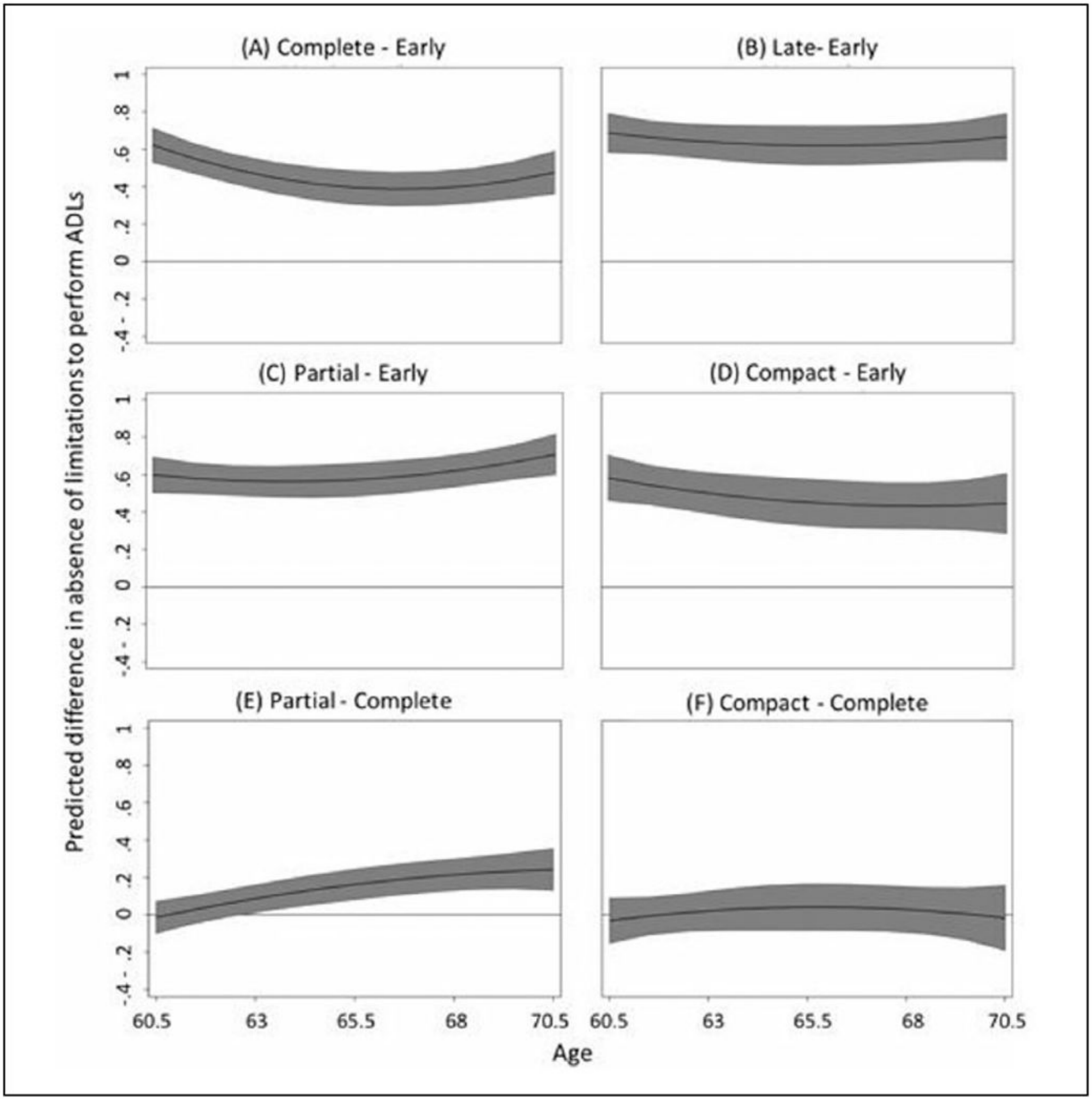

Figure 2.

Average treatment effects of retirement sequences on functional ability.

Note. Average treatment effects are represented by plotting differences in predicted values of functional ability for treated individuals and controls in each fully matched sample. The heading of each panel indicates the sequence that is modeled as the treatment group, followed by the sequence modeled as control. All estimations were conducted using fully matched balanced samples with individuals grouped in blocks: A = 4,335 individuals and 1,620 blocks, B = 3,809 individuals and 1,130 blocks, C = 4,113 individuals and 1,410 blocks, D = 3,425 individuals and 774 blocks, E = 2,670 individuals and 1,100 blocks, and *F* = 1,982 individuals and 625 blocks. The 95% confidence intervals (CI) around difference scores are represented with a gray area. ADLs = activities of daily living.

Table 1.

Descriptive Statistics by Type of Retirement Sequence at Ages 60 to 61.

	Complete	Partial	Early	Late	Ambiguous	Compact
Functioning to perform ADLs	9.34[a]	9.33[a]	8.70[b]	9.43[a]	8.42[c]	9.34[a]
	(1.10)	(1.09)	(1.85)	(1.03)	(2.06)	(1.16)
Female	44.54%[a]	42.57%[a]	55.59%[b]	36.20%[c]	94.91%[d]	78.17%[e]
Race						
White non-Hispanic	72.0%[a]	79.2%[b]	73.6%[a]	71.3%[a,c]	65.0%[c]	77.1%[a,b]
Black non-Hispanic	16.3%[a,b]	13.7%[a,b]	17.1%[a]	14.5%[a,b]	12.5%[b]	12.7%[a,b]
Other non-Hispanic	2.1%[a]	1.8%[a]	1.8%[a]	2.4%[a]	2.2%[a]	3.0%[a]
Hispanic	9.6%[a,c]	5.3%[b]	7.5%[a,b]	11.8%[c]	20.3%[d]	7.3%[a,b,c]
Education						
Less than 12 years	24.5%[a]	16.0%[b]	28.0%[a]	23.5%[a]	43.4%[c]	23.1%[a]
12 years	36.0%[a]	36.0%[a]	37.5%[a]	33.2%[a]	37.6%[a]	36.0%[a]
More than 12 years	39.6%[a]	48.0%[b]	34.6%[c]	43.4%[a,b]	19.1%[d]	40.9%[a,b,c]
Total household wealth in US$1,000	383.2[a]	528.8[b]	422.8[a]	462.6[c]	389.6[a]	558.5[b, c]
	(744.9)	(869.2)	(768.3)	(462.6)	(788.9)	(1,297.1)
Self-reported health (1-5)	3.45[a]	3.59[b]	3.10[c]	3.63[b]	2.94[d]	3.52[a,b]
	(1.04)	(1.00)	(1.19)	(1.06)	(1.20)	(1.11)
Depressive symptomology (0-8)	1.29[a]	0.95[a]	1.60[b]	1.13[a]	2.00[c]	1.20[a]
	(1.81)	(1.50)	(2.01)	(1.71)	(2.30)	(1.73)
BMI						
Underweight	1.0%[a,b]	0.4%[a]	0.9%[a,b]	0.8%[a,b]	1.6%[a,b]	1.9%[b]
Normal	28.8%[a]	31.9%[a,b]	30.9%[a,b]	30.9%[a,b]	34.7%[b]	36.0%[b,c]
Overweight	46.3%[a]	43.6%[a,b]	40.6%[b]	43.9%[a,b]	31.4%[c]	40.3%[a,b]
Obese	24.0%[a]	24.1%[a]	27.6%[a,b]	24.5%[a]	32.3%[b]	21.8%[a]
Chronic diseases (0-8)	1.62[a]	1.41[b]	1.85[c]	1.60[a,b]	1.84[c]	1.64[a,b,c]
	(1.59)	(1.44)	(1.62)	(1.79)	(1.59)	(1.72)
Drinking						
Abstainer	45.9%[a]	37.5%[b]	48.5%[a]	47.0%[a]	67.1%[c]	50.6%[a]
Soft (<1/day)	40.0%[a]	47.5%[b]	38.2%[a]	39.0%[a]	27.5%[c]	39.9%[a,b]
Moderate (1-2/day)	10.3%[a]	11.4%[a]	9.2%[a]	11.5%[a]	4.5%[b]	7.5%[a,b]
Heavy (3+/day)	3.8%[a]	3.7%[a]	4.1%[a]	2.5%[a,b]	0.9%[b]	2.1%[a,b]
Smoking						
Never	35.3%[a]	39.2%[a]	36.0%[a]	37.8%[a]	50.1%[b]	47.6%[b]
Ever	39.4%[a]	41.4%[a]	38.5%[a]	37.0%[a]	25.2%[b]	27.4%[b]
Current	25.3%[a]	19.4%[b]	25.5%[a]	25.2%[a]	24.7%[a]	25.0%[a,b]
Occupation						
Never worked	0.04%	0.2%[a]	1.5%[b]	0.04%	21.5%[c]	0.04%
White-collar	31.5%[a,e]	39.3%[b]	25.9%[c]	33.5%[a,b]	9.8%[d]	25.4%[c,e]
Pink-collar	34.4%[a]	35.0%[a]	38.7%[a]	36.3%[a]	52.0%[b]	56.2%[b]

	Complete	Partial	Early	Late	Ambiguous	Compact
Blue-collar	34.1%[a]	25.5%[b]	34.0%[a]	30.2%[a,b]	16.6%[c]	18.5%[c]
Parental education						
<8 years	21.4%[a]	15.0%[b]	21.9%[a]	21.1%[a]	33.4%[c]	19.4%[a,b]
8 years	17.9%[a]	18.1%[a]	18.9%[a]	16.3%[a]	19.0%[a]	19.6%[a]
>8 years	60.7%[a]	66.9%[b]	59.1%[a]	62.6%[a,b]	47.6%[c]	61.0%[a,b]
Number of individuals	1,446	1,224	2,889	920	865	536

Note. For dichotomous variables we report percentages rather than means. Standard errors are reported in parentheses. Values in the same row that do not share the same superscript are significantly different at $p < .05$. For time-varying variables, we show values at ages 60 to 61. ADLs = activities of daily living; BMI = body mass index.

Table 2.

Mixed-Effects Regression Results for Trajectories in Functional Ability (N = 7,880).

	Model 1	Model 2	Model 3
Intercept	8.89 (0.02) ***	9.33 (0.04) ***	7.98 (0.08) ***
Age (slope)		−0.05 (0.01) ***	−0.02 (0.01) *
Age^2 (slope^2)		0.00 (0.00)	−0.00 (0.00)
Sequence			
Early		−0.63 (0.05) ***	−0.42 (0.04) ***
Ambiguous		−0.90 (0.06) ***	−0.44 (0.06) ***
Late		0.09 (0.06)	0.01 (0.05)
Partial		0.00 (0.06)	−0.13 (0.05) ***
Compact		0.01 (0.07)	0.02 (0.06)
Early × Age		0.08 (0.01) ***	0.05 (0.01) ***
Ambiguous × Age		0.09 (0.02) ***	0.07 (0.02) ***
Late × Age		0.04 (0.02) **	0.02 (0.02)
Partial × Age		0.04 (0.02) **	0.02 (0.02)
Compact × Age		−0.00 (0.02)	−0.02 (0.02)
Early × Age^2		−0.01 (0.00) ***	−0.00 (0.00) ***
Ambiguous × Age^2		−0.01 (0.00) ***	−0.01 (0.00) ***
Late × Age^2		−0.00 (0.00)	−0.00 (0.00)
Partial × Age^2		−0.00 (0.00)	0.00 (0.00)
Compact × Age^2		0.00 (0.00)	0.00 (0.00)
Gender			
Female			−0.13 (0.03) ***
Race			
Black non-Hispanic			0.08 (0.04) **
Hispanic			0.02 (0.05)
Other non-Hispanic			−0.01 (0.09)
Education			
<12 years			−0.13 (0.03) ***
>12 years			−0.03 (0.03)
Total household wealth (log)			−0.08 (0.01) ***
Self-reported health (1-5)			0.29 (0.0l) ***
Depressive symptomatology (0-8)			−0.13 (0.00) ***
Chronic diseases at age 60 (0-8)			−0.01 (0.05)
BMI			
Underweight			−0.04 (0.02) **

	Model 1	Model 2	Model 3
Overweight			−0.18 (0.02)***
Obese			−0.14 (0.01)***
Drinking			
Abstainer			−0.08 (0.03)***
Soft (<l/day)			−0.02 (0.02)
Heavy (3+/day)			0.02 (0.04)
Smoking			
Ever			−0.02 (0.02)
Current			0.09 (0.02)***
Occupation			
Never worked			−0.18 (0.08)**
Pink-collar			−0.05 (0.03)
Blue-collar			−0.05 (0.04)
Parental education			
<8 years			−0.08 (0.04)**
>8 years			0.01 (0.03)
Allostatic load (*z* scores)			0.03 (0.03)
Goodness of fit			
AIC	157,482.7	154,239.6	149,333.15
BIC	157,509.0	154,423.7	149,727.52
Log-likelihood	−78,738.3	−77,098.8	−74,621.58
Variance/covariance			
Individuals (intercept)	1.70	1.43	0.84
Individuals age		0.01	0.01
Residual	1.11	0.91	0.89

Note. Reference categories are *complete* retirement sequence (and corresponding interactions), White non-Hispanic 12 years of education, normal BMI, moderate drinking, never smoked, white-collar occupation, and 8 years parental education. BMI = body mass index; AIC = Akaike information criterion; BIC = Bayesian information criterion.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 3.

ATE of Retirement Sequences on Functional Ability (Propensity Score Full Matching).

	Complete-early	Late-early	Partial-early	Compact-early	Partial-complete	Compact-complete
Age (slope)	0.02 (0.01) **	0.02 (0.01) **	0.02 (0.01) **	0.02 (0.01) **	−0.05 (0.01) ***	−0.05 (0.01) ***
Age^2 ($slope^2$)	−0.01 (0.00) ***	−0.01 (0.00) ***	−0.00 (0.00) ***	−0.01 (0.00) ***	0.00 (0.00)	0.00 (0.00)
ATE	0.62 (0.05) ***	0.69 (0.05) ***	0.60 (0.05) ***	0.58 (0.06) ***	−0.01 (0.04)	−0.03 (0.06)
ATE × Age	−0.08 (0.02) ***	−0.02 (0.02)	−0.02 (0.02)	−0.04 (0.03)	0.04 (0.02) ***	0.03 (0.03)
ATE × Age^2	0.01 (0.00) ***	0.00 (0.00)	0.00 (0.00) *	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Observations	26,010	22,854	24,678	20,550	16,020	11,892
Individuals	4,335	3,809	4,113	3,425	2,670	1,982
Blocks	1,620	1,130	1,410	774	1,100	625

Note. As the full matching procedure creates blocks of individuals, where one treated individual is matched with one or more controls (or vice versa), the ATE is estimated using a hierarchical regression model with weights that correct for the number of treated and control individuals in each block. Intercepts and random components are omitted. ATE = average treatment effect.

* $p < .05$.

** $p < .01$.

*** $p < .001$.