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ABSTRACT

Physical and cognitive abilities of older workers decline with age, which can cause a mismatch between abilities and job demands, potentially leading to early retirement. We link longitudinal Health and Retirement Study data to O*NET occupational characteristics to estimate to what extent changes in workers' physical and cognitive resources change their work-limiting health problems, mental health, subjective probabilities of retirement, and labor market status. While we find that physical and cognitive decline strongly predict all outcomes, only the interaction between large-muscle resources and job demands is statistically significant, implying a strong mismatch at older ages in jobs requiring large-muscle strength. The effects of declines in fine motor skills and cognition are not statistically different across differing occupational job demands.

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Introduction

Poor health is one of the strongest drivers of early retirement (Blundell, Britton, Costa Dias, and French, 2017; Cahill, Giandrea, and Quinn 2006; Fisher, Chaffee, and Sonnega 2016; McGarry 2004; Rice et al. 2011; van Rijn et al. 2014) and it reduces the likelihood of continuing work after separation from career jobs (Topa et al. 2009). Poor health or declining cognitive ability makes it more burdensome to carry out job tasks, and the magnitude of the added burden depends on job characteristics. For example, someone with minor back pain may have little difficulty carrying out the tasks of an office clerk but may be unable to carry heavy objects, a task frequently performed by construction workers. Conversely, an accountant whose memory starts to deteriorate may have more trouble performing well on the job compared to a hairdresser with early-stage memory decline.

When workers' capabilities become mismatched with the demands of their jobs, there are several ways to adjust, but changes in their work status are more likely to occur. For example, workers may initially stay in their current job positions and increase their level of effort to compensate for their decline in cognitive and physical resources. This greater effort, however, may lead to dissatisfaction with work, exhaustion, and (mental) health problems. Alternatively, employers may accommodate the changing capabilities of their aging employees. Workers may also reduce their work hours to compensate for their increased difficulty working, or switch to different jobs or tasks better suited to their changing abilities, either in the same or in a less-demanding occupation. In most scenarios workers will likely leave the labor force earlier than they would have in the absence of physical or cognitive decline.

Understanding how mismatch between individuals' resources and job demands affects labor force participation at older ages is important because early retirement may leave individuals and their families financially vulnerable at older ages. To the extent that better accommodation of mismatch allows individuals to work longer it will not only improve their own financial security, but it would also relieve financial pressures on public programs such as Social Security or Medicare. Even if employers wanted to accommodate work limitations, the mismatch between the worker's abilities and the job demands may eventually become too large, resulting in job separation. Policymakers need to understand how often this happens: such mismatches and separations may prevent workers from working to the ages they desire or had planned on.

In this paper, we study how age-related mismatch between job demands and workers' health and cognitive abilities affects retirement outcomes. We use longitudinal data from the Health and Retirement Study (HRS) linked to detailed occupational characteristics from the O*NET project.[2] We considered a large set of outcomes that signaled mismatch, but focus on five of them in this study: work-limiting health problems, depressive symptoms, the subjective probability of working full time after age 65, transition probabilities from work to retirement, and transitions to disability.

When possible, we use panel econometric models to estimate how changes in individuals' resources and the interactions between resources and job demands affect *changes* in these outcome variables. These empirical models control for individuals' initial conditions and hence are more credible than models relying on cross-sectional variation.

We consider mismatch in two physical and two cognitive domains. Regarding physical domains, we use measures from the HRS of deficits in individuals' resources or capabilities:

[2] The O*NET database (www.onetcenter.org) contains information on hundreds of standardized and occupation-specific descriptors that capture, among other things, the characteristics and requirements of the jobs, including the intensity of various activities involved in doing a particular job.

whether they have large muscle problems such as having difficulties with stooping, kneeling, or crouching, or with pushing or pulling large objects; or whether they have fine motor skill problems such as having difficulties with picking up a dime from a table and dressing. Regarding cognitive domains, we use a 27-point working and episodic memory score from the HRS, which is closely linked to fluid intelligence and decision-making abilities (Del Missier et al. 2013).

We pair these resource measures with data on detailed job demands from the O*NET project. The O*NET, sponsored by the U.S. Department of Labor's Employment and Training Administration, is based on a combination of surveys, expert assessments, and tests. The ratings are available for occupations identified by three-digit codes that can be linked to occupations of HRS respondents.

We use four O*NET job-demand measures: First, we use measures on dynamic strength, i.e., the ability to exert muscle force repeatedly or continuously. We paired these with the HRS large-muscle resource measure. Second, we use measures on finger dexterity, i.e., the ability to make precisely coordinated movements of the fingers. We pair these with the HRS fine-motor skill resource measure. Third, we use measures on memorization, i.e., the ability to remember information. We pair these with the HRS cognition-resource measure. Fourth, we use O*NET measures on analyzing data or information, also pairing them with the HRS cognition-resource measure.

We found that, among HRS respondents, large-muscle strength, fine-motor skills, and cognitive abilities significantly and strongly decline with age. Furthermore, these declines lead to higher reports of work-limiting health problems, more depressive symptoms, lower subjective probabilities of working full-time past age 65, and more transitions from full-time work to retirement and disability.

To capture the degree of job mismatch for respondents, we use terms capturing the interaction between resource decline and job demands.[3] Such terms, for example, show whether cognitive decline reduces the ability to work in all jobs or only in cognitively demanding ones. We found only one statistically significant interaction term: that for large muscle problems. Workers who develop large-muscle limitations are more likely to report changes in most outcomes when they work in occupations that rely heavily on physical strength than when they work in occupations that do not rely on physical strength. The interaction effects were large and statistically significant for work-limiting health problems, mental health, subjective work expectations, and transitions to disability. In contrast to the large muscle results, the interaction terms of workers' resources and job demands for fine motor skills and for cognition were not statistically significant, suggesting that declines in workers' fine motor skills or cognition did not lead to significant differences in their outcomes by occupational job demands.

Our preferred statistical models use panel variation for identification rather than cross-sectional variation. But, because our data are observational, we discuss threats to identification, including omitted factors, selection, and reverse causality, and we estimate alternative specifications and tests. For example, we estimate models with alternative sets of controls, we estimate models on different samples, and we estimate placebo regressions on lagged values of the outcome variables. These results support a causal interpretation, perhaps because within-person changes in the resources (health) are relatively random events in this age range.

[3] The term "mismatch" has been used in the economics literature to describe different issues, such as the misalignment of the demand and supply of skills in countries or regions (Cappelli 2015); or the difference between students' abilities and the qualities of their schools (Dillon and Smith, 2017). We, instead, define it based on workers' resources and the demands of their current jobs.

It is important to point out, however, that finding a significant causal effect (or absence of effect) does not necessarily reveal much about the mechanisms linking changes in resources to labor market outcomes. When an exogenous change in a worker's health or capabilities occurs that reduces productivity or increases the disutility of work, the consequences of that change may lead to responses by the employer or the employee to offset these effects through medical treatment, equipment, changes in hours, organization of work, task assignments and so on. A significant causal effect of an exogenous change in resources on retirement outcomes depends on whether the present value of pecuniary and non-pecuniary costs to the employer and employee of offsetting adjustments are smaller than the net benefits to both parties of continued employment. Heterogeneity in task demands and skill supplies across firms and workers due to variation in firm technology and worker skills and preferences[4] is likely to lead to considerable heterogeneity in the net costs of mismatch both within and across occupations and, therefore, to considerable unmeasured variation in the effects of exogenous changes in worker resources on retirement outcomes. In this paper, we estimate the average causal effect of mismatch for workers in the equilibrium match. The plausibly large variance in the magnitude of effects implies that there is considerable room for general equilibrium effects of policy changes that are not captured by our analysis. However, we believe that our analysis of mismatch helps distinguish types of workers and occupations for which private or public interventions to overcome mismatch are likely to be helpful.

Our work builds on several previous strands of research. Several studies have shown the role of occupational characteristics in explaining job polarization, wage inequality, and career decisions (Acemoglu and Autor 2011; Autor, Levy, and Murnane 2003; James 2011; Yamaguchi

[4] See Lindenlaub (2017) for outcomes of equilibrium sorting on multiple dimensions in the labor market.

2012, 2018), and a smaller number of papers explored the role of occupational characteristics in the retirement process (Angrisiani, Kapteyn, and Meijer 2015; Bowlus, Mori, and Robinson, 2016; Belbase, Sanzenbacher, and Gillis 2016; Sonnega et al. 2018).

The study of Belbase et al. (2016) is most closely related to ours. It showed that individuals in occupations that heavily rely on skills that tend to decline with age are more likely to retire earlier. Nevertheless, our work differs from theirs in several ways. First, we identified four dimensions of job characteristics for which the HRS elicits respondents' abilities: two cognitive and two physical. Second, in addition to analyzing the role of job demands in the timing of retirement we analyzed the role of respondents' corresponding abilities at the individual level and changes therein, which is an important but often neglected heterogeneity (Bowlus et al., 2016). Third, and maybe most importantly, we analyzed the *interaction* between abilities and job demands, whereas Belbase et al. (2016) did not use reports about workers' abilities. Fourth, we used retirement expectations data, allowing us to observe the immediate impact of changes in abilities and job mismatch. This has the further advantages of increased sample size and panel variation for identification.

Other related research in psychology explores the person-environment fit. Wang and Shultz (2010) suggested that the match between various aspects of the persons (workers) and their work environment may affect work and retirement outcomes, including well-being and retirement timing. Liebermann, Wegge, and Muller (2013) used a person-environment framework in a study of German insurance workers to explore several hypotheses related to workers' expectations of remaining in the same job until retirement. McGonagle, et al. (2015) investigate how the match between job demands, job resources and "perceived work ability" affects work-related stress and work outcomes. Sonnega et al. (2018) compared objective

(O*NET) and subjective (HRS) job-demand measures and how they interacted with HRS resource measures to predict retirement timing. We use a broader set of variables, and we use panel econometric models that are less restrictive than cross-sectional models.

In the next section, we describe the HRS and O*NET data we analyze. We then present separate sections on our methods and results. The final section presents our conclusions and a discussion of the implications and limitations of our work.

2. Data

The HRS is the primary U.S. data source for studying the retirement process.[5] It has a large sample—approximately 20,000 responses per wave—of persons at least 50 years of age, and very detailed panel information on them, including information about work, health, cognitive abilities, and socioeconomic status. The HRS has interviewed respondents biennially since 1992.

2.1. Measurement of physical and cognitive resources

The HRS has very detailed information about individuals' health, limitations in the activities of daily living (ADLs), and cognitive abilities. We use three summary measures, created by the RAND-HRS (2016),[6] in this project. Table 1 provides an overview.

The first measure is termed "large-muscle problems" and represents difficulties with mild-to-moderate physical activities. The measure comprises four items, each corresponding to the respondent's mention of any difficulty with:

1. sitting for about two hours

[5] The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan: http://hrsonline.isr.umich.edu/
[6] The RAND HRS Data file is an easy to use longitudinal data set based on the HRS data. It was developed at RAND with funding from the National Institute on Aging and the Social Security Administration www.rand.org/labor/aging/dataprod/hrs-data.html.

2. getting up from a chair after sitting for long periods
3. stooping, kneeling, or crouching
4. pulling or pushing large objects like a living room chair.

The second measure is termed “fine motor problems” and it aims to capture problems with the precise coordination of fingers, such as picking up small objects or buttoning a shirt (Hoogendam et al. 2014). Our measure sums three items from the HRS about reporting difficulties with:

1. dressing, including putting on shoes and socks
2. eating, including cutting food
3. picking up a dime from a table

The average value of this 0-3 score in our sample is only 0.047 (Table 2). Thus we anticipate that this measure will not be very discriminatory, but it will distinguish people with substantial problems (Carmeli, Patish, and Coleman 2003).

Our measure of cognitive ability is the 27-point scale of episodic memory (see Crimmins et al. 2011), which is strongly related to fluid cognitive abilities (Del Missier et al. 2013). The measure sums performance on four cognitive tests:

1. Immediate word recall of a list of 10 words (10 points)
2. Delayed word recall of the same list a few minutes later (10 points)
3. Serial subtraction of 7 from 100 five times (5 points)
4. Backward counting from 20 to 10 with two trials (2 points)

The physical measures are consistently available since 1994 for all interviews, including interviews of proxy respondents for persons unwilling or unable to do the interview. The cognition score is consistently available since 1996 but is not available in proxy interviews because cognitive abilities can only be directly tested. All three resource measures are recoded so that higher values represent more resources (better health). For the regression models we also standardized the measures to have a zero mean and a standard deviation of one in our main analytic sample, which comprises respondents 50 to 70 years of age who are working full-time.

2.2. Measurement of job demands

The HRS provides information on workers' occupations by three-digit occupational codes of the U.S. Census Bureau. The classification changed in 2006 from the 1980 to the 2000 census classifications, but cross-walks are available between these specifications (Hudomiet 2015; Carr et al. 2016). The detailed occupations are linked to detailed occupational characteristics from the O*NET data, similarly to Belbase, Sanzenbacher, and Gillis (2016) and Carr et al. (2016). We extract four key dimensions of job demands that are closely related to the resource measures. Table 1 provides an overview.

The dynamic strength dimension relates to individuals' ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue. Occupations that score the highest on this measure include fire fighters, masons and construction workers; occupations that score lowest include management, engineering and financial ones. We pair the dynamic strength measure with the HRS large-muscle resource measure.

The finger dexterity dimension describes individuals' ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects. Occupations scoring highest on this measure include dentists, aircraft mechanics, data entry keyers, and precision textile, apparel, and furnishings machine workers. Occupations scoring lowest include real estate sales, management analysists, human resource clerks and clergy. We pair this job-demand measure with the HRS fine-motor skill resource measure.

The memorization dimension describes individuals' ability to remember information such as words, numbers, pictures, and procedures. Occupations scoring highest on this measure include clergy, primary school teachers, lawyers, bartenders, and waiters/waitresses. Occupations scoring lowest include janitors, painters, vehicle washers, and textile sewing machine operators. We pair this job-demand measure with the HRS cognition-resource measure.

The "analyzing data or information" dimension captures work activities of identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts. Occupations scoring highest include management analysts and various science jobs; occupations scoring lowest include mail carriers, vehicle washers, door-to-door sales, and laundry workers. We also pair this job-demand measure with the HRS cognition-resource measure.

Appendix A.1. discusses details of defining the four job-demand measures based on the detailed HRS occupation codes. The job-demand measures range from 0 to 1. In our regression analyses we use standardized measures that have a mean of zero and standard deviation of 1.0 among 50 to 70 years old full-time workers.

2.3. The outcome variables

Our conceptual framework considers how an increasing mismatch between the resources of workers and the demands of their jobs will influence a number of outcomes. We considered a large set of outcome variables and chose the following for analysis:

- Self-reports of any impairment or health problem that limits the kind or amount of paid work respondents can do. We expect that any mismatch between individuals' resources and the demands of their jobs would increase the report of such impairments.
- The number of depressive symptoms individuals have, using the eight-item HRS version of the Center for Epidemiological Studies-Depression (CESD) Scale. We expect that any mismatch between individuals' resources and the demands of their jobs would increase the number of depressive symptoms.
- Subjective expectations to work full-time after age 65 (or 62). The HRS asks respondents, *Thinking about work in general and not just your present job, what do you think the chances are that you will be working full-time after you reach age 65 [or 62]?* This measure of expected future work is highly predictive of actual future work at age 65 or 62 (Hurd, 2009). We expect that a mismatch between a worker's resources and job demands decreases the subjective probabilities of working full-time in the future and so will predict earlier retirement.

These outcome variables are available for both workers and non-workers. They are therefore well-suited for panel econometric modeling. Depressive symptoms and subjective expectations, however, are not collected in proxy interviews due to their subjective nature.

Missing outcome variables were typically ignored in our analysis, except for subjective expectations. Beginning in 2006, the HRS asked all respondents their subjective probabilities of working full-time after age 62 and 65. Prior to 2006, however, non-working individuals were only asked about the probabilities that they would ever work in the future, resulting in partial responses to P65: a 0% answer about any work in the future implies a 0% chance of working full-time after ages 62 or 65. Those, who provided a non-zero answer before 2006, however, were not asked about full-time work after ages 62 and 65. These observations were imputed using a regression-based imputation model with many predictors including lagged values of these variables. See Appendix A.2. for details.

We also analyze wave-to-wave transition probabilities from full-time work to either full-retirement or disability. The labor force status variables are based on the RAND-HRS (2016) definitions. We expected that mismatch between worker resources and job demands would increase the transition probability from work to retirement or disability status. Because actual transitions between these states are infrequent, with many workers experiencing just one transition, panel statistical methods are not well suited for their analysis, so we have to use other, more restrictive methods.

We also analyze the effect of mismatch between worker resources and job demands on the probabilities of a worker switching employers between HRS waves, the enjoyment individuals derive from work, and the likelihood an individual will seek another job while working.

2.4. Other variables

Other variables we use in our analysis are

- Age
- Gender
- Race (white, black, other)
- Education (high-school dropout, high school graduate, college dropout, college graduate)
- Marital status (married or not)
- Whether one's spouse works

- Whether individuals have DB or DC pension plans
- Whether individuals are covered by health insurance either by their own or their spouse's employers.
- Self-employment status
- Job tenure
- Total household income
- Total household wealth, excluding employer-based retirement wealth[7] (such as 401k balances or defined benefit plan entitlements) and value of secondary residence[8]

We use the RAND-HRS dataset for these variables. Total household income and total household wealth were imputed in case of missing information by the RAND team as explained by RAND-HRS (2016). In a handful of cases some control variables (such as education) were also missing. As discussed in Appendix A.2. missing controls were replaced by the modes of the variables. Missing outcome variables or explanatory variables (other than the subjective expectations discussed above), however, were not imputed.

2.5. The sample

We restrict our sample in several ways. We use the 1994-2014 waves of the HRS, excluding the 1992 data because many variables of interest to this study were missing in that wave. We also limit our analysis sample to person-year observations when individuals were

[7] Information about employer sponsored pensions is collected by HRS for all current and previous employers (although limited to jobs held for 5 years or more for employment prior to the first HRS interview). Measurement error on pension plan type, changes in survey design across waves and the large number of components involved makes the derivation of pension wealth measures a major and complicated undertaking, with considerable ambiguity in the profession how best to accomplish this task.
[8] HRS did not ask for the value of any secondary residence in the third wave (1996), so the total wealth measure we use excludes that.

between 50 and 70 years of age. Individuals with missing gender (only two person-year observations) or occupations (322 person-year observations) are also excluded.

Some variables are not available in the 1994 wave or in proxy interviews (e.g., cognitive abilities, expectations, CESD), so we exclude these from analyses where necessary.

Our main analyses are carried out on those who work full-time in one wave and are observed in the succeeding wave, irrespective of labor force status in the next wave. In a few cases, however, we do not restrict the sample based on current or future labor force statuses.

The HRS data comes with survey weights. Some individuals were initially interviewed before they were age-eligible in which case they have a sample weight of zero. To maximize information about initial job matches we report unweighted results.[9] Weighted results are very similar, probably because our panel econometric models are little affected by weights that (mostly) correct for stratified sampling.

Table 2 presents descriptive information about our unweighted sample, including 50-70-year-old full-time workers (not restricted by future labor force status). Altogether we have about 47,000 person-year observations, but some variables are missing for various reasons discussed earlier. About half of the sample is female, almost one-fourth is non-white, more than one-fourth has a college degree, and nearly three-fourths is married. Most individuals in our sample have only a few, if any, physical limitations, with less than one in ten reporting a health condition that limits working. On average, they report having one (of eight queried) depressive symptoms. Appendix A.3. includes a table with weighted statistics that are very similar.

[9] The HRS interviews spouses of age-eligible HRS respondents. Some spouses were not themselves age-eligible at their initial interview and so have an HRS weight of zero.

3. Methods

Suppose that as workers enter their early 50's they are in job equilibrium: their physical and cognitive capabilities are well matched to the demands of their job. Comparing responses across individuals about job demands may reveal few mismatches because those workers most suited to the demands will have sorted into those jobs. For example, strong men will have taken up jobs that require considerable strength. If they are asked, however, whether the job requires strength, they may not acknowledge the full extent of those demands. Because of such good matches, there may be little relationship between anticipated retirement and job demands. Yet a person of medium strength put into such a job would likely anticipate early retirement. Similarly, as time passes the quality of the match may deteriorate even for a strong worker because of decreases in physical health.

Our empirical strategy is based on the observation that because of health shocks or gradual declines in physical and cognitive resources, jobs that were once a good match to a worker's characteristics may become increasingly mismatched.

3.1. Panel models

A strength of our approach is its use of panel data. By using panel-data methods, we can control for initial conditions, in particular the initial quality of job matches. We illustrate our empirical strategy with the example of the subjective probability of working past age 65, but similar methods are used for the other outcomes.

We estimate the following model

$$\Delta p_{i,t+1}^{65} = \beta_0 + \beta_1 r_{it} + \beta_2 \Delta r_{i,t+1} + \beta_3 d_{it} + \beta_4 d_{it} \times \Delta r_{i,t+1} + \beta_5 X_{it} + \varepsilon_{it}, \qquad (1)$$

where p_{it}^{65} is the subjective probability of working full time after age 65 for individual *i* at wave *t*; r_{it} denotes individuals' resources, d_{it} represents job demands; X_{it} is a set of control variables (such as changes in marital status, and interview wave indicators), ε_{it} is the error term; and Δ indicates changes from wave *t* to wave *t+1*. The coefficients of interest are the interaction terms (β_4).

We interpret the coefficients in (1) as the causal effect of resources (health) on the outcomes by job demands. This specification is similar to a first-difference estimator, but the job demands are fixed at the time *t* values so that changes in the right hand side variables only reflect health rather than job changes. The model assumes a zero correlation between the error term in (1) and changes in the HRS resources, as well as between the error and job demands and the interaction terms.

The main threat to identification is omitted variable bias: that is, a left-out factor simultaneously triggers changes in health and the outcomes. For example, a large inheritance may allow people to quit their jobs and invest more in their health (Schwandt, 2018); or if employers offer health insurance that may change workers' health and labor supply. To explore the extent of omitted variable bias we estimate models with different set of control variables as robustness checks.

Another threat to identification is reverse causality: retirement itself may affect the physical and mental health of individuals (Atalay and Barrett, 2014; Blundell, et al. (2017); Insler, 2014; Mazzonna and Peracchi, 2016; Rohwedder and Willis, 2010). As a robustness check we restrict the sample to full-time workers at both time t and t+1. These alternative estimates are likely biased toward zero, because retirement is also a channel though which health shocks affect the outcome variables. For these reasons, we interpret the estimates on this reduced sample as lower bounds of the true effects.

A third threat to identification is selection into jobs: people in different jobs may have different trajectories in their health and/or the outcome variables, but these differences may be independent of their jobs. For example, blue collar workers may be a selected sample with faster than average declines in health and labor supply. To explore this hypothesis, we estimated placebo regressions on past values of the outcome variables. This is a form of balancing test à la Pei et al. (2017). Our identification assumptions predict no effect on past outcomes, while the job selection hypothesis predicts similar coefficients to the contemporaneous variable model.

3.2. Transition models

When modeling wave-to-wave transition probabilities, we use the same models as (1) above, but we use transition indicators on the left side of the equation. The identification assumptions are technically speaking the same as in the panel models. However, these models do not difference out individual fixed effects in the transition probabilities, and thus, these models rely on stronger identification assumptions than the panel models. We perform the same robustness checks on these models as on the panel models when feasible.

4. Results

4.1: Descriptive patterns

The four panels of Figure 1 show age patterns of work-limiting health problems and the physical and cognitive resource measures for all HRS respondents 50 to 70 years of age. Our theory predicts an increase in work-limiting health problems with age and a decrease in the three resource measures.

Panel A indeed shows a sharp increase in the fraction reporting a work-limiting health problem by age. The prevalence of such problems increases from about 20 percent among 50-year-olds to more than 30% among 70-year-olds.

Panels B, C, and D show sharp declines in physical and cognitive resources. The measures are standardized (zero mean and standard deviation of one) among 50-70-year old full-time workers, but the graph includes everyone in that age range. All resource measures are negative, on average, which indicates that full-time workers have more resources than the general population at all ages between 50 and 70. We find a decrease of 0.25 standard deviations in the large-muscle index among persons 50 to 70 years of age (Panel B), as well as a decline of 0.3 standard deviations in the fine-motor skills index (Panel C), and 0.4 standard deviations in the cognition score (Panel D).

To get a sense of the quality of the pairings of HRS resources and O*NET job demands pairs, Appendix A.4. shows correlations between these measures. We found large positive correlations between cognitive ability and the two cognitive job demands which suggests that the qualities of these pairs are good, and individuals with high cognitive abilities sort into cognitively demanding jobs to take advantage of their comparative advantages (Ben-Porath 1967, Roy 1951; Willis and Rosen 1979). We, however, found small negative correlations between the physical resources and job demands. This may suggest that the quality of these pairings is less good, in which case we would not expect a strong interaction effect between these measures in the retirement regressions. It is also possible that too much exposure to the demands of these jobs depletes individuals' resources, leading to a negative correlation between these measures at older ages. For example, exposure to repeated heavy physical activities may lead to physical health issues.

4.2. Main analysis

Tables 3 through 7 show the regression results using our preferred specifications. Changes in the outcome variables or the transitions are regressed on job demands, changes in resources, their interactions, changes in age and marital status, and interview wave dummies. The next section (4.3) discusses alternative specifications. Appendix A.5. shows simple descriptive tables that do not use any control variables. The patterns are very similar across all specifications.

Declines in resources strongly and statistically significantly predict all outcome variables. For example, a one standard deviation decline in the large muscle index increases the chances of reporting a work limiting health problem by 7.5 percentage point (Table 3); it increases the number of depressive symptoms by 0.209 (Table 4); it decreases the subjective probability of working full-time after age 65 by 1.9 percentage points (Table 5); it increases work to retirement transitions by 2.6 percentage points (Table 6); and work to disability transitions by 1.1 percentage points. The effects of changes in fine motor skills and cognition also have the expected signs and they are all statistically significant.

The decline in the physical measures tend to have larger effects than declines in cognition, especially on depressive symptoms and reporting of work-limiting health problems. For example, Table 3 shows that a one standard deviation decline in the fine motor skill increases the probability of a work limiting health problem by only 4.4 percentage points (vs. 7.5 for the large muscle index); and the corresponding number for a decline in cognition is 1 percentage point.

The interactions between the large-muscle resource index and dynamic strength job demands, which capture mismatch in specific dimensions, are statistically significant in all regressions even at the 1% level, except for transitions from full-time work to retirement (Table 6). The magnitudes of the interactions are also large. In the regressions of subjective expectations (Table 5), the interaction coefficient (0.82 in the fourth row) is almost half as much in absolute value as the coefficient on health change (1.921 in the second row). Given that all coefficients are standardized, this means that changes in the large-muscle index do not predict retirement expectations in occupations whose demand for dynamic strength are about 2.3 standard deviations below the average level of demand for dynamic strength.

The interaction effects between the large-muscle index and dynamic strength job demands are almost always strong and statistically significant, affecting work-limiting health problems, depressive symptoms as measured by CESD, and work-to-disability transitions (Tables 3 ,4 and 7). This means that developing large-muscle problems increases depressive symptoms, reported work-limiting health problems, and work-to-disability transitions in all occupations, but the effects are larger in occupations that demand dynamic strength. Only the interaction in the regression of the transition from full-time work to retirement is not significant.

The interaction effects between fine-motor skills (resource) and finger dexterity (job demand) as well as those between cognition and cognitive job demands are close to zero and almost never statistically significant. The only exception is column 3 in Table 4, in which the interaction term has an unexpectedly positive sign and is statistically significant at the 5% level. The model predicts that cognitive decline increases depression relatively more in occupations that do not demand memorization.

Overall, even though fine-motor skills and cognition strongly predict the five outcomes, they do not seem to interact with job demands along these dimensions.

Appendix B reports results on additional outcome variables. We summarize the results briefly here. The effects on the subjective probabilities of working past age 62 are similar to the subjective probabilities of working past age 65. The two physical-decline measures are statistically significant predictors of disliking work (i.e., of disagreeing or strongly disagreeing with the statement that “I really enjoy going to work”), but cognitive decline is not. The interactions of these measures with job demands are not statistically significant in the regression on the dislike of work. The outcome variable is only available for workers—those not working at t+1 are not in the analysis sample—and an important part of the sample is therefore missing and may bias the coefficients toward zero. Decline in the large-muscle and the fine motor indices make it less likely that an individual will switch employers, but none of the interaction effects with job demands are statistically significant.

4.3. Robustness checks

Even though we use panel variation for identification, which we believe is more likely to be valid than cross-section variation, our data are observational and therefore our estimates may not capture the true causal effects of health on the outcome variables. This section discusses alternative specifications and tests we performed to learn if there is evidence against our causal interpretation.

First, Appendix A.5. provides simple descriptive tables showing mean changes in the outcome variables by job demands and changes in resources. These tables use mean splits in the explanatory variables and no controls. These specifications show the raw output without imposing much structure on the data. The tables largely agree with the preferred regression results: changes in any resources predict the outcome variables, but the effects are largest for large-muscle resources in large muscle jobs.

Second, we estimated models with alternative sets of control variables. Our preferred specification in Section 4.2. only used changes in a cubic function of age, changes in marital status and wave indicators. Appendix tables C1-C5 show regressions of the five main outcome variables using the following additional controls: gender, race, education, change in household income, change in household wealth, change in spouse labor force status, whether employer sponsored DB or DC retirement plans, whether self-employed, tenure at the main job, and whether health insurance through employer or spouse. The main coefficients are indistinguishable from the preferred ones reported in the previous section. We prefer using fewer controls, because some of these additional controls are potential outcomes (such as whether the spouse works, or family income), but it is reassuring that the control variables do not change our coefficients of interest, perhaps because changes in health are relatively random in this age range.

Third, people in different jobs may have different trajectories in their health and/or the outcome variables. For example, blue collar workers may face sharper declines in health and the outcome variables compared to white collar workers. To explore this hypothesis, we estimated placebo regressions on past values of three outcome variables as shown in Tables C6-C8. This test was not feasible on the transition models. The main coefficients (changes in resources and interactions with job demands) are close to zero and almost never statistically significant. One exception is that apparently changes in fine motor skills are mildly correlated with past changes in the subjective probabilities of working past age 65. Additionally, one more interaction coefficient is significant at 5% and another one at 10%.

Fourth, retirement itself may simultaneously predict changes in health and the outcome variables. To explore, we ran separate regressions on a narrower sample that included only full-time workers at *t* and *t+1*. Appendix Table C9 shows the specification on three main outcomes and the large muscle index. These models cannot be estimated on the transition models; and the appendix only focuses on the large muscle index with the strongest results. Coefficients in these regressions are likely biased toward zero because individuals who transition into retirement may be worse off compared to those who remain in the labor force. Indeed, the coefficients are all closer to zero compared to the preferred models. Nevertheless, changes in the large muscle index still strongly predict all three outcomes, and the interaction terms are statistically significant at 5% in two out of three cases and significant at 10% in the third case.

5. Discussion and conclusion

5.1. Summary

We used longitudinal data from the HRS to find how decline in individuals' physical and cognitive resources as well as the mismatch between resources and occupational job demands affected various retirement-related outcomes. We considered three resource measures: 1) a large-muscle index representing strength and overall physical fitness; 2) fine-motor skills representing individuals' ability to perform precise manipulations with their hands (as well as general physical fitness); and 3) cognitive abilities that mostly focused on the quality of individuals' working memories.

We paired these three resource measures with four corresponding job-demand measures derived from the O*NET project. These were dynamic strength (paired with the large-muscle index), finger dexterity (paired with fine-motor skills), memorization (paired with cognition) and analyzing data and information (also paired with cognition).

We merged the O*NET characteristics with the detailed 3-digit occupations of HRS participants and focused on five outcome variables: self-reported work-limiting health problems, the number of depressive symptoms (as measured by the CESD scale), subjective probabilities of working full-time after age 65, transitions from work to retirement, and to disability. We tested whether HRS resources and O*NET job demands predicted these outcome variables. We expected that the decline in resources would lead to more work-limiting problems, more depressive symptoms, smaller subjective probabilities of working longer, and more transitions out of work, especially in occupations that rely on specific skills. This latter effect was tested by the interactions between resources and job demands.

The main novelty of our approach was to use panel econometric models when possible that identified solely intra-personal rather than inter-personal variation in physical and cognitive resources. Under reasonable assumptions this variation captures the causal effect of resource decline on the outcomes. We were able to use panel econometric models because we had repeated observations in our outcome variables that were collected among both working and non-working individuals. In standard models of retirement transitions (which we also estimated) such panel variation is not available to researchers, because (most) individuals retire only once. Our approach therefore highlights a main advantage of using subjective probabilities such as the chances of working full-time after age 65: they provide more variation both in the cross-section (probabilities as opposed to 0-1 indicators available at the individual level) and over time (see also Hurd 2009; Manski 2004).

We found that physical and cognitive resources all had a strong effect on the five outcome variables. Decline in the physical measures (large-muscle and fine-motor) tended to have a stronger effect than declines in cognitive abilities. For example, a decline of one standard deviation in the large-muscle index decreased the subjective probability of working after age 65 by about 1.9 percentage points. The corresponding effect of cognitive ability was about half as much at one percentage point.

The differences between physical and cognitive resources was even larger for CESD depression. While a decline of one standard deviation in the large-muscle index increased the number of depressive symptoms (out of 8) by about 0.21, a decline of one standard deviation in cognition increased the number of such symptoms by 0.04 (both increases statistically significant at 1%).

We also found that decline in the large-muscle index had a strong interaction effect with dynamic strength job demands, implying the importance of mismatch in large muscle problems for retirement. For example, an increase of one standard deviation from the mean in the importance of dynamic strength on the job increased the effect of the large-muscle index on the subjective probability of working past age 65 from 1.9 to 2.7 percentage points. Such an increase also increased the effect on depressive symptoms from 0.21 to 0.25.

We found weak and statistically insignificant interaction effects between the fine-motor index (resource) and finger dexterity (job demands), as well as between cognition (resource) and memorization or analyzing data and information (job demands). There are several possible explanations for this: It may be that fine motor skills and cognitive abilities are important determinants of working in all occupations; or workers in cognitive and fine-motor occupations may have good jobs that protect them from the adverse effects of mismatch (their employers may accommodate the changing capabilities, or such workers may be able to switch to tasks or jobs that better align with their reduced skills); or, finally, the pairing of the O*NET measures with the HRS resource measures was not very good, which may have biased the interaction effect toward zero.

5.2. Implications

Our findings demonstrate the importance for retirement research to consider the considerable heterogeneity in individuals' skills and in their jobs' demands. Different jobs rely on different skills. As workers age, their physical and cognitive resources decline, for some more rapidly than for others. By simultaneously considering the heterogeneity in job demands and resources, we showed that mismatch may be an important obstacle for the employability of some workers, especially those working in occupations that rely on muscular endurance.

While we found that cognitive decline was associated with some outcomes (depressive symptoms, retirement expectations, actual retirement), the association was considerably weaker than with physical decline. We also did not find any interaction between cognitive decline and job demands.

There are many potential reasons why decline in cognitive abilities is less crucial for retirement outcomes. Workers in cognitively demanding jobs who experience declines in their fluid cognitive abilities can rely on their crystallized intelligence (general knowledge and experience) that is found to be more resistant to aging (Cattell 1987). Such workers also may be in good jobs with more accommodating employers or have better outside options. Regardless, cognitive decline appears to be less of a problem for workers at older ages than decline in physical skills.

We found decline in fine-motor skills was a very strong predictor of retirement outcomes, but we found little interaction effects with job demands.

We did find very large interaction effects between large-muscle problems and corresponding job demands (dynamic strength). Employability in physically demanding jobs appears to be very sensitive to an individual's physical capabilities, or at least much more so than employability in cognitive jobs is to declines in cognitive skills.

Workers in physically demanding jobs, thus, are more likely to face mismatch with the demands of their jobs, especially those who experience a decline in their physical capabilities. These mismatched workers are more likely to leave the labor force, perhaps because they are not able to effectively work in their occupations and their options for work in other occupations are limited. This is particularly a concern, because individuals in low socioeconomic status are both overrepresented in physically demanding jobs, and are less financially prepared for retirement.

The fraction of the labor force in physical jobs has been shrinking in recent decades (Brownson, Boehmer, and Luke, 2005; Sturm, 2004), and this trend may continue. Consequently, age related mismatch may become a less important limitation for workers who would like to continue working. But physical jobs still take up a non-trivial fraction of the current labor force.

Delaying the decline in the physical health of these workers may increase the chances that they can work to the ages they desired or had planned on. They may also be better off if their employers accommodated their changing skills or if they could find alternative work arrangements that better fit their abilities.

5.3. Limitations

There are several limitations to our study. We used observational data, and we could not directly test the exogeneity of our explanatory variables. Our robustness checks and placebo regressions, however, largely support our causal interpretation. Our models identify from changes in resources (health), which are relatively random events.

The job-demand measures were defined by occupations, and so any heterogeneity within occupations was ignored. We used occupational measures, because they are based on more objective information than self-reported survey data and because O*NET provided a large number of measures from which to choose. Future research might consider within-occupation heterogeneity in job demands.

The two physical-resource measures may be too general and focused on problems for individuals at older ages than those analyzed. This is particularly true for the fine-motor index that included problems with eating and dressing. Such issues are rare in the working-age population and typically manifest long after an individual leaves the labor force. This may explain why we found no interaction effects between the fine-motor index and the corresponding job demand (finger dexterity).

An important element of our methods was pairing HRS resource measures with O*NET job characteristics and to analyze the interactions between these. The success of this method depends on the quality of the pairing. If the resource and the job-demand measures are misaligned because, for example, they correspond to somewhat different factors, then we would expect muted coefficients. This problem may have contributed to the lack of significance between the fine-motor index and finger dexterity, but we think the quality of the other pairs was better.

Our preferred sample included those non-workers who had a job in the previous HRS waves. But before 2006 the HRS did not ask the subjective probability of working after ages 62/65 question of some non-workers. We imputed these cases using a relatively simple single-imputation methodology that flexibly included age, gender, labor force status and past expectations. Imputation, however, is never perfect. In the future, when more HRS waves become available, researchers might estimate similar models using only post-2006 data that need no imputation.

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Data

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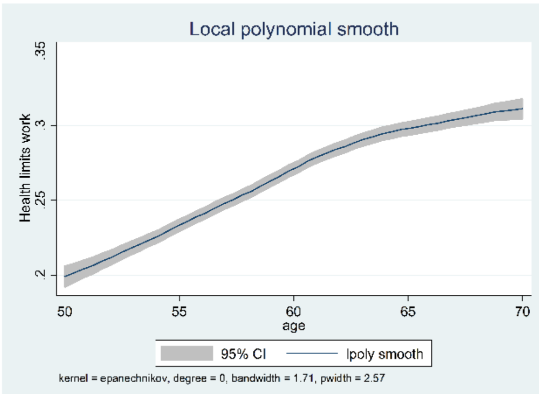
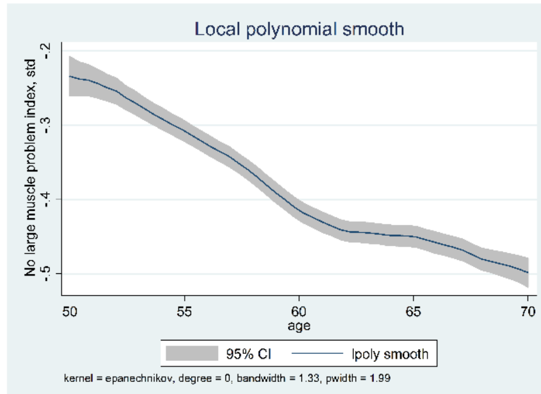
Tables and Figures

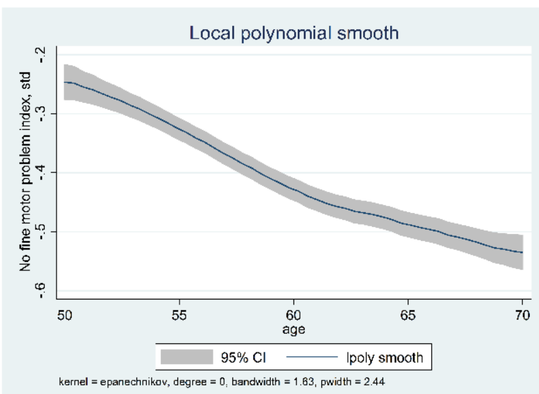
Figure 1. Age patterns in whether health limits working and three resource measures, non-parametric regressions, HRS, Age 50-70, 1994-2014, unweighted



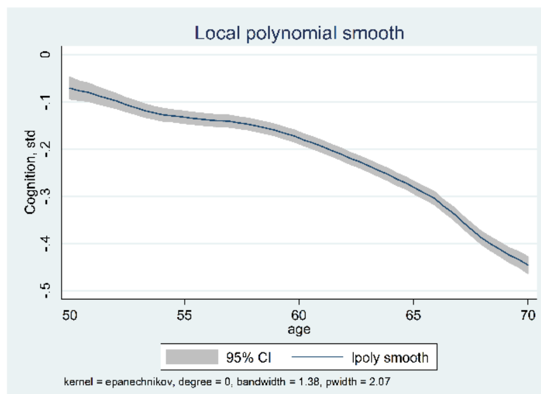
Panel A: Whether health limits work



Panel B: Large muscle index



Panel C: Fine motor skills index



Panel D: Cognition

*The three resource measures are standardized to have zero mean and standard deviation of one among 50-70 years old full-time workers, but the graphs include everyone regardless of labor force status. Higher values indicate better health. The confidence intervals assume i.i.d. data, and they are likely too narrow due to the positive correlations in the panel.

Table 1. Definition of the HRS resource measures and the O*NET job demands

#	Pair #	HRS resource measures	Definition*
R1	D1	Large muscle problems	Having problems with 1) sitting for 2 hours; 2) getting up from a chair; 3) stooping, kneeling or crouching; 4) pushing or pulling large objects
R2	D2	Fine motor problems	Having problems with the following activities: 1) picking up a dime; 2) eating; 3) dressing
R3	D3, D4	Cognition	27-point scale involving immediate word recall (10 words), delayed word recall (10 words), serial subtraction of 7 from 100 (5 times) and backward counting from 20 to 10 (2 trials)

#	Pair #	O*NET job demands	Definition**
D1	R1	Dynamic strength	The ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue.
D2	R2	Finger dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
D3	R3	Memorization	The ability to remember information such as words, numbers, pictures, and procedures.
D4	R3	Analyzing data or information	Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.

* See the RAND-HRS (2016) documentation for details.

** See the O*NET documentation for details at https://www.onetcenter.org/content.html.

Table 2. Descriptive statistics of the main variables, HRS, Age 50-70, full-time workers, unweighted

	N	mean	sd	min	max
Age	46935	57.9	4.597	50	70
Female	46935	0.477	0.499	0	1
White	46935	0.767	0.423	0	1
Black	46935	0.163	0.369	0	1
Other race	46935	0.070	0.256	0	1
Hispanic	46935	0.106	0.308	0	1
High school dropout	46935	0.177	0.382	0	1
High school graduate	46935	0.285	0.452	0	1
College dropout	46935	0.258	0.438	0	1
College graduate	46935	0.280	0.449	0	1
Married	46935	0.713	0.452	0	1
Spouse works	46935	0.493	0.500	0	1
Household income	46935	90797	147927	0	13570429
Total household wealth	46935	355945	1086466	-4383000	90648200
Has a DB pension	46935	0.326	0.469	0	1
Has a DC pension	46935	0.397	0.489	0	1
Self employed	46935	0.158	0.365	0	1
Tenure at job, in years	46935	13.747	11.494	0	55
Has health insurance from employer	46935	0.680	0.467	0	1
Has health insurance from spouse	46935	0.149	0.356	0	1
HRS interview wave	46935	6.933	3.236	2	12
Dynamic strength, O*NET	46935	0.178	0.126	0.000	0.562
Finger dexterity, O*NET	46935	0.393	0.097	0.177	0.718
Memorization, O*NET	46935	0.339	0.080	0.104	0.580
Analyzing data or information, O*NET	46935	0.523	0.147	0.157	0.877
Large muscle problem index	46927	0.740	1.075	0	4
Fine motor problem index	46935	0.047	0.236	0	3
Cognition	39357	17.020	3.876	0	27
Full-time work → retirement transition	39699	0.104	0.306	0	1
Full-time work → disability transition	39699	0.008	0.087	0	1
Subjective probability working full time after age 62	34674	57.053	36.894	0	100
Subjective probability working full time after age 65	37449	36.661	35.693	0	100
Health limits work	46651	0.078	0.267	0	1
CESD depression score	43876	1.088	1.665	0	8
Moves to a different employer	33158	0.094	0.292	0	1
Does not enjoy going to work	42991	0.121	0.326	0	1

Table 3. OLS regressions of the change in whether health limits working as a function of job demands, resources and their interactions

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.038			
	[0.002]***			
Change in large muscle index, R1	-0.075			
	[0.003]***			
Dynamic strength at t, D1	0.007			
	[0.001]***			
R1 x D1	-0.012			
	[0.003]***			
Fine motor index at t		-0.026		
		[0.003]***		
Change in fine motor index, R2		-0.044		
		[0.002]***		
Finger dexterity at t, D2		0.005		
		[0.001]***		
R2 x D2		0.000		
		[0.002]		
Cognition at t			-0.011	-0.010
			[0.002]***	[0.002]***
Change in cognition, R3			-0.010	-0.010
			[0.002]***	[0.002]***
Memorization at t, D3			-0.008	
			[0.002]***	
R3 x D3			-0.003	
			[0.002]	
Analyzing data or information at t, D4				-0.008
				[0.002]***
R3 x D4				0.001
				[0.002]
Change in age	-0.019	-0.018	-0.021	-0.021
	[0.005]***	[0.005]***	[0.005]***	[0.005]***
Change in age - 50 squared	0.001	0.001	0.001	0.001
	[0.000]**	[0.000]**	[0.000]***	[0.000]***
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	0.006	0.002	0.006	0.006
	[0.010]	[0.010]	[0.011]	[0.011]
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.052	0.048	0.049	0.048
	[0.008]***	[0.009]***	[0.009]***	[0.009]***
R-squared	0.045	0.026	0.006	0.006
N	38272	38279	31149	31149

*Sample: HRS, Age 50-70, full-time workers at t, valid interviews at t+1, and non-missing resources and outcome. Job demands and resources are standardized and higher values indicate higher demands and more resources (better health). Change measures are all defined from wave t to t+1. Robust standard errors clustered on the household id are in brackets. *, **, and *** indicate statistical significance at 10, 5, and 1% respectively.

Table 4. OLS regressions of the change in the CESD depressive symptoms as a function of job demands, resources and their interactions

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.043			
	[0.009]***			
Change in large muscle index, R1	-0.209			
	[0.014]***			
Dynamic strength at t, D1	0.014			
	[0.007]**			
R1 x D1	-0.040			
	[0.013]***			
Fine motor index at t		-0.031		
		[0.011]***		
Change in fine motor index, R2		-0.110		
		[0.012]***		
Finger dexterity at t, D2		0.012		
		[0.007]*		
R2 x D2		0.004		
		[0.012]		
Cognition at t			-0.004	-0.002
			[0.010]	[0.010]
Change in cognition, R3			-0.045	-0.043
			[0.013]***	[0.013]***
Memorization at t, D3			-0.013	
			[0.008]	
R3 x D3			0.023	
			[0.012]**	
Analyzing data or information at t, D4				-0.019
				[0.008]**
R3 x D4				0.015
				[0.012]
Change in age	0.030	0.036	0.021	0.021
	[0.027]	[0.027]	[0.028]	[0.028]
Change in age - 50 squared	-0.001	-0.001	-0.001	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	-0.482	-0.489	-0.484	-0.484
	[0.065]***	[0.065]***	[0.068]***	[0.068]***
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.024	0.016	0.051	0.051
	[0.047]	[0.047]	[0.048]	[0.048]
R-squared	0.020	0.013	0.009	0.009
N	35720	35724	31623	31623

*See notes after Table 3 for additional details.

Table 5. OLS regressions of the change in the subjective probabilities of working full-time after age 65 as a function of job demands, resources and their interactions

	[1]	[2]	[3]	[4]
Large muscle index at t	1.252			
	[0.166]***			
Change in large muscle index, R1	1.921			
	[0.243]***			
Dynamic strength at t, D1	-0.297			
	[0.152]*			
R1 x D1	0.820			
	[0.237]***			
Fine motor index at t		1.105		
		[0.208]***		
Change in fine motor index, R2		1.010		
		[0.196]***		
Finger dexterity at t, D2		-0.041		
		[0.149]		
R2 x D2		0.120		
		[0.182]		
Cognition at t			0.676	0.644
			[0.221]***	[0.219]***
Change in cognition, R3			1.049	1.027
			[0.271]***	[0.269]***
Memorization at t, D3			0.498	
			[0.177]***	
R3 x D3			-0.221	
			[0.254]	
Analyzing data or information at t, D4				0.580
				[0.172]***
R3 x D4				-0.246
				[0.245]
Change in age	1.009	0.944	0.785	0.787
	[0.594]*	[0.595]	[0.622]	[0.622]
Change in age - 50 squared	-0.079	-0.075	-0.080	-0.080
	[0.063]	[0.063]	[0.066]	[0.066]
Change in age - 50 cube	0.004	0.004	0.005	0.005
	[0.003]	[0.003]	[0.003]	[0.003]
Change in married	-1.863	-1.762	-1.686	-1.692
	[1.166]	[1.170]	[1.251]	[1.252]
Wave dummies	Yes	Yes	Yes	Yes
Constant	-2.230	-2.144	-1.997	-1.999
	[0.994]**	[0.995]**	[1.016]**	[1.016]**
R-squared	0.008	0.006	0.006	0.006
N	28176	28177	24798	24798

* Subjective probabilities of working are only collected in non-proxy interviews from people younger than age 65. Prior to 2006, the HRS did not ask this question from non-workers. The values of expectations for the 50-64-year-old non-proxy non-workers are imputed with a model described in Appendix A. See notes after Table 3 for additional details.

Table 6. OLS regressions of the transitions from full-time work to retirement as a function of job demands, resources and their interactions

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.028			
	[0.002]***			
Change in large muscle index, R1	-0.026			
	[0.002]***			
Dynamic strength at t, D1	0.010			
	[0.001]***			
R1 x D1	-0.002			
	[0.002]			
Fine motor index at t		-0.020		
		[0.002]***		
Change in fine motor index, R2		-0.018		
		[0.002]***		
Finger dexterity at t, D2		0.011		
		[0.002]***		
R2 x D2		0.000		
		[0.002]		
Cognition at t			-0.015	-0.015
			[0.002]***	[0.002]***
Change in cognition, R3			-0.009	-0.009
			[0.002]***	[0.002]***
Memorization at t, D3			-0.004	
			[0.002]**	
R3 x D3			-0.001	
			[0.002]	
Analyzing data or information at t, D4				-0.004
				[0.002]**
R3 x D4				-0.001
				[0.002]
Change in age	-0.056	-0.057	-0.054	-0.054
	[0.004]***	[0.004]***	[0.004]***	[0.004]***
Change in age - 50 squared	0.004	0.004	0.004	0.004
	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	-0.001	-0.003	0.001	0.001
	[0.009]	[0.009]	[0.010]	[0.010]
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.069	0.068	0.067	0.067
	[0.007]***	[0.007]***	[0.007]***	[0.007]***
R-squared	0.061	0.057	0.051	0.051
N	38829	38838	31645	31645

* See notes after Table 3 for additional details.

Table 7. OLS regressions of the transitions from full-time work to disability as a function of job demands, resources and their interactions

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.009			
	[0.001]***			
Change in large muscle index, R1	-0.011			
	[0.001]***			
Dynamic strength at t, D1	0.002			
	[0.000]***			
R1 x D1	-0.002			
	[0.001]**			
Fine motor index at t		-0.008		
		[0.001]***		
Change in fine motor index, R2		-0.011		
		[0.001]***		
Finger dexterity at t, D2		0.002		
		[0.000]***		
R2 x D2		0.000		
		[0.001]		
Cognition at t			-0.004	-0.004
			[0.001]***	[0.001]***
Change in cognition, R3			-0.002	-0.002
			[0.001]***	[0.001]***
Memorization at t, D3			-0.002	
			[0.001]***	
R3 x D3			0.000	
			[0.001]	
Analyzing data or information at t, D4				-0.002
				[0.001]***
R3 x D4				-0.001
				[0.001]
Change in age	0.001	0.001	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]
Change in age - 50 squared	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	0.001	0.000	0.001	0.001
	[0.003]	[0.003]	[0.003]	[0.003]
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.008	0.008	0.009	0.009
	[0.002]***	[0.002]***	[0.002]***	[0.002]***
R-squared	0.018	0.022	0.004	0.004
N	38829	38838	31645	31645

* See notes after Table 3 for additional details.

Appendix A: Additional information about the data and the sample

A.1. Measurement of job demands

The O*NET database contains measures for 974 occupations, corresponding to the occupations in the most recent HRS. However, the occupational coding schemes in the restricted HRS data have changed over time (Nolte, Turf, and Servais 2014). To ensure comparability across waves of HRS data, we use a coding scheme that is consistent over time and that aggregates across small, similar occupation groups. This coding scheme was developed to use in conjunction with the O*NET data and contains 192 separate occupations/occupational groupings derived from the original occupational codes.[10]

If HRS respondents report working more than one job HRS elicits and codes the occupation information for all jobs a respondent may hold. The interview also asks respondents to name the job they consider to be their main occupation, which is the occupation we use here.

For each occupation in the database, O*NET provides information on the level and importance of each required work activity. Following Firpo, Fortin, and Lemieux (2011), we use Cobb-Douglas weighted means to combine occupation-level importance and level measures. Importance weights are 2/3; level weights are 1/3. Given the smaller number of somewhat aggregated occupations in our HRS data, we average across multiple O*NET occupations that crosswalk to the HRS occupation categories to create O*NET measures for the HRS occupations.

[10] The coding scheme was originally developed by Peter Hudomiet for his dissertation, and it has been used by a number of researchers since then (e.g. Carr et al., 2016; Sonnega et al. 2018). It can be accessed at https://sites.google.com/site/phudomiet/Occupation-Crosswalks-MRRC-2015.xlsx.

We use CPS detailed occupation frequencies to weight O*NET measures to the level of the 192 detailed occupation categories used in this paper.

The HRS typically only asks about workers' occupations if they reported a change in their employment situation (different employer or different tasks at the same employer) or they are newly recruited sample members. To maximize the available information, workers with missing occupations were imputed their previously reported occupations. Of the 46,935 person-year observations in our total sample 20,457 (43.6%) occupations were carried forward from earlier waves. 20,254 of them (43.2%) reported to have the same employer and job title as in the previous wave; and 203 of them (0.4%) were missing for other reasons. Our results are virtually identical if the latter 203 cases are excluded from the sample.

A.2. Imputations

Beginning in 2006, the HRS asked all respondents their subjective probabilities of working full-time after age 62 and 65. Prior to 2006, however, non-working individuals were only asked about the probabilities that they would ever work, resulting in partial responses to P65: a 0% answer implies a 0% chance of working full-time after ages 62 or 65. Those, who provided a non-zero answer before 2006, however, were not followed up with a question about full-time work after ages 62 and 65.

We seek to include in our sample those who currently do not work but who did work in the prior wave. Because expectations of such individuals are partially missing before 2006, we developed a regression-based imputation model estimated over complete data from 2006 to 2014, reported in Table A1.

Table A1. Imputation model used to impute the subjective probabilities of working full-time after age 62 and 65, HRS, Age 50-61 (column 1) and Age 50-64 (column 2), non-proxy, non-workers in the current wave, full-time workers in the previous wave, reported a positive chance of working in the future, 2006-2014

	pw62	pw65
Age - 50 (A)	-0.15	-0.952
	[0.639]	[0.336]***
Age - 50 squared (A2)	-0.004	0.046
	[0.035]	[0.015]***
Age - 50 cube (A3)	2.538	5.644
	[3.533]	[2.353]**
Female (F)	1.419	2.197
	[2.961]	[2.096]
Retired	ref.	ref.
Unemployed (U)	43.224	29.404
	[6.455]***	[5.032]***
Disabled (D)	31.404	16.137
	[11.037]***	[8.899]*
OLF other reason (O)	21.322	20.842
	[9.459]**	[8.277]**
U x A	-1.725	-0.926
	[0.761]**	[0.505]*
D x A	-1.613	-0.428
	[1.403]	[1.042]
O x A	0.38	-0.127
	[1.071]	[0.844]
U x F	-3.087	-2.757
	[4.085]	[3.222]
D x F	-7.553	-10.837
	[7.336]	[6.482]*
O x F	-0.31	-10.054
	[7.302]	[6.176]
Lagged Pr(works after 62)	0.27	
	[0.027]***	
Lagged Pr(works after 65)		0.298
		[0.023]***
Constant	1.349	-3.941
	[7.623]	[6.183]
R-squared	0.323	0.256
N	977	1328

The model uses data on age, gender, labor force status, prior expectations, and the probability of any work in the future. We then used the model estimates to predict subjective probabilities of working full time after age 65 for the relevant missing cases in the 1994 to 2004 waves: those who were not working, but were full-time workers in the prior wave, who did not have proxy interviews (expectations are only collected in non-proxy interviews), and who provided a non-zero probability of working in the future.

Some of the resource measures were imputed by the RAND team as explained by RAND-HRS (2016). The physical measures only use logical imputations (e.g. not knowing about a limitation implies no limitation, unless all items from the score are missing, in which case the score is missing). Missing cognitive resource items were imputed by the HRS (Fisher et al. 2017) using past and future values of the cognitive items; the 2014 missing values are not yet imputed because 2016 HRS is not yet available.

In a handful of cases some control variables (such as education) are also missing. To maximize the available sample, missing discrete controls are replaced by the modes of the variables. Missing household income and wealth were imputed by RAND-HRS (2016). Missing job tenure was replaced by 10 years (about the median). Missing outcome variables or explanatory variables (other than the subjective expectations and resources discussed above), however, are not imputed.

A.3. Weighted descriptive statistics.

In the paper we showed unweighted results, because the weights were zeros for sample members who entered the survey before age eligibility. Table A2 shows that the weighted characteristics of the sample are very similar to unweighted ones (Table 2), but the unweighted sample has more racial and ethnic minorities who are over-sampled by HRS.

Table A2. Descriptive statistics about the main variables, HRS, Age 50-70, full-time workers, weighted by HRS survey weights

	N	mean	sd	min	max
Age	43759	57.7	4.290	50	70
Female	43759	0.429	0.495	0	1
White	43759	0.852	0.356	0	1
Black	43759	0.090	0.287	0	1
Other race	43759	0.058	0.234	0	1
Hispanic	43759	0.072	0.258	0	1
High school dropout	43759	0.128	0.334	0	1
High school graduate	43759	0.268	0.443	0	1
College dropout	43759	0.267	0.442	0	1
College graduate	43759	0.337	0.473	0	1
Married	43759	0.707	0.455	0	1
Spouse works	43759	0.505	0.500	0	1
Household income	43759	105043	162553	0	13570429
Total household wealth	43759	428069	1142513	-4383000	90648200
Has a DB pension	43759	0.335	0.472	0	1
Has a DC pension	43759	0.440	0.496	0	1
Self employed	43759	0.164	0.370	0	1
Tenure at job, in years	43759	14.139	11.614	0	55
Has health insurance from employer	43759	0.704	0.457	0	1
Has health insurance from spouse	43759	0.150	0.357	0	1
HRS interview wave	43759	7.764	2.981	2	12
Dynamic strength, O*NET	43759	0.168	0.125	0.000	0.562
Finger dexterity, O*NET	43759	0.389	0.099	0.177	0.718
Memorization, O*NET	43759	0.345	0.078	0.104	0.580
Analyzing data or information, O*NET	43759	0.539	0.146	0.157	0.877
Large muscle problem index	43752	0.709	1.059	0	4
Fine motor problem index	43759	0.046	0.236	0	3
Cognition	36900	17.361	3.684	0	27
Full-time work → retirement transition	37105	0.091	0.288	0	1
Full-time work → disability transition	37105	0.006	0.077	0	1
Subjective probability working full time after age 62	31995	60.217	35.878	0	100
Subjective probability working full time after age 65	34771	40.083	35.880	0	100
Health limits work	43484	0.076	0.265	0	1
CESD depression score	40929	1.041	1.640	0	8
Moves to a different employer	30909	0.094	0.292	0	1
Does not enjoy going to work	40140	0.125	0.331	0	1

A.4. Correlations between resources and job demands

Table A3 shows the correlation between the HRS resource measures and their O*NET job demand pairs among respondents 50 to 55 years old. We focus on the ages when most individuals have yet to experience decline in these resources. We seek to get a sense of the quality of the pairings, but this is difficult because of conflicting theories on how these resources may decline with age.

Table A3. Correlations between the O*NET job demands and the HRS resources measures, HRS, Age 50-55, full-time workers

	N	Correlation
Dynamic strength vs. no large muscle problem index	16052	-0.056
Finger dexterity vs. no fine motor problem index	16055	-0.030
Memorization vs. Cognition	13233	0.279
Analyzing data vs. cognition	13233	0.274

* Higher values indicate higher job demands and more resources (better health).

There are, for example, at least two reasons to expect positive correlations between resources and job demands. First, human capital theory suggests that individuals tend to sort into jobs that maximize their lifetime income (Ben-Porath 1967) by pursuing education and occupations that capitalize on their comparative advantage (Roy 1951; Willis and Rosen 1979). If physical strength and cognitive resources are positively correlated, those with high levels of both cognitive and strength resources will tend to sort into high paying “cognitive” occupations if the variance of worker productivity is greater in relatively cognition-intensive jobs than in relatively strength-intensive manual jobs (Willis 1986). Second, investment in on-the-job training and learning-by-doing over their careers in a given occupation (or career ladder) would reduce any mismatch between their initial resources and the demands of the job. Indeed, to the extent to which learning new skills depends on cognitive ability, as is likely to be most important in cognitive jobs, the match between worker resources and job demands is likely to strengthen as job tenure increases. In addition, investments in health capital (Grossman 1972) to maintain physical and mental health during the career would be important in maintaining match-quality.

At the same time, there is at least one reason to expect negative correlations between resources and job demands. Specifically, too much exposure to the demands of a job may deplete individuals' resources, leading to a negative correlation between their resources and job demands. For example, exposure to repeated heavy physical activities may lead to physical health issues. We do not expect this mechanism to play a role in cognition.

Table A3 shows that there are large positive correlations between cognitive ability and the two cognitive job demands, each with a correlation coefficient of about 0.3. This suggests that individuals with high cognitive abilities sort into cognitively demanding jobs, or that individuals occupying cognitively demanding jobs experience slower declines in cognition whether or not the job is causal for the reduced decline. These mechanisms may operate simultaneously.

At the same time, we found small negative correlations between the physical resources and job demands. This may mean that sorting into physical jobs and learning-by-doing are less important for physical attributes and that, instead, depletion of physical resources does occur in physically demanding jobs (Fraade-Blanar et al. 2017). It is also possible that workers in physically demanding jobs have riskier habits (e.g., smoking, heavy drinking) than workers in less physically demanding jobs, leading to depletion of their resources relevant to such jobs. Finally, the physical resource and job-demand measures may not pair well, because they correspond to different attributes of individuals. In such a case, we would not expect a strong interaction effect between these measures in the retirement regressions.

A.5. Descriptive patterns in resources, job demands and the various outcome variables

Tables A4 through A7 show how the change in resources when interacted with job demands predict the main outcome variables: work-limiting health problems, depressive symptoms, and expectations to work in the future. Here we seek descriptive evidence from data without imposing modeling assumptions. The main patterns we are looking for are increased mismatches between job demands and personal resources as physical and cognitive resources decline, and for differences in mismatches for workers in jobs with high versus low demand for a given resource.

Each table focuses on a separate dimension of job demands and workers' corresponding resources. Table A4 shows the results for the large muscle index. The cells of the table show the means of the outcome variables at wave t and t+1. The rows of the table indicate transitions in the workers' resource measures as observed across two waves in the HRS data: from high (above the mean) or low (below the mean) at wave t to high/low at t+1. The columns indicate the waves (t and t+1) with the left panel showing results for workers in occupations with high demand for dynamic strength (O*NET index above the mean) and the right panel showing results for workers in occupations with low demand for dynamic strength (O*NET index below the mean). We expect larger changes in the outcome variables from wave t to t+1 when individuals' resources (HRS large muscle index) decline from high to low, especially in jobs that demand those resources.

Health limitations increase over two-year periods as shown by the line "all" in the first panel: among those with jobs that have a high demand for dynamic strength, 8.3% had a limitation in the initial wave and 13.5% had a limitation in the following wave; among those with jobs that have a low demand, 6.1% had a limitation in the initial wave and 9.2% had a limitation in the following wave It is notable that both the initial level and the rate of increase are greater when the job has high demand for dynamic strength than when the job has low demand.

Among individuals who score high on the large muscle index at both waves t and t+1 (workers' resources observed in HRS: high → high), very few report any work-limiting health problems. Specifically, only 2.2% of such individuals in occupations demanding a lot of dynamic strength report work-limiting health problems at t, and only 3.3% report such problems at t+1. Among workers who score high on the large muscle index in both t and t+1 and who are in occupations with relatively low demand for dynamic strength, less than 3 percent report any work-limiting health problems at either t or t+1.

Among individuals for whom the large-muscle index deteriorates from high to low, there is a sharp increase in reported work-limiting health problems, especially in occupations that demand dynamic strength. Specifically, the percentage of such individuals reporting work-limiting health increased from 4.5% to 18.5%, while the proportion of such individuals in other jobs reporting such problems increased from 3.5% to 11.3%.

Among individuals whose large-muscle index improved, there are small decreases in work-limiting health problems. At the same time, among individuals whose large-muscle index was low in both waves, the proportion of individuals reporting work-limiting health problems was high and increased sharply: from 18.5% to 27.3% among individuals in occupations that demand dynamic strength, and from 15.3% to 22.3% among such individuals in other occupations.

Table A4. Mean health limitations, CESD depressive symptoms and subjective probabilities of working full-time after age 65 by the dynamic strength O*NET measures and changes in the HRS large muscle index

Workers' Resources (HRS)	**HIGH job demand for dynamic strength (O*NET) at t**			**LOW job demand for dynamic strength (O*NET) at t**		
Transition in Large		Fraction with health limitations			Fraction with health limitations	
Muscle Index	N	t	t+1	N	t	t+1
High → high	7682	0.022	0.033	9737	0.016	0.023
High → low	2736	0.045	0.185	2621	0.035	0.113
Low → high	2127	0.074	0.064	2138	0.066	0.044
Low → low	5771	0.185	0.273	5460	0.153	0.223
All	18316	0.083	0.135	19956	0.061	0.092
Transition in Large		Mean CESD score			Mean CESD score	
Muscle Index	N	t	t+1	N	t	t+1
High → high	6771	0.811	0.823	9213	0.626	0.621
High → low	2427	1.157	1.493	2485	0.920	1.111
Low → high	1909	1.285	1.117	2020	1.048	0.829
Low → low	5511	1.841	1.962	5384	1.424	1.491
All	16618	1.257	1.332	19102	0.934	0.952
Transition in Large		Mean P(work after 65)			Mean P(work after 65)	
Muscle Index	N	t	t+1	N	t	t+1
High → high	5168	35.4	36.5	7134	38.8	40.2
High → low	1814	33.5	30.1	1855	35.1	35.7
Low → high	1411	30.3	32.1	1563	35.6	37.6
Low → low	3968	30.6	28.7	3909	35.9	35.8
All	13000	32.4	31.9	15176	36.3	37.2

*Sample: HRS, Age 50-70, full-time workers at t and non-missing answers to the three questions at t and t+1. The CESD score is only collected in non-proxy interviews. Subjective probabilities of working are only collected in non-proxy interviews from people younger than age 65. Prior to 2006, the HRS did not ask this question from non-workers. The values of expectations for the 50-61-year-old non-proxy non-workers are imputed with a model described in section 3.3. High and low values of the O*NET and the HRS measures are defined as being above (=high job demands or high individual resources) or below the mean (=low job demands or low individual resources) in the sample of 50-70-year-old full-time workers.

These patterns are as our theory predicts: declining resources increase the chances that individuals report work-limiting health problems, especially in occupations where dynamic strength is needed.

We see the same general patterns in the CESD depression scores. For example, among individuals who develop large-muscle problems and work in occupations that demand dynamic strength, the average number of reported depressive symptoms increased from 1.157 to 1.493. The increase is somewhat smaller, from 0.920 to 1.111, among such individuals who do not work in occupations that demand dynamic strength.

There are also similar patterns for subjective probabilities of working past age 65. Individuals who develop large-muscle problems (large muscle index from high to low) report a decline in the subjective probabilities of working past age 65 if they work in occupations that demand such skills. That is in contrast to those with the same change in the large muscle index who work in occupations that do not require dynamic strength. For them the average subjective probability of working past age 65 remained about the same.

Table A5 shows changes among workers by their reports of fine-motor skills and the demand for such skills on their jobs. Levels and changes in fine motor skills all strongly predict whether workers will report developing health limitations on work, more depressive symptoms, or expectation of working past age 65, although the interaction with relevant job demands is less strong than it is with the large muscle index.

Among individuals who develop fine-motor skill problems and work in occupations that demand finger dexterity, the propensity to report work-limiting health problems increases from 19.4% to 48.8%, or by 29.4 percentage points. Yet such workers who do not work in jobs requiring finger dexterity report a similarly sharp increase in work-limiting health problems, from 19.1% to 42.4%, or a change of 23.3 percentage points.

Table A5. Mean health limitations, CESD depressive symptoms and subjective probabilities of working full-time after age 65 by the finger dexterity O*NET measures and changes in the HRS fine motor skill index

Workers' Resources (HRS)	**HIGH job demand for finger dexterity (O*NET) at t**			**LOW job demand for finger dexterity (O*NET) at t**		
Transition in Fine Motor Index	N	Fraction with health limitations t	Fraction with health limitations t+1	N	Fraction with health limitations t	Fraction with health limitations t+1
High → high	15945	0.062	0.098	19347	0.051	0.078
High → low	783	0.194	0.488	655	0.191	0.424
Low → high	442	0.285	0.290	424	0.250	0.241
Low → low	392	0.360	0.497	291	0.364	0.495
All	17562	0.080	0.129	20717	0.064	0.098
Transition in Fine Motor Index	N	Mean CESD score t	Mean CESD score t+1	N	Mean CESD score t	Mean CESD score t+1
High → high	14383	1.083	1.139	18496	0.920	0.929
High → low	712	2.021	2.605	633	1.912	2.436
Low → high	406	2.283	1.990	413	1.954	1.826
Low → low	386	2.772	2.847	295	2.285	2.356
All	15887	1.197	1.268	19837	0.994	1.017
Transition in Fine Motor Index	N	Mean P(work after 65) t	Mean P(work after 65) t+1	N	Mean P(work after 65) t	Mean P(work after 65) t+1
High → high	10896	33.9	34.2	13941	36.8	37.6
High → low	506	32.4	26.7	437	32.8	28.5
Low → high	287	29.9	30.2	285	34.8	33.3
Low → low	267	30.2	24.5	205	31.3	29.0
All	12573	33.0	32.9	15604	35.8	36.2

*Sample: HRS, Age 50-70, full-time workers at t and non-missing answers to the three questions at t and t+1. The CESD score is only collected in non-proxy interviews. Subjective probabilities of working are only collected in non-proxy interviews from people younger than age 65. Prior to 2006, the HRS did not ask this question from non-workers. The values of expectations for the 50-61-year-old non-proxy non-workers are imputed with a model described in section 3.3. High and low values of the O*NET and the HRS measures are defined as being above (=high job demands or high individual resources) or below the mean (=low job demands or low individual resources) in the sample of 50-70-year-old full-time workers.

Table A6. Mean health limitations, CESD depressive symptoms and subjective probabilities of working full-time after age 65 by the memorization O*NET measures and changes in the HRS cognition score

Workers' Resources (HRS)	**HIGH job demand for memorization (O*NET) at t**			**LOW job demand for memorization (O*NET) at t**		
Transition in		Fraction with health limitations			Fraction with health limitations	
Cognition	N	t	t+1	N	t	t+1
High → high	7002	0.053	0.079	3148	0.076	0.107
High → low	2883	0.064	0.108	2141	0.077	0.127
Low → high	2747	0.071	0.091	1955	0.080	0.116
Low → low	4764	0.082	0.115	6509	0.078	0.144
All	17396	0.066	0.096	13753	0.078	0.129

Transition in		Mean CESD score			Mean CESD score	
Cognition	N	t	t+1	N	t	t+1
High → high	7084	0.810	0.850	3196	1.013	1.063
High → low	2928	0.935	0.960	2172	1.202	1.245
Low → high	2788	0.915	0.895	1985	1.178	1.190
Low → low	4843	1.170	1.202	6627	1.519	1.590
All	17643	0.946	0.972	13980	1.306	1.359

Transition in		Mean P(work after 65)			Mean P(work after 65)	
Cognition	N	t	t+1	N	t	t+1
High → high	5569	38.5	40.0	2467	38.4	38.2
High → low	2201	38.6	39.2	1623	36.4	34.7
Low → high	2168	37.7	39.3	1524	34.7	35.3
Low → low	3556	37.3	37.1	4650	31.4	30.5
All	14043	37.3	38.2	10755	33.8	33.1

*Sample: HRS, Age 50-70, full-time workers at t and non-missing answers to the three questions at t and t+1. The CESD score is only collected in non-proxy interviews. Subjective probabilities of working are only collected in non-proxy interviews from people younger than age 65. Prior to 2006, the HRS did not ask this question from non-workers. The values of expectations for the 50-61-year-old non-proxy non-workers are imputed with a model described in section 3.3. High and low values of the O*NET and the HRS measures are defined as being above (=high job demands or high individual resources) or below the mean (=low job demands or low individual resources) in the sample of 50-70-year-old full-time workers.

Table A7. Mean health limitations, CESD depressive symptoms and subjective probabilities of working full-time after age 65 by the analyzing data or information O*NET measures and changes in the HRS cognition score

Workers' Resources (HRS)	**HIGH job demand for analyzing data or information (O*NET) at t**			**LOW job demand for analyzing data or information (O*NET) at t**		
Transition in Cognition	N	Fraction with health limitations: t	t+1	N	Fraction with health limitations: t	t+1
High → high	6430	0.049	0.073	3720	0.080	0.115
High → low	2515	0.062	0.106	2509	0.077	0.126
Low → high	2360	0.069	0.094	2342	0.080	0.109
Low → low	3763	0.073	0.107	7510	0.083	0.144
All	15068	0.060	0.090	16081	0.081	0.130
Transition in Cognition	N	Mean CESD score: t	t+1	N	Mean CESD score: t	t+1
High → high	6502	0.799	0.822	3778	1.001	1.079
High → low	2555	0.931	0.951	2545	1.167	1.212
Low → high	2394	0.911	0.877	2379	1.138	1.160
Low → low	3827	1.131	1.170	7643	1.492	1.554
All	15278	0.922	0.939	16345	1.276	1.334
Transition in Cognition	N	Mean P(work after 65): t	t+1	N	Mean P(work after 65): t	t+1
High → high	5123	37.9	39.6	2913	39.4	39.2
High → low	1953	38.1	38.2	1871	37.2	36.4
Low → high	1881	37.1	38.3	1811	35.8	37.0
Low → low	2854	36.7	36.5	5352	32.5	31.7
All	12300	36.8	37.6	12498	34.8	34.4

*Sample: HRS, Age 50-70, full-time workers at t and non-missing answers to the three questions at t and t+1. The CESD score is only collected in non-proxy interviews. Subjective probabilities of working are only collected in non-proxy interviews from people younger than age 65. Prior to 2006, the HRS did not ask this question from non-workers. The values of expectations for the 50-61-year-old non-proxy non-workers are imputed with a model described in section 3.3. High and low values of the O*NET and the HRS measures are defined as being above (=high job demands or high individual resources) or below the mean (=low job demands or low individual resources) in the sample of 50-70-year-old full-time workers.

Table A6 shows our analysis for mismatches between cognitive resources and memorization demands on the job, and Table A7 shows the same analysis for mismatches between cognitive resources and analytical demands of a job. The patterns are more similar to the fine-motor skill results in Table A5 than to the large-muscle results in Table A4. Cognitive decline predicts the outcome variables relatively strongly (though less strongly than fine-motor skills do), but there are only weak interactions with job demands.

For example, among individuals who develop cognitive problems and work in occupations that demand memorization, the propensity to report work-limiting health problems increases from 6.4% at t to 10.8% at t+1. Among such workers in occupations that do not demand memorization, work-limiting health problems increase even more, from 7.7% to 12.7%.

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Appendix B: Additional outcome variables

Table B1. OLS regressions of the change in the subjective probabilities of working full-time after age 62 as a function of job demands, resources and their interactions

	[1]	[2]	[3]	[4]
Large muscle index at t	1.516			
	[0.211]***			
Change in large muscle index, R1	2.014			
	[0.294]***			
Dynamic strength at t, D1	-0.642			
	[0.181]***			
R1 x D1	0.655			
	[0.287]**			
Fine motor index at t		1.451		
		[0.252]***		
Change in fine motor index, R2		1.351		
		[0.242]***		
Finger dexterity at t, D2		-0.367		
		[0.181]**		
R2 x D2		0.269		
		[0.228]		
Cognition at t			1.088	1.089
			[0.264]***	[0.264]***
Change in cognition, R3			1.371	1.374
			[0.324]***	[0.323]***
Memorization at t, D3			0.384	
			[0.214]*	
R3 x D3			-0.009	
			[0.287]	
Analyzing data or information at t, D4				0.385
				[0.205]*
R3 x D4				0.177
				[0.284]
Change in age	0.664	0.591	0.429	0.427
	[0.717]	[0.719]	[0.747]	[0.747]
Change in age - 50 squared	-0.142	-0.139	-0.091	-0.090
	[0.094]	[0.094]	[0.098]	[0.098]
Change in age - 50 cube	0.012	0.012	0.009	0.009
	[0.005]**	[0.005]**	[0.005]	[0.005]
Change in married	-2.184	-2.051	-1.545	-1.539
	[1.248]*	[1.259]	[1.335]	[1.336]
Wave dummies	Yes	Yes	Yes	Yes
Constant	-1.350	-1.231	-1.270	-1.278
	[1.073]	[1.075]	[1.097]	[1.098]
R-squared	0.008	0.007	0.006	0.006
N	24226	24227	21064	21064

Table B2. OLS regressions of the transitions from full-time work to a different employer as a function of job demands, resources and their interactions

	[1]	[2]	[3]	[4]
Large muscle index at t	0.007			
	[0.002]***			
Change in large muscle index, R1	0.004			
	[0.002]**			
Dynamic strength at t, D1	0.005			
	[0.002]**			
R1 x D1	0.001			
	[0.002]			
Fine motor index at t		0.002		
		[0.002]		
Change in fine motor index, R2		0.002		
		[0.001]		
Finger dexterity at t, D2		0.000		
		[0.002]		
R2 x D2		0.000		
		[0.001]		
Cognition at t			0.003	0.002
			[0.003]	[0.003]
Change in cognition, R3			0.002	0.001
			[0.002]	[0.002]
Memorization at t, D3			-0.005	
			[0.002]**	
R3 x D3			-0.001	
			[0.002]	
Analyzing data or information at t, D4				-0.003
				[0.002]
R3 x D4				0.001
				[0.002]
Change in age	0.026	0.026	0.029	0.029
	[0.005]***	[0.005]***	[0.005]***	[0.005]***
Change in age - 50 squared	-0.001	-0.001	-0.001	-0.001
	[0.000]	[0.000]	[0.000]	[0.000]
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	-0.017	-0.017	-0.024	-0.024
	[0.010]*	[0.010]*	[0.011]**	[0.011]**
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.054	0.054	0.050	0.050
	[0.007]***	[0.007]***	[0.008]***	[0.008]***
R-squared	0.006	0.005	0.006	0.006
N	32563	32570	26760	26760

*Those who lose their jobs or become self-employed are coded as zeros (they did not switch employers).

Table B3. OLS regressions of the change in disliking to work as a function of job demands, resources and their interactions

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.001			
	[0.002]			
Change in large muscle index, R1	-0.007			
	[0.003]**			
Dynamic strength at t, D1	-0.002			
	[0.002]			
R1 x D1	0.002			
	[0.003]			
Fine motor index at t		-0.004		
		[0.002]*		
Change in fine motor index, R2		-0.007		
		[0.002]***		
Finger dexterity at t, D2		-0.002		
		[0.001]		
R2 x D2		0.000		
		[0.002]		
Cognition at t			0.003	0.002
			[0.002]	[0.002]
Change in cognition, R3			0.003	0.003
			[0.003]	[0.003]
Memorization at t, D3			-0.001	
			[0.002]	
R3 x D3			0.000	
			[0.002]	
Analyzing data or information at t, D4				0.002
				[0.002]
R3 x D4				0.001
				[0.003]
Change in age	0.011	0.011	0.010	0.010
	[0.006]*	[0.006]*	[0.006]*	[0.006]*
Change in age - 50 squared	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	0.005	0.005	0.011	0.011
	[0.012]	[0.012]	[0.012]	[0.012]
Wave dummies	Yes	Yes	Yes	Yes
Constant	-0.007	-0.008	-0.008	-0.008
	[0.010]	[0.010]	[0.010]	[0.010]
R-squared	0.001	0.001	0.001	0.001
N	29818	29823	26863	26863

*Disliking to work is defined as disagreeing or strongly disagreeing with the statement that "I really enjoy going to work."

Appendix C: Robustness checks

Table C1. OLS regressions of the change in whether health limits working as a function of job demands, resources and their interactions, using many control variables

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.038			
	[0.002]***			
Change in large muscle index, R1	-0.075			
	[0.003]***			
Dynamic strength at t, D1	0.005			
	[0.002]***			
R1 x D1	-0.012			
	[0.003]***			
Fine motor index at t		-0.025		
		[0.003]***		
Change in fine motor index, R2		-0.043		
		[0.002]***		
Finger dexterity at t, D2		0.002		
		[0.002]*		
R2 x D2		0.000		
		[0.002]		
Cognition at t			-0.007	-0.007
			[0.002]***	[0.002]***
Change in cognition, R3			-0.009	-0.009
			[0.003]***	[0.002]***
Memorization at t, D3			-0.005	
			[0.002]***	
R3 x D3			-0.003	
			[0.002]	
Analyzing data or information at t, D4				-0.005
				[0.002]***
R3 x D4				0.001
				[0.002]
Female	-0.003	0.005	0.009	0.008
	[0.003]	[0.003]*	[0.003]***	[0.003]**
White	ref.	ref.	ref.	ref.
Black	0.002	0.003	0.003	0.003
	[0.004]	[0.004]	[0.005]	[0.005]
Other race	0.001	0.004	0.001	0.001
	[0.006]	[0.006]	[0.007]	[0.007]
Hispanic	-0.001	-0.003	0.001	0.001
	[0.005]	[0.005]	[0.006]	[0.006]
Less than high school	0.016	0.020	0.022	0.022
	[0.005]***	[0.005]***	[0.006]***	[0.006]***
High school	ref.	ref.	ref.	ref.
Some college	0.005	0.001	0.003	0.003
	[0.004]	[0.004]	[0.004]	[0.004]

College graduate	0.002	-0.009	-0.009	-0.009
	[0.003]	[0.003]***	[0.004]**	[0.004]**
Change in age	-0.019	-0.018	-0.022	-0.022
	[0.005]***	[0.005]***	[0.005]***	[0.005]***
Change in age - 50 squared	0.001	0.001	0.001	0.001
	[0.000]*	[0.000]**	[0.000]***	[0.000]***
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	0.014	0.011	0.015	0.015
	[0.010]	[0.010]	[0.011]	[0.011]
Change in spouse works	0.001	0.002	0.002	0.002
	[0.005]	[0.005]	[0.005]	[0.005]
Change in log household income	-0.019	-0.019	-0.021	-0.021
	[0.003]***	[0.003]***	[0.003]***	[0.003]***
Change in positive household income	-0.010	-0.007	-0.010	-0.010
	[0.020]	[0.021]	[0.023]	[0.023]
Change in log household wealth	-0.001	-0.001	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]
Change in household wealth positive	0.001	-0.003	-0.003	-0.003
	[0.022]	[0.023]	[0.025]	[0.025]
Has a DB pension	0.002	0.002	0.003	0.003
	[0.004]	[0.004]	[0.004]	[0.004]
Has a DC pension	0.001	-0.001	0.001	0.002
	[0.003]	[0.003]	[0.004]	[0.004]
Self-employed	-0.005	-0.008	-0.003	-0.003
	[0.005]	[0.005]*	[0.005]	[0.005]
Tenure at job, in years	0.000	0.000	0.000	0.000
	[0.000]*	[0.000]*	[0.000]**	[0.000]**
Tenure missing	0.013	0.008	-0.008	-0.010
	[0.018]	[0.019]	[0.022]	[0.022]
Has health insurance from employer	0.003	0.003	0.005	0.005
	[0.004]	[0.005]	[0.005]	[0.005]
Has health insurance from spouse	0.010	0.008	0.012	0.012
	[0.005]*	[0.005]	[0.005]**	[0.005]**
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.047	0.045	0.041	0.041
	[0.010]***	[0.010]***	[0.010]***	[0.010]***
R-squared	0.047	0.029	0.010	0.010
N	38272	38279	31149	31149

Table C2. OLS regressions of the change in the CESD depressive symptoms as a function of job demands, resources and their interactions, using many control variables

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.044			
	[0.009]***			
Change in large muscle index, R1	-0.208			
	[0.014]***			
Dynamic strength at t, D1	0.018			
	[0.008]**			
R1 x D1	-0.040			
	[0.013]***			
Fine motor index at t		-0.029		
		[0.011]***		
Change in fine motor index, R2		-0.108		
		[0.012]***		
Finger dexterity at t, D2		0.011		
		[0.007]		
R2 x D2		0.004		
		[0.012]		
Cognition at t			-0.001	0.000
			[0.011]	[0.011]
Change in cognition, R3			-0.043	-0.042
			[0.013]***	[0.013]***
Memorization at t, D3			-0.006	
			[0.009]	
R3 x D3			0.023	
			[0.012]**	
Analyzing data or information at t, D4				-0.013
				[0.009]
R3 x D4				0.015
				[0.012]
Female	-0.011	-0.006	0.002	0.001
	[0.013]	[0.013]	[0.014]	[0.014]
White	ref.	ref.	ref.	ref.
Black	-0.027	-0.019	-0.023	-0.025
	[0.019]	[0.019]	[0.022]	[0.022]
Other race	0.015	0.025	0.012	0.012
	[0.035]	[0.035]	[0.038]	[0.038]
Hispanic	-0.036	-0.037	-0.014	-0.015
	[0.031]	[0.032]	[0.033]	[0.033]
Less than high school	-0.006	0.006	0.040	0.038
	[0.023]	[0.023]	[0.025]	[0.025]
High school	ref.	ref.	ref.	ref.
Some college	-0.001	-0.009	0.003	0.005
	[0.017]	[0.017]	[0.018]	[0.019]
College graduate	0.012	-0.007	-0.005	0.000
	[0.017]	[0.017]	[0.020]	[0.019]

Change in age	0.029	0.034	0.018	0.018
	[0.027]	[0.027]	[0.028]	[0.028]
Change in age - 50 squared	-0.001	-0.001	-0.001	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	-0.445	-0.450	-0.449	-0.449
	[0.065]***	[0.066]***	[0.069]***	[0.069]***
Change in spouse works	-0.037	-0.035	-0.032	-0.032
	[0.028]	[0.028]	[0.030]	[0.030]
Change in log household income	-0.046	-0.047	-0.051	-0.051
	[0.016]***	[0.016]***	[0.017]***	[0.017]***
Change in positive household income	0.230	0.247	0.255	0.257
	[0.125]*	[0.128]*	[0.141]*	[0.141]*
Change in log household wealth	-0.013	-0.013	-0.006	-0.006
	[0.007]*	[0.007]*	[0.007]	[0.007]
Change in household wealth positive	0.152	0.145	0.005	0.006
	[0.133]	[0.133]	[0.140]	[0.140]
Has a DB pension	-0.018	-0.019	-0.014	-0.014
	[0.018]	[0.018]	[0.019]	[0.019]
Has a DC pension	0.016	0.010	0.013	0.014
	[0.018]	[0.018]	[0.019]	[0.019]
Self-employed	-0.005	-0.007	-0.013	-0.012
	[0.022]	[0.022]	[0.024]	[0.024]
Tenure at job, in years	-0.001	-0.001	-0.002	-0.002
	[0.001]**	[0.001]**	[0.001]**	[0.001]**
Tenure missing	-0.200	-0.211	-0.200	-0.200
	[0.093]**	[0.095]**	[0.100]**	[0.100]**
Has health insurance from employer	-0.019	-0.023	-0.037	-0.035
	[0.024]	[0.024]	[0.025]	[0.025]
Has health insurance from spouse	0.015	0.009	-0.006	-0.005
	[0.025]	[0.025]	[0.026]	[0.026]
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.066	0.066	0.099	0.096
	[0.053]	[0.053]	[0.055]*	[0.055]*
R-squared	0.021	0.014	0.011	0.011
N	35720	35724	31623	31623

Table C3. OLS regressions of the change in the subjective probabilities of working full-time after age 65 as a function of job demands, resources and their interactions, using many control variables

	[1]	[2]	[3]	[4]
Large muscle index at t	1.267			
	[0.171]***			
Change in large muscle index, R1	1.908			
	[0.245]***			
Dynamic strength at t, D1	0.037			
	[0.178]			
R1 x D1	0.802			
	[0.237]***			
Fine motor index at t		1.032		
		[0.207]***		
Change in fine motor index, R2		0.966		
		[0.196]***		
Finger dexterity at t, D2		0.173		
		[0.163]		
R2 x D2		0.112		
		[0.181]		
Cognition at t			0.508	0.492
			[0.242]**	[0.241]**
Change in cognition, R3			0.979	0.964
			[0.277]***	[0.276]***
Memorization at t, D3			0.302	
			[0.201]	
R3 x D3			-0.215	
			[0.254]	
Analyzing data or information at t, D4				0.414
				[0.196]**
R3 x D4				-0.227
				[0.246]
Female	0.793	0.525	0.265	0.321
	[0.301]***	[0.289]*	[0.315]	[0.312]
White	ref.	ref.	ref.	ref.
Black	0.005	0.019	0.567	0.612
	[0.424]	[0.424]	[0.473]	[0.475]
Other race	-1.024	-1.111	-0.893	-0.893
	[0.716]	[0.717]	[0.743]	[0.743]
Hispanic	0.952	1.047	1.265	1.292
	[0.630]	[0.628]*	[0.675]*	[0.675]*
Less than high school	-1.273	-1.421	-1.831	-1.804
	[0.498]**	[0.493]***	[0.555]***	[0.553]***
High school	ref.	ref.	ref.	ref.
Some college	-0.366	-0.260	-0.672	-0.708
	[0.384]	[0.382]	[0.419]	[0.423]*
College graduate	0.157	0.552	-0.071	-0.150
	[0.389]	[0.383]	[0.445]	[0.439]

Change in age	0.915	0.874	0.788	0.782
	[0.595]	[0.596]	[0.624]	[0.624]
Change in age - 50 squared	-0.069	-0.067	-0.079	-0.079
	[0.063]	[0.063]	[0.067]	[0.067]
Change in age - 50 cube	0.004	0.004	0.005	0.005
	[0.003]	[0.003]	[0.003]	[0.003]
Change in married	-1.875	-1.780	-1.736	-1.736
	[1.188]	[1.192]	[1.276]	[1.276]
Change in spouse works	-0.048	-0.087	-0.225	-0.221
	[0.588]	[0.587]	[0.631]	[0.631]
Change in log household income	0.357	0.371	0.578	0.580
	[0.310]	[0.310]	[0.330]*	[0.331]*
Change in positive household income	2.510	2.491	3.472	3.452
	[2.570]	[2.583]	[2.740]	[2.743]
Change in log household wealth	-0.091	-0.093	-0.057	-0.058
	[0.136]	[0.136]	[0.143]	[0.143]
Change in household wealth positive	1.216	1.287	0.418	0.423
	[2.591]	[2.596]	[2.741]	[2.742]
Has a DB pension	-0.158	-0.147	-0.268	-0.271
	[0.394]	[0.395]	[0.423]	[0.423]
Has a DC pension	0.542	0.597	0.517	0.465
	[0.369]	[0.369]	[0.396]	[0.398]
Self-employed	-1.302	-1.213	-0.943	-0.961
	[0.566]**	[0.567]**	[0.598]	[0.598]
Tenure at job, in years	0.035	0.034	0.045	0.045
	[0.014]**	[0.014]**	[0.015]***	[0.015]***
Tenure missing	-1.019	-1.270	-1.224	-1.162
	[2.890]	[2.862]	[3.058]	[3.067]
Has health insurance from employer	0.499	0.520	0.578	0.527
	[0.523]	[0.525]	[0.551]	[0.551]
Has health insurance from spouse	1.935	2.021	2.036	2.016
	[0.529]***	[0.529]***	[0.557]***	[0.557]***
Wave dummies	Yes	Yes	Yes	Yes
Constant	-3.489	-3.476	-3.174	-3.110
	[1.148]***	[1.146]***	[1.180]***	[1.181]***
R-squared	0.009	0.007	0.008	0.008
N	28176	28177	24798	24798

Table C4. OLS regressions of the transitions from full-time work to retirement as a function of job demands, resources and their interactions, using many control variables

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.025			
	[0.002]***			
Change in large muscle index, R1	-0.024			
	[0.002]***			
Dynamic strength at t, D1	0.008			
	[0.002]***			
R1 x D1	-0.003			
	[0.002]			
Fine motor index at t		-0.018		
		[0.002]***		
Change in fine motor index, R2		-0.017		
		[0.002]***		
Finger dexterity at t, D2		0.007		
		[0.002]***		
R2 x D2		0.000		
		[0.002]		
Cognition at t			-0.012	-0.012
			[0.002]***	[0.002]***
Change in cognition, R3			-0.007	-0.007
			[0.002]***	[0.002]***
Memorization at t, D3			-0.003	
			[0.002]	
R3 x D3			-0.001	
			[0.002]	
Analyzing data or information at t, D4				-0.003
				[0.002]*
R3 x D4				-0.001
				[0.002]
Female	0.000	0.004	0.005	0.004
	[0.003]	[0.003]	[0.003]	[0.003]
White	ref.	ref.	ref.	ref.
Black	0.004	0.005	0.002	0.001
	[0.004]	[0.004]	[0.005]	[0.005]
Other race	0.000	0.001	-0.003	-0.003
	[0.006]	[0.006]	[0.007]	[0.007]
Hispanic	-0.017	-0.018	-0.017	-0.018
	[0.005]***	[0.006]***	[0.006]***	[0.006]***
Less than high school	0.007	0.010	0.005	0.005
	[0.005]	[0.005]**	[0.006]	[0.006]
High school	ref.	ref.	ref.	ref.
Some college	-0.002	-0.004	-0.004	-0.004
	[0.004]	[0.004]	[0.004]	[0.004]
College graduate	-0.020	-0.026	-0.027	-0.026
	[0.004]***	[0.004]***	[0.005]***	[0.005]***

Change in age	-0.054	-0.055	-0.053	-0.053
	[0.004]***	[0.004]***	[0.004]***	[0.004]***
Change in age - 50 squared	0.003	0.003	0.003	0.003
	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	0.033	0.032	0.037	0.037
	[0.009]***	[0.009]***	[0.010]***	[0.010]***
Change in spouse works	-0.035	-0.035	-0.035	-0.036
	[0.005]***	[0.005]***	[0.006]***	[0.006]***
Change in log household income	-0.057	-0.057	-0.059	-0.059
	[0.003]***	[0.003]***	[0.003]***	[0.003]***
Change in positive household income	0.104	0.104	0.100	0.100
	[0.017]***	[0.017]***	[0.019]***	[0.019]***
Change in log household wealth	0.002	0.002	0.002	0.002
	[0.001]**	[0.001]**	[0.001]**	[0.001]**
Change in household wealth positive	-0.035	-0.035	-0.034	-0.034
	[0.015]**	[0.015]**	[0.016]**	[0.016]**
Has a DB pension	0.050	0.050	0.051	0.051
	[0.004]***	[0.004]***	[0.004]***	[0.004]***
Has a DC pension	-0.008	-0.009	-0.009	-0.008
	[0.003]**	[0.003]***	[0.004]**	[0.004]**
Self-employed	-0.045	-0.046	-0.043	-0.043
	[0.004]***	[0.004]***	[0.005]***	[0.005]***
Tenure at job, in years	0.002	0.002	0.001	0.001
	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Tenure missing	0.030	0.028	0.018	0.017
	[0.018]*	[0.019]	[0.022]	[0.022]
Has health insurance from employer	0.000	-0.001	0.000	0.001
	[0.004]	[0.004]	[0.005]	[0.005]
Has health insurance from spouse	0.012	0.011	0.012	0.012
	[0.005]***	[0.005]**	[0.005]**	[0.005]**
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.048	0.048	0.049	0.049
	[0.008]***	[0.008]***	[0.009]***	[0.009]***
R-squared	0.099	0.096	0.092	0.092
N	38829	38838	31645	31645

Table C5. OLS regressions of the transitions from full-time work to disability as a function of job demands, resources and their interactions, using many control variables

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.009			
	[0.001]***			
Change in large muscle index, R1	-0.011			
	[0.001]***			
Dynamic strength at t, D1	0.001			
	[0.000]*			
R1 x D1	-0.002			
	[0.001]**			
Fine motor index at t		-0.008		
		[0.001]***		
Change in fine motor index, R2		-0.010		
		[0.001]***		
Finger dexterity at t, D2		0.001		
		[0.000]*		
R2 x D2		0.000		
		[0.001]		
Cognition at t			-0.003	-0.003
			[0.001]***	[0.001]***
Change in cognition, R3			-0.002	-0.002
			[0.001]***	[0.001]***
Memorization at t, D3			-0.001	
			[0.001]*	
R3 x D3			0.000	
			[0.001]	
Analyzing data or information at t, D4				-0.001
				[0.001]**
R3 x D4				-0.001
				[0.001]
Female	-0.002	0.000	0.003	0.002
	[0.001]**	[0.001]	[0.001]***	[0.001]**
White	ref.	ref.	ref.	ref.
Black	0.006	0.006	0.004	0.004
	[0.002]***	[0.002]***	[0.002]**	[0.002]**
Other race	-0.001	0.000	0.000	0.000
	[0.002]	[0.002]	[0.002]	[0.002]
Hispanic	0.003	0.002	0.001	0.000
	[0.002]	[0.002]	[0.002]	[0.002]
Less than high school	0.005	0.005	0.004	0.004
	[0.002]***	[0.002]***	[0.002]**	[0.002]**
High school	ref.	ref.	ref.	ref.
Some college	0.002	0.001	0.001	0.001
	[0.001]*	[0.001]	[0.001]	[0.001]
College graduate	0.002	0.000	0.000	0.000
	[0.001]*	[0.001]	[0.001]	[0.001]

Change in age	0.001	0.001	-0.001	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]
Change in age - 50 squared	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]*	[0.000]*
Change in married	0.003	0.002	0.004	0.004
	[0.003]	[0.003]	[0.003]	[0.003]
Change in spouse works	0.000	0.000	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]
Change in log household income	-0.005	-0.005	-0.004	-0.004
	[0.001]***	[0.001]***	[0.001]***	[0.001]***
Change in positive household income	-0.005	-0.005	-0.002	-0.002
	[0.008]	[0.008]	[0.009]	[0.009]
Change in log household wealth	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in household wealth positive	0.006	0.006	0.004	0.004
	[0.008]	[0.008]	[0.008]	[0.008]
Has a DB pension	-0.002	-0.002	-0.001	-0.001
	[0.001]*	[0.001]*	[0.001]	[0.001]
Has a DC pension	-0.001	-0.001	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]
Self-employed	-0.004	-0.004	-0.003	-0.003
	[0.001]***	[0.001]***	[0.001]**	[0.001]**
Tenure at job, in years	0.000	0.000	0.000	0.000
	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Tenure missing	0.001	-0.001	0.004	0.004
	[0.006]	[0.006]	[0.008]	[0.008]
Has health insurance from employer	-0.003	-0.003	-0.004	-0.004
	[0.001]**	[0.001]**	[0.001]***	[0.001]***
Has health insurance from spouse	-0.003	-0.003	-0.003	-0.003
	[0.001]**	[0.001]**	[0.002]**	[0.002]*
Wave dummies	Yes	Yes	Yes	Yes
Constant	0.011	0.010	0.012	0.012
	[0.003]***	[0.003]***	[0.003]***	[0.003]***
R-squared	0.023	0.027	0.008	0.008
N	38829	38838	31645	31645

Table C6. OLS regressions of lagged work limiting health problems as a function of job demands, resources and their interactions, balancing tests

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.018			
	[0.002]***			
Change in large muscle index, R1	0.001			
	[0.002]			
Dynamic strength at t, D1	0.000			
	[0.001]			
R1 x D1	0.002			
	[0.002]			
Fine motor index at t		-0.016		
		[0.003]***		
Change in fine motor index, R2		-0.003		
		[0.002]		
Finger dexterity at t, D2		0.000		
		[0.001]		
R2 x D2		0.000		
		[0.002]		
Cognition at t			0.001	0.001
			[0.002]	[0.002]
Change in cognition, R3			0.003	0.002
			[0.002]	[0.002]
Memorization at t, D3			0.000	
			[0.002]	
R3 x D3			0.000	
			[0.002]	
Analyzing data or information at t, D4				0.001
				[0.002]
R3 x D4				-0.004
				[0.002]**
Change in age	0.008	0.007	0.005	0.005
	[0.005]	[0.005]	[0.006]	[0.006]
Change in age - 50 squared	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	-0.004	-0.005	-0.003	-0.003
	[0.009]	[0.009]	[0.010]	[0.010]
Wave dummies	Yes	Yes	Yes	Yes
Constant	-0.016	-0.015	-0.011	-0.011
	[0.010]	[0.010]	[0.011]	[0.011]
R-squared	0.006	0.005	0.003	0.003
N	31775	31781	25208	25208

Table C7. OLS regressions of lagged CESD depressive symptoms as a function of job demands, resources and their interactions, balancing tests

	[1]	[2]	[3]	[4]
Large muscle index at t	-0.057			
	[0.011]***			
Change in large muscle index, R1	0.024			
	[0.015]			
Dynamic strength at t, D1	-0.012			
	[0.009]			
R1 x D1	0.006			
	[0.015]			
Fine motor index at t		-0.002		
		[0.013]		
Change in fine motor index, R2		-0.013		
		[0.008]		
Finger dexterity at t, D2		0.009		
		[0.012]		
R2 x D2		0.000		
		0.000		
Cognition at t			0.020	0.020
			[0.014]	[0.014]
Change in cognition, R3			0.008	0.005
			[0.009]	[0.009]
Memorization at t, D3			-0.007	
			[0.013]	
R3 x D3			0.000	
			0.000	
Analyzing data or information at t, D4				-0.007
				[0.013]
R3 x D4				-0.027
				[0.063]
Change in age	0.025	0.023	0.024	0.024
	[0.034]	[0.034]	[0.034]	[0.034]
Change in age - 50 squared	-0.004	-0.004	-0.003	-0.003
	[0.002]	[0.002]	[0.002]	[0.002]
Change in age - 50 cube	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Change in married	-0.087	-0.091	-0.082	-0.081
	[0.075]	[0.075]	[0.076]	[0.076]
Wave dummies	Yes	Yes	Yes	Yes
Constant	-0.029	-0.024	-0.027	-0.027
	[0.062]	[0.062]	[0.063]	[0.063]
R-squared	0.007	0.006	0.005	0.005
N	25617	25622	25178	25178

Table C8. OLS regressions of lagged subjective probabilities of working after age 65 as a function of job demands, resources and their interactions, balancing tests

	[1]	[2]	[3]	[4]
Large muscle index at t	0.454			
	[0.182]**			
Change in large muscle index, R1	-0.090			
	[0.256]			
Dynamic strength at t, D1	-0.301			
	[0.166]*			
R1 x D1	-0.491			
	[0.252]*			
Fine motor index at t		0.716		
		[0.227]***		
Change in fine motor index, R2		0.416		
		[0.207]**		
Finger dexterity at t, D2		-0.263		
		[0.163]		
R2 x D2		-0.104		
		[0.186]		
Cognition at t			0.386	0.402
			[0.235]	[0.235]*
Change in cognition, R3			-0.258	-0.246
			[0.303]	[0.302]
Memorization at t, D3			0.115	
			[0.202]	
R3 x D3			0.125	
			[0.280]	
Analyzing data or information at t, D4				0.063
				[0.194]
R3 x D4				-0.079
				[0.273]
Change in age	0.241	0.265	0.428	0.428
	[0.666]	[0.666]	[0.723]	[0.723]
Change in age - 50 squared	-0.285	-0.283	-0.327	-0.327
	[0.062]***	[0.062]***	[0.067]***	[0.067]***
Change in age - 50 cube	0.015	0.015	0.017	0.017
	[0.003]***	[0.003]***	[0.003]***	[0.003]***
Change in married	-2.528	-2.508	-2.290	-2.291
	[1.179]**	[1.180]**	[1.270]*	[1.270]*
Wave dummies	Yes	Yes	Yes	Yes
Constant	1.282	1.268	1.228	1.237
	[1.331]	[1.332]	[1.378]	[1.379]
R-squared	0.010	0.010	0.009	0.009
N	24675	24677	20643	20643

Table C9. OLS regressions of work limiting health problems, CESD depressive symptoms, subjective probabilities of working after age 65, and transitions from full-time work to disability as a function of job demands, resources and their interactions, restricted to full-time workers at t+1

	health limitation	CESD	PW65
Large muscle index at t	-0.009	-0.006	0.441
	[0.002]***	[0.010]	[0.194]**
Change in large muscle index, R1	-0.041	-0.171	1.020
	[0.003]***	[0.016]***	[0.293]***
Dynamic strength at t, D1	0.002	0.001	-0.159
	[0.001]	[0.008]	[0.169]
R1 x D1	-0.005	-0.037	0.746
	[0.003]*	[0.016]**	[0.290]**
Change in age	-0.014	0.026	0.698
	[0.005]***	[0.029]	[0.662]
Change in age - 50 squared	0.000	-0.001	-0.205
	[0.000]	[0.002]	[0.070]***
Change in age - 50 cube	0.000	0.000	0.016
	[0.000]	[0.000]	[0.003]***
Change in married	-0.004	-0.497	-2.116
	[0.010]	[0.077]***	[1.361]
Wave dummies	Yes	Yes	Yes
Constant	0.028	-0.010	-0.555
	[0.009]***	[0.051]	[1.114]
R-squared	0.017	0.017	0.009
N	28950	26903	22043