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# Aging and work capacity☆

Italo Lopez Garcia[a], Nicole Maestas[b,*], Kathleen J. Mullen[c]

[a] University of Southern California, United States and IZA, Germany
[b] Harvard University and NBER, United States
[c] University of Oregon and NBER, United States and IZA, Germany

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ABSTRACT

Declining health with age can limit individuals' work capacity, increasing the likelihood of mismatch between their abilities to perform certain tasks and the minimum demands of the jobs available to them. Traditional measures of health status are insufficient for understanding how labor supply outcomes are influenced by the match between individuals' abilities and job demands. We use unique survey data on individuals' self-reported ability levels, harmonized with occupational ability requirements from the O*NET database, to develop a new measure of work capacity. We find that average abilities overall and across different domains are high relative to average occupational demands. At the same time, age-related declines in abilities are modest, at least through age 70. Putting these elements together, individuals' work capacity is relatively stable with age. Finally, we show that our measures of work capacity are predictive of current and expected future labor supply outcomes, with and without controls for standard health variables.

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## Introduction

The U.S. population is aging rapidly, partly due to dramatic gains in life expectancy. The share of individuals aged 65+ was 16.8 percent in 2020 and is projected to reach 20.6 percent by 2030 (US Census Bureau 2018; 2023). As a result, labor force growth—and consequently, economic growth—has slowed (Maestas, Mullen, and Powell 2023a), and, in the absence of policy action to update their funding mechanisms, the long-run fiscal health of Social Security and Medicare has eroded (The Board of Trustees 2024). One policy response is to incentivize older individuals to delay retirement and work longer, for example by raising eligibility ages for claiming Social Security and Medicare benefits. If older workers worked longer, their additional payroll tax contributions would help shore up the social insurance system, and they would draw benefits from the system for fewer years, offsetting some of the social costs of living longer.

But even if working longer was a net positive for the U.S. economy, it is not obvious that all older individuals *could* work longer or would even want to work longer (Berkman and Truesdale, 2022). By some accounts, there appears to be significant capacity to work among today's older Americans relative to earlier cohorts (Coile, Milligan and Wise 2017; Cutler, Meara and Richards-Shubik 2014). Biodemographic research

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* Corresponding author.
*E-mail address:* maestas@hcp.med.harvard.edu (N. Maestas).

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corroborates this; individuals of a given chronological age today are biologically younger than same-aged individuals of the past by about a decade (Vaupel 2010). However, while these estimates provide an idea of how much additional employment by older workers could potentially be achieved in the aggregate, particularly in the absence of changes in job demands, they cannot tell us about the level and distribution of work capacity in the economy, how work capacity changes with age or with the onset of health problems, or how abilities and job demands interplay and evolve over time.

Indeed, one important driver of early retirement is age-related declines in health (see e.g., McGarry 2004, Disney et al. 2006). Health problems arise more frequently with age, and they may lead to declines in individuals' *functional abilities*. We adopt O*NET's definition of abilities as "relatively enduring attributes of an individual's capability for performing a particular range of different tasks" (Fleishman, Costanza, and Marshall-Mies 1999). Abilities are distinct from skills, which are "proficiencies that are developed through training or experience" (Tsacoumis and Willison 2010). We define *work capacity* as the share of all jobs in the national economy (conditional on education) that an individual can do based on their functional abilities. That is, we abstract from the skills, knowledge and any occupation-specific training requirements needed to perform a given job and focus solely on whether an individual possesses the functional abilities needed to perform a job at or above the required levels.

To better understand the relationship between aging and work capacity, we develop a new way of measuring work capacity. Our method starts from the insight that if individuals' functional abilities were measured in the same terms as the functional requirements of occupations, then one could compare an individual's ability levels to the ability requirements of different occupations and deduce which occupations the individual could likely perform. To create such a data set, we asked a nationally representative sample of Americans ages 35–71 in the RAND American Life Panel Survey (ALP) to rate their abilities along 52 dimensions, corresponding exactly to the 52 dimensions of ability used by the Occupational Information Network (O*NET) to rate the occupational ability requirements for nearly 800 occupations in the U.S. economy. The survey items, scales and scale anchors were exactly the same as those used by O*NET to rate occupations. Combining our new survey data with the O*NET database, we then determine for each respondent their occupation-specific work capacity—that is, whether they likely can or cannot perform a given occupation—by comparing their reported levels of functional ability to those required by each occupation. Once we determine an individual's set of potential occupations—conditional on their education—we can calculate the share of all jobs in the national economy that the individual can do based on their functional abilities.

Next, we investigate the properties of our new work capacity measure, comparing two alternative versions. The relatively strict version requires an individual to meet or exceed all ability requirements that are important for an occupation in order to be credited with the occupation. The more generous version gives credit for an occupation as long as the individual meets most, but not necessarily all, occupational ability requirements. The two measures may be relevant for different margins of labor supply. Specifically, the strict work capacity measure may be more relevant for the entry margin, since potential hires may need to demonstrate they have all of the abilities required to perform a new job, and the generous work capacity measure may be more relevant for the exit margin, since job incumbents may be able to compensate for ability declines by leveraging their experience and job-specific knowledge and skills to maintain job performance. We show how the two measures of work capacity vary across our nationally representative sample, how they compare to one another, how they vary by age, and how they compare to average occupational requirements in the national economy.

Third, we test whether our new measure of work capacity is useful for understanding current and future labor force participation decisions by testing whether work capacity adds explanatory power to models of employment, disability benefit receipt, future retirement intentions, and future return-to-work intentions among those not in the labor force.

Finally, we analyze whether our measures are robust to potential biases in self-reported functional abilities. Specifically, even though we provide anchors to help respondents situate their ability levels on the O*NET scale, it is possible that some respondents may systematically over- or under-estimate their own abilities, leading to systematic biases in our measures of work capacity. There is a growing literature in psychology examining differences between individuals' beliefs and objective reality. For example, individuals tend to over-estimate their own abilities for complex tasks, while they under-estimate their abilities for easier tasks (Moore and Healy, 2008), and individuals with mild cognitive impairments tend to over-estimate their cognitive abilities (Okonkwo et al., 2008). Other studies consistently find that individual personality traits such as extraversion correlate with overestimation, while openness to experience correlates with unbiased and accurate assessments (Schaefer et al., 2004). To correct for these potential biases, we estimate versions of the models controlling for the Big Five personality traits on a subsample of respondents (64 %) who also completed a prior ALP survey eliciting personality measures.

We have three main findings. First, average abilities overall and across four domains—cognitive, psychomotor, physical, and sensory ability—are high relative to average occupational demands. Second, we find that age-related declines in ability are modest, with physical abilities declining the most by age 71 and cognitive abilities declining the least. As a result, these observed declines are largely inframarginal to job demands, at least on average. This suggests that the potential set of occupations individuals can do based on their functional abilities is relatively stable over the life-course, on average. Third, our measures of work capacity have predictive power for all of the different objective and subjective labor supply outcomes we examined. We show that they reflect underlying health to an important degree but also contribute explanatory variation that is independent of health. We find that an increase in the fraction of jobs (for a given education level) that an individual can do based on their abilities relative to job demands—specifically, an increase from being unable to do any job to being able to do all jobs—is significantly associated with a 17–23 percentage point increase in labor force participation and a 12–20 percentage point decrease in the percentage receiving Social Security Disability benefits. The same change in an individual's work capacity is associated with a 28–35 percentage point increase in the subjective expectation of working past age 70 if the individual is age 65 or older and a 12–15 percentage point increase in the subjective expectation of working past age 65 if the individual is between ages 55 and 64. Finally, the same change in an individual's work capacity is associated with a 10–13 percentage point increase in the subjective expectation that retired individuals will return to the labor force. The magnitudes of these changes are all economically relevant and reflect that the measures of work capacity contribute explanatory variation that is independent of standard measures of health alone, coming specifically from the (mis)match between abilities and job demands. Our results are robust to the inclusion of standardized measures of the Big Five personality traits to account for potential overestimation of abilities.

Our findings advance the literature in several ways. A large literature has shown that both physical and cognitive health declines with age, but for the most part these studies have not directly examined how these health declines interact with occupational requirements to determine work capacity (see Belbase et al. (2015) for an extensive literature review). Most relevant to our current paper are two previous studies that specifically examine how age-related mismatches between abilities and job demands influence labor supply and retirement outcomes. Using data on cognitive and physical abilities from the Health and Retirement Study (HRS) and job demands from O*NET, Hudomiet et al. (2017) study the effect of mismatches between individuals' abilities and the demands of their own job on retirement expectations; they focus, by necessity, on a limited number of ability dimensions, and they evaluate these with respect to the current job. In contrast, our new data allows us to examine a comprehensive set of abilities (52 in total) and evaluate these with respect to all potential jobs. Using the same data sources as Hudomiet et al., Belbase et al. (2015) construct a Susceptibility Index, which captures how likely the abilities required for an occupation are to decline with age for all occupations in the economy in O*NET. By relating the index to retirement behaviors, they find that workers in occupations that rely more on abilities with faster age decline tend to retire earlier. A limitation of their approach is that they do not have information on workers' actual abilities, so they identify abilities prone to decline by relying on an extensive literature review. Since our new survey data is harmonized with the O*NET database, we can compare individuals' actual abilities to the levels of those same abilities required for nearly all occupations in the national economy.

At the same time, the current survey-based approach has a number of limitations. First, it relies on self-reported measures of ability levels that, as noted above, may be prone to bias. To correct for these potential biases, we estimate versions of the models controlling for the Big Five personality traits (conscientiousness, agreeableness, neuroticism, openness and extraversion) on a subsample of respondents for whom we have personality measures from a prior ALP survey. Ideally, we would collect objective performance data on specific abilities that we could compare to the corresponding self-reported ability measures and correct for any systematic biases we observe, especially if they are associated with age. We plan to conduct such tests in future work on this topic. Second, as noted below, occupational requirements in O*NET are assessed by occupational analysts, who may rate requirements differently than hiring managers would evaluate new applicants, managers would assess workers' job performance, or employees would describe the abilities they need to perform their job tasks. Peterson et al. (2001) provide more details on the conceptual underpinnings of the O*NET content model as it relates to applications in human resources management and industrial/organizational psychology. Note that our approach conceptualizes work capacity as the fraction of jobs that an individual has the *abilities* to do, but does not take into account the ease with which an individual can do them or how much they would enjoy doing them. Finally, in this paper we compare cross-sectional differences in ability, and work capacity, across individuals in different age groups; planned longitudinal data collection will enable us to examine within-person changes over time in future work.

## Data

### *O*NET database and the American work capacity and abilities survey*

We use data from two sources. The first is the U.S. Department of Labor's O*NET database, which contains comprehensive information about the job requirements of all occupations in the U.S. economy. In this paper, we focus on occupational ability requirements. O*NET identifies 52 abilities broadly applicable to jobs in the "world economy," and grouped into four functional domains: cognitive, psychomotor, physical, and sensory abilities. Abilities in the cognitive domain include, for example, oral and written comprehension and expression, fluency of ideas and originality, problem sensitivity, deductive and inductive reasoning, information ordering and mathematical reasoning, pattern recognition and perceptual speed, spatial orientation and visualization, and selective attention and time sharing. Psychomotor abilities include arm-hand steadiness, manual and finger dexterity, multilimb coordination and speed of limb movement, rate control and reaction time. Physical abilities include measures of strength, stamina, flexibility, and gross body coordination. Sensory abilities include aspects of vision, hearing sensitivity and sound localization, speech recognition and speech clarity. Appendix Table A1 lists the 52 abilities and their definitions.

Each occupation is rated along these 52 dimensions of ability by eight independent occupational analysts who follow standardized procedures (Fleisher and Tsacoumis, 2012a). For each ability, analysts rate the *importance* of the ability for the performance of the occupation's associated work activities and tasks, and the *level* of ability needed to carry out those work activities and tasks. Importance is rated on a scale of 1 to 5, where 1="Not Important," 2="Somewhat Important," 3="Important," 4="Very Important," and 5="Extremely Important." The level of ability needed is rated on a scale from 0 to 7, where 0 means not relevant and 7 is the highest level of ability.[1] Each ability scale has a unique set of scale anchors that provide an example of an activity that could be done at particular ability levels. For example, the ability arm-hand steadiness has anchors at levels 2, 4, and 6 corresponding to the degree of arm-hand steadiness needed to "light a candle," "thread a needle," and "cut facets in a diamond," respectively.[2] Final ability level needed and importance ratings for each occupation are averages of the individual ratings provided by the eight raters.[3]

O*NET uses the Standard Occupational Classification (SOC) 2010 system to identify occupations at a detailed, six-digit level. Six-digit occupations are narrowly defined to include workers who perform similar job tasks. O*NET further subdivides certain six-digit occupations (approximately six percent) to an eight-digit level using its O*NET-SOC taxonomy (which is identical to the SOC taxonomy for six-digit occupations that are not further subdivided). For example, the six-digit SOC code "33-3051 Police and Sheriff's Patrol Officers," is further subdivided by O*NET into "33-3051.01 Police Patrol Officers," who "Patrol assigned area to enforce laws and ordinances, regulate traffic, control crowds, prevent crime, and arrest violators" and "33-3051.03 Sheriffs and Deputy Sheriffs" who "Enforce law and order in rural or unincorporated districts or serve legal processes of courts." In contrast, the six-digit SOC code "29-2051 Pharmacy Technicians" who "Prepare medications under the direction of a pharmacist" has no further subdivisions. The O*NET-SOC taxonomy also includes some "new and emerging occupations" that have not yet been added to the SOC. We use the O*NET 22.1 Database (October 2017 Release), which contains 773 six-digit SOC occupations and 966 O*NET-SOC occupations (which encompass the 773 SOC occupations).[4] In this paper, we work at the six-digit level, averaging required ability levels across eight-digit occupations to obtain the average required level for the six-digit occupation.

Our second data set comes from the American Work Capacity and Abilities Survey, a survey we administered in 2018 to participants in the RAND American Life Panel (ALP), a nationally representative sample of Americans ages 18 and older who speak English or Spanish and who have agreed to participate in regular online social science surveys.[5] Specifically, for each of the 52 O*NET abilities, we asked respondents to *rate their own level of ability*, using the same scales and level anchors that the O*NET analysts use to rate occupational requirements. The innovation of this technique is that it measures individuals' functional abilities, which are asked about in general and not in relation to their

[1] Abilities that are not important for an occupation are assigned a required ability level of 0.

[2] A description of the ability scales and their level anchors can be found at https://www.onetcenter.org/dl_files/MS_Word/Abilities.pdf, which was used to elicit ability ratings from job incumbents at the beginning of the O*NET program. O*NET now obtains ability ratings from occupational analysts, but the rating scales and level anchors are the same. O*NET has since revised some of the ability scales in its 2021 update.

[3] O*NET ability rating is ongoing and performed in cycles; approximately 10 percent of occupations are re-rated each year, and new occupations are added as needed.

[4] These figures give the number of occupations for which data is collected. The database includes an additional 136 six-digit SOC occupations for which data is not collected. These include military occupations and occupations in the catch-all category "All Other" that are not classified elsewhere.

[5] For more information about the ALP, see https://www.rand.org/research/data/alp.html. The "American Work Capacity and Abilities Survey" was survey module number 508.

current job or past jobs, *in the same terms and on the same scales* as occupational requirements are measured.

The instructions provided to survey respondents stated: “In this survey, you will be asked to rate your level of functioning for a series of different abilities. When giving your rating, please rate your *current* level of ability, not what you were able to do in the past or what you could do in the future with additional training. If you use an assistive device (e.g., glasses), please rate your ability when using the assistive device.” For each question, we first defined an ability (using the same language as O*NET) and we then asked the respondent to rate their level of ability on a scale from 1 to 7, with 3 anchor points (using the same anchors as O*NET). Respondents who could not perform any level of ability were instructed to select a response button marked “I cannot do any level of this ability” (which we subsequently recoded as 0 in our analysis data set). Respondents were told that these examples are “meant to help you find your own rating with the scale; do not focus on whether you perform the *specific* activity, which may come from an unfamiliar context.” Appendix Fig. A1 is a screenshot of the survey question about arm-hand steadiness, as viewed by a respondent who rated their arm-hand steadiness at level 2.

Only after they rated their abilities, respondents were asked about their current labor force status (e.g., “working now,” “unemployed and looking for work,” “retired,” etc.) and (if currently working) their job title, descriptions of 3–5 “usual activities or duties at this job” and (two-digit) industry, all of which we used to code their current occupation at the six-digit SOC level.[6] Next, respondents were asked a question about their subjective expectation, on a scale of 0–100. of the chances “that you will be working full-time after you reach age 65” (if working, unemployed or temporarily laid off, and if age <65), “that you will be working full-time after you reach age 70” (if working, unemployed or temporarily laid off, and if 65>=age <70), or “that you will return to work sometime in the future” (if out of the labor force because the respondent is retired, disabled, or “homemaker,” regardless of age). Finally, respondents were asked to rate their health on a scale from excellent (1) to poor (5), indicate whether they have “any impairment or health problem that limits the kind or amount of paid work you can do” (yes/no), and indicate whether they receive Social Security Disability Insurance (SSDI) benefits (yes/no).

### *Summary Statistics*

Table 1 presents descriptive statistics for our analysis sample. We invited all English-speaking ALP participants aged 18 to 70 to take the survey between July 18, 2018, and September 17, 2018, The survey had a response rate of 82 % (N = 2,270).[7] Because the focus of this paper is on retirement intentions, we restrict our analysis sample to those aged 35 to 71 years old (N = 2,044). We further exclude respondents with any missing ability rating or missing health variables for a final sample of 1,934 individuals. We use survey weights to match the demographic distribution of the sample to that of the Current Population Survey.[8] Of the respondents in our sample, 51 percent are female, 69 percent are married, 69 percent are White non-Hispanic, 12 percent are Black non-Hispanic, 16 percent are Hispanic, and 4 percent are another race/ethnicity. In terms of age, 41 percent are younger than 50 years old, 29 percent are between 50 and 59 years old, and 30 percent are between 60 and 71 years old. Regarding education, 39 percent have a high school degree or less, 28 percent some college education, 17 percent a bachelor’s degree, and 16 percent a postgraduate degree. Regarding labor force status, 68 percent are active workers, 3 percent are unemployed or temporarily laid-off, 7 percent are disabled, 17 percent are retired, and 5 percent are homemakers. Individuals in the sample are relatively healthy, with 43 percent reporting excellent or very good health, 39 percent reporting good health, and only 18 percent reporting fair or poor health. Approximately one-fifth report a work-limiting health problem, and 10 percent report receiving SSDI benefits.

**Table 1**
Summary Statistics, ALP Sample.

| | % (Weighted) |
|---|---|
| Percent female | 51.2 % |
| Percent married | 68.5 % |
| Percent White non-Hispanic | 68.5 % |
| Percent Black non-Hispanic | 11.7 % |
| Percent Hispanic | 15.9 % |
| Other race | 3.9 % |
| Age group | |
| 35–39 | 12.8 % |
| 40–44 | 16.5 % |
| 45–49 | 11.8 % |
| 50–54 | 15.9 % |
| 55–59 | 12.7 % |
| 60–64 | 14.8 % |
| 65–71 | 15.4 % |
| Education | |
| High school or less | 39.3 % |
| Some college | 27.5 % |
| Bachelor’s degree | 17.1 % |
| Postgraduate | 16.1 % |
| Labor status | |
| Working now | 68.0 % |
| Unemployed and looking | 2.8 % |
| Temporarily laid off | 0.5 % |
| Disabled | 7.0 % |
| Retired | 16.5 % |
| Homemaker | 4.9 % |
| Health Status | |
| Excellent | 8.1 % |
| Very good | 34.6 % |
| Good | 39.2 % |
| Fair | 14.1 % |
| Poor | 4.0 % |
| Work-limiting health problem | 21.0 % |
| Receive SSDI | 9.5 % |
| Number of observations | 1,934 |

Note: Sample excludes individuals with any missing abilities or health information

Table 2 presents summary statistics for our main outcomes: respondents’ subjective probability of working full-time past age 65 or 70 (depending on current age), and their subjective probability of returning to work in the future (if currently retired or disabled). Among those currently in the labor force (working or unemployed) who are under age 65, the average self-reported chance of working full-time past age 65 is 61 percent. Only 5 percent report a zero chance of working full-time after age 65, and fewer than one-third—29 percent—report less than a 50 percent chance of working full-time after age 65. A substantial fraction of respondents (14 percent) report exactly 50 percent; excess mass at 50 percent is a common feature of subjective probability data and may indicate epistemic uncertainty among some respondents (Hurd,). Approximately 58 percent of labor force participants under age 65 report a greater-than 50 percent chance of working full-time after age 65. Among labor force participants aged 65–71, the average self-reported percent chance of working full-time after age 70 is 55 percent.[9] Just under four in ten older labor force participants report

[6] Respondents who were not currently working were asked for the job title, 3–5 usual activities, and industry of their “last paid job.” Those who never worked could check the response option “I never had a paying job.”.

[7] One of the respondents turned 71 before the survey closed in September 17, 2018.

[8] Specifically, the following demographic characteristics are matched in the weighting algorithm: gender by age, gender by ethnicity, gender by education, gender by household income, household income by household size. See Pollard and Baird (2017) for more details.

[9] As noted above, one respondent turned 71 after being invited and before completing the survey.

**Table 2**
Subjective Expectations about Work in the Future.

| Subjective Probability of: | N | Mean | Sd. | Percent with Response 0 | 1–49 | 50 | 51–99 | 100 |
|---|---|---|---|---|---|---|---|---|
| Working past age 65 | 1,175 | 61.1 | 31.8 | 4.9 % | 23.6 % | 13.7 % | 44.6 % | 13.3 % |
| Working past age 70 | 121 | 55.4 | 36.1 | 10.9 % | 28.0 % | 8.2 % | 37.0 % | 15.8 % |
| Returning to work in the future if retired | 390 | 19.9 | 29.6 | 31.9 % | 48.0 % | 9.2 % | 8.8 % | 2.1 % |
| Returning to work in the future if disabled | 157 | 21.1 | 26.4 | 42.5 % | 39.9 % | 4.2 % | 7.7 % | 5.7 % |
| Total Observations | 1,843 | | | | | | | |

Note: We exclude N = 89 respondents who report subjective probabilities of returning to work in the future, but who are currently homemakers.

their chance of working full-time after age 70 as under 50 percent, and more than half (53 percent) report chances greater than 50 percent.

The last two rows of Table 2 provide summary statistics on the self-assessed percent chance of returning to work (among those not in the labor force that are either retired or disabled).[10] The average percent chance of returning to work is 20 percent among retired respondents and 21 percent among disabled respondents. Disabled respondents are more likely than retired respondents to report no chance of returning to work (43 vs. 32 percent), but among both groups a large majority report their return-to-work chances as less than 50 percent (82 and 80 percent of disabled and retired respondents, respectively). Nonetheless, it is notable that nearly 20 percent of disabled respondents (most of whom receive SSDI benefits) report their chances of returning to work as 50 percent or greater. This is in line with recent evidence showing that return-to-work rates among SSDI recipients are significantly lower than other groups, but they have been rising in recent years (Maestas 2019).

Next, we show the age-ability profiles for our sample. The left panel of Fig. 1 plots respondents' average reported ability level by O*NET ability domain and five-year age group for the full ability scale, and the right-panel presents a standardized version (across all age groups) to better appreciate the differences across ability domains. To create each age profile, we first compute the respondent-level average across all abilities in a given domain (equally weighted), and then we plot the average across all respondents in a given age group, weighted by the ALP sampling weights. The four O*NET domains are cognitive (consisting of 20 abilities), psychomotor (11 abilities), physical (9 abilities) and sensory (12 abilities). Recall that all abilities are measured on a 0–7 scale. The most notable feature of the figure is that the ability profiles are relatively stable by age. Average cognitive ability is 4.6 for individuals in their late 30s, 4.3 among respondents in their 50s and 4.4 among respondents in their 60s. Average psychomotor ability is 4.9 among respondents in their late 30s and just slightly lower—4.6—among respondents in their late 60s. Average physical ability declines the most, from 4.5 among respondents in their late 30s to 3.8 among those in their late 60s. Finally, average sensory ability declines over the 40s, from 4.7 to 4.4, but holds steady thereafter through age 71. Although when shown at full scale the curves in Fig. 1 appear similar, when we standardize ability levels to be mean 0 and standard deviation 1 (bottom panel), we can clearly appreciate bigger declines in physical, psychomotor, and sensory abilities than in cognitive abilities. Furthermore, confidence bands around each curve (not shown) are narrow and the patterns of differential decline are statistically distinct.

However, abilities alone do not determine work capacity; work capacity is determined by the match between an individual's abilities and occupational requirements. Before turning to the match between respondent abilities and occupational requirements, we briefly examine the latter—average occupational requirements in the U.S. Table 3 shows the average minimum ability requirement for each ability domain, first across all occupations in the O*NET database, and then across occupations requiring a certain education level. To obtain the averages across all occupations in Table 3, we first compute the occupation-level

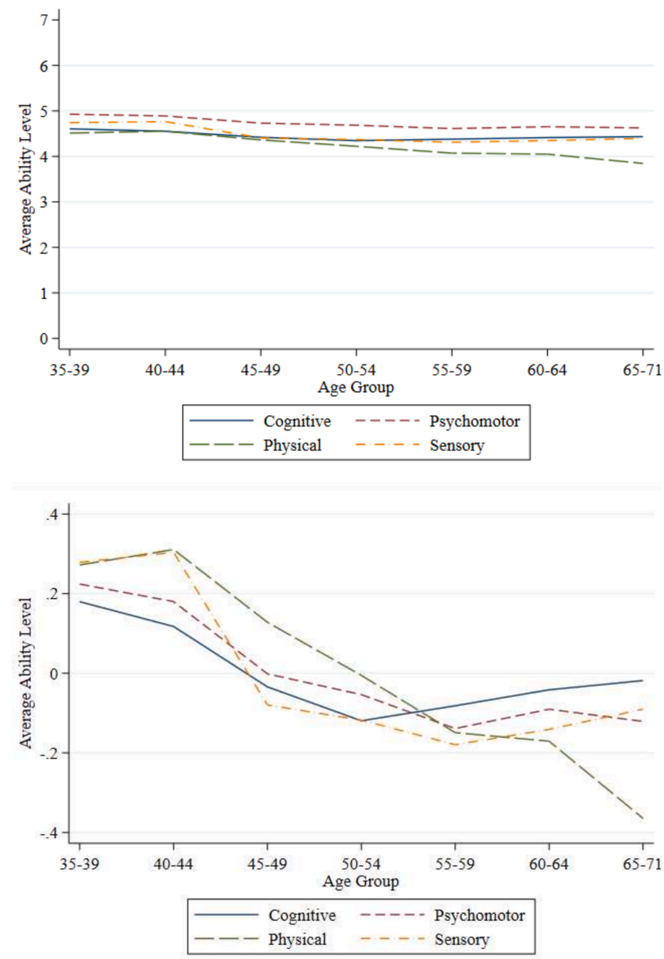


**Fig. 1.** Average Ability Levels by Domain and Five-Year Age Group: Full Scale (top) and Standardized Scale (bottom).

**Table 3**
Average Occupational Demands in National Economy, Overall and by Education Level.

| Ability Domain | All Occupations | Occupations Requiring: High school or less | Some college | Bachelor's degree | Postgraduate |
|---|---|---|---|---|---|
| Cognitive | 2.78 | 2.53 | 2.88 | 3.15 | 3.3 |
| Psychomotor | 1.65 | 1.94 | 1.57 | 1.07 | 1.06 |
| Physical | 1.25 | 1.58 | 1.12 | 0.61 | 0.64 |
| Sensory | 1.85 | 1.87 | 1.82 | 1.8 | 1.8 |

Source: Authors' tabulations of O*NET 22.1 Database (October 2017 Release) and Occupational Employment Statistics data.

[10] We omit "homemakers" from the analysis, under the assumption that their main reasons for being out of the labor force are not health-related.

average across all abilities in a given domain (with abilities equally weighted), and then for each ability domain, we find the weighted average across all occupations, where the weights are each occupation's share of jobs in the national economy (obtained from the Bureau of Labor Statistics' Occupational Employment Statistics program).[11] To obtain averages across occupations requiring a certain education level, we follow the same procedure as before but we use as weights the occupation's share of jobs requiring a given education level. These are obtained by combining information on an occupation's share of jobs in the national economy with educational requirements for each occupation, extracted from the O*NET Education and Training requirements dataset.

The most striking feature of the table is that the average minimum ability levels needed for occupations in the U.S. economy—across all occupations and across occupations requiring a given education level—are quite low; in fact, much lower than the average ability levels in the population. For example, the average minimum physical ability required by occupations is 1.3 overall, and the average minimum physical ability necessary for occupations that require only a high school degree or less is 1.6; yet Fig. 1 shows that the average 65–71 year old has an average physical ability of 3.8, over twice as high. (Recall that ability is measured on the same 0–7 scale for both level and requirement.) Similarly, most cognitively demanding jobs—those held predominantly by individuals with postgraduate degrees—require an average minimum cognitive ability of 3.3, well below the average cognitive ability level of a 65–71 year old in our sample (4.4, see Fig. 1). This suggests that, though underlying abilities may decline somewhat with age, these declines are on average inframarginal relative to job requirements; this in turn suggests that individual work capacity itself (that is, the occupations one's abilities enable one to do) may be relatively stable with age for most people. In the next section, we turn to how we measure individual work capacity.

## Measuring work capacity

We conceive of an individual's "work capacity" as the *fraction of jobs in the national economy that the individual possesses the functional abilities to perform.* Importantly, the measure is based solely on the relationship between the individual's cognitive, physical, psychomotor and sensory functional abilities and the corresponding levels required by each potential occupation in their education set. It purposefully does not take into account whether the individual also meets the specific skill requirements for an occupation. In this paper, abilities are distinct from skills, which are "proficiencies that are developed through training or experience" (Fleisher and Tsacoumis, 2012b). As discussed in Berger, Lopez Garcia, Maestas and Mullen (2022), other possible conceptual definitions of work capacity are the number of *occupations* that an individual can perform (i.e., to assess how *transferable* are an individual's abilities to other occupations) or the individual's potential earnings in the occupations they can perform. Such measures can be constructed with and without conditioning on education (to assess how much education requirements constrain work capacity). Additionally, one can consider the fraction of jobs or occupations an individual can do in the *national* economy and also in their local labor market (to assess the degree of excess work capacity in local areas). The definition we use here corresponds most closely with an upper bound on the individual's employment prospects in the national economy (i.e., based on their functional abilities, but not necessarily their skills, knowledge or other certification requirements).

[11] The Occupational Employment Statistics (OES) gives the number of jobs for each occupation in the national economy. See https://www.bls.gov/oes/home.htm. To obtain job shares by education, we use the distribution of jobs by education for each occupation in the O*NET training requirements data.

### *A measure of work capacity*

We start by defining an indicator variable denoting an individual's ability to perform the tasks required by an occupation by comparing individual $i$'s level of ability $k$, $\theta_{i,k}$, to the level of $k$ required to perform occupation $j$, $c_{j,k}$. If $\theta_{i,k} \geq c_{j,k}$, then we classify the individual as having the required level of that ability for that occupation and the indicator variable takes the value 1. If $\theta_{i,k} < c_{j,k}$, then the individual is classified as not having the required level of that ability for that occupation and the indicator variable takes the value 0. For each potential occupation, we create $K = 52$ indicators summarizing which ability requirements the individual meets.

We next define an individual's *occupation-specific work capacity* as the fraction of abilities required to perform a given (hypothetical) occupation that an individual possesses, weighted by the relative importance of the ability for that occupation, denoted by $\pi_{j,k}$. Formally, the occupation-specific work capacity for individual $i$ in occupation $j$, $OWC_{i,j}$, is the single index constructed by taking the weighted sum of all ability indicators, where the weights are the relative importance ratings of the abilities re-normed so a rating of "not important" is given zero weight and normalized such that $\sum_{k=1}^{K}\pi_{j,k} = 1$:

$$OWC_{i,j} = \sum_{k=1}^{K} \pi_{j,k} 1\left(\theta_{i,k} \geq c_{j,k}\right) \tag{1}$$

This index ranges between 0 and 1, where 0 signifies the individual is unable to perform any of the abilities at the level required for the occupation and 1 signifies the individual is able to perform all abilities required for that occupation.

Finally, we define the individual's *total work capacity* (or simply, work capacity) $TWC_i$ as the weighted sum over all jobs $j = 1, .., J$ of a series of indicators for whether the individual's occupation-specific work capacity for a given job $j$, $OWC_{i,j}$, exceeds a threshold $T \in (0, 1]$ above which the individual is considered to have sufficient *functional* capacity to do the occupation:

$$TWC_i = \sum_{j=1}^{J} \omega_{j|Ed} * 1(OWC_{i,j} \geq T) \tag{2}$$

where $\omega_{j|Ed}$ is occupation $j$'s share of all jobs held by workers with education $Ed$, and where $Ed$ is always chosen to be the education level of person $i$, and $T$ is some threshold above which an individual is considered able to do any given job. Higher values of $T$ make $TWC$ more strict (crediting people with an occupation only when they meet a higher share of the occupation's ability requirements), while lower values of $T$ make the measure more generous (crediting individuals with an occupation when they meet a lower share of requirements). Under $T = 1$, an individual must meet or exceed all ability requirements for an occupation for it to be included in their potential occupation set.[12] Under a partial credit approach, setting $T < 1$ allows individuals who are missing a small number of abilities to still be considered eligible for that occupation. In our analysis, we calculate a "strict" version of work capacity where $T = 1$, and also a "generous" version where $T = 0.88$, which means we require individuals to be able to do at least 88 percent of an occupation in order to receive credit for the occupation.[13]

We use an occupation's share of jobs *by education level* in order to create a measure of work capacity that reflects the fact that some

[12] When $T$=*1*, we add the additional restriction that abilities must be rated "important," "very important" or "extremely important" to be considered, and we exclude from consideration abilities that are rated "somewhat important" or "not important."

[13] We choose $T$=*0.88* because 75 percent of employed individuals in our sample can perform at least 88 percent of the required abilities for their own occupation.

occupations are not accessible to all individuals because of minimum education requirements. To fix ideas with a simple example, suppose there is only one ability that matters and it is required to perform two occupations, one that requires low education (occupation 1) and another that requires high education (occupation 2), so that everyone with low education works in occupation 1 and no one with low education works in occupation 2 (then $\omega_{1|low} = 1$ and $\omega_{2|low} = 0$), and most individuals with high education work in occupation 2 (say 90 %), with the remainder working in occupation 1 (then $\omega_{1|high} = 0.1$ and $\omega_{2|high} = 0.9$). Consider an individual who is able to do occupation 2 but not occupation 1. If he has low education, then his work capacity is 0 (=1*0 + 0*1); on the other hand, if he has high education, then his work capacity is 0.9 (=0.1*0 + 0.9*1). Thus, measured work capacity increases with ability but is determined by the *relationship* between the individual's ability and the occupational demands in the economy, conditional on education level. Two individuals with the same ability levels but different education levels may have different levels of work capacity in our framework, depending on the occupation set available to a worker with a given level of education.

In the next subsection, we describe the distributions of the two measures of work capacity and how they relate to one another, to age and to self-reported health status.

*Empirical patterns*

Fig. 2 displays the cumulative distribution function for each of the two measures of work capacity. From the figure it is apparent that the strict measure is skewed towards zero while the generous measure is skewed towards one. For example, 27 percent of the sample has work capacity of less than 0.05 (that is, they can do less than 5 percent of jobs for their education level based on their abilities) based on the strict measure, while just 10.4 percent of the sample can do less than 5 percent of jobs for their education level based on the generous measure. On the other hand, only 10.7 percent of individuals are classified as able to do more than 95 percent of jobs for their education level based on the strict measure, compared with 44.6 percent based on the generous measure. The mean and median of the strict measure are 0.39 and 0.27, respectively; the mean and median of the generous measure are 0.70 and 0.88, respectively. The standard deviations of the two measures are very similar and around 0.35.

Since we are interested in how work capacity relates to retirement intentions, Fig. 3 plots mean work capacity by five-year age group for each measure. Both measures show slight declines from age 35 to 45, though the decline is only statistically significant for the strict measure. Perhaps surprisingly, neither measure of work capacity exhibits a decline at older ages. This is because, as we saw in Section 2, ability

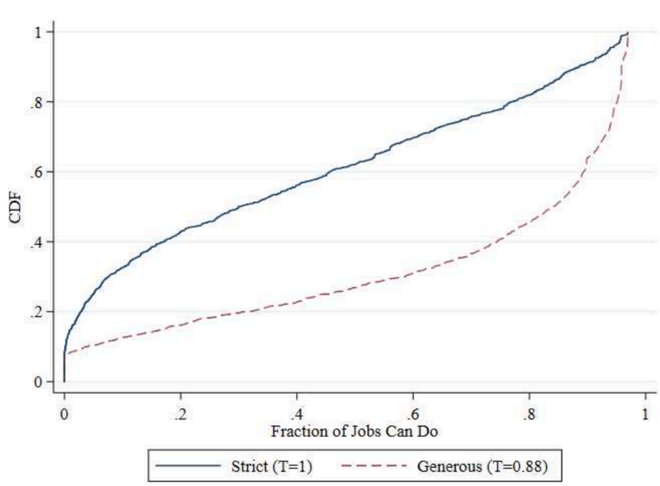


**Fig. 2.** Cumulative Distributions of Measures of Work Capacity.

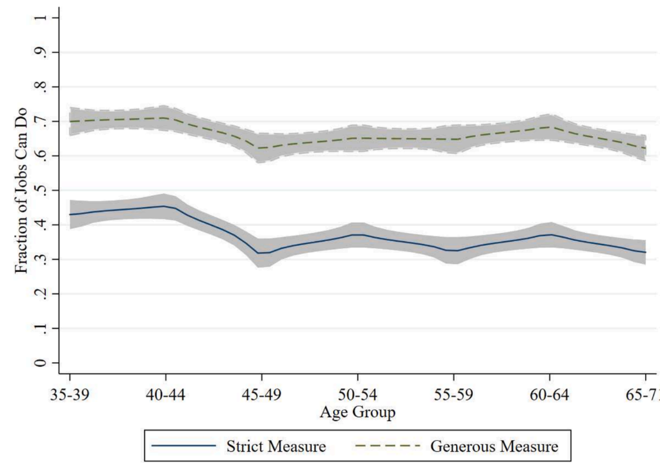


**Fig. 3.** Average Work Capacity by Five-Year Age Group.

levels tend to be much higher than corresponding job demands, even at older ages. As a result, age-related declines in abilities are not large enough to push many individuals below the thresholds required for many jobs. Fig. A2 examines the 10th, 25th, 50th, 75th and 90th percentiles by age group for each work capacity measure and shows that there are relatively large drops in the early 40s for the 50th and 75th percentiles of the strict measure and the 25th percentile of the generous measure of work capacity, but the age pattern is relatively flat after age 45 for all percentiles of the work capacity distribution for either measure.

Finally, we are interested in understanding how much value is added by modeling work and retirement decisions using work capacity—which is uniquely driven by the *intersection* between individuals' abilities and corresponding job requirements—compared with using health alone (which is strongly correlated with individuals' abilities). Fig. 4 presents average work capacity by self-reported health status. For both measures, average work capacity is statistically indistinguishable between individuals who rate their health "excellent" or "very good," and declines as health status falls from "good" to "fair" to "poor." Fig. 5 shows average work capacity for individuals with and without self-reported work-limiting health problems. In both cases, those with work-limiting health problems have significantly lower measured work capacity (around 18–20 percentage points) than those without work-limiting health problems. At the same time, by both measures, individuals with work-limiting health problems can still do a substantial fraction of jobs at their education level, on average—27 percent according to the strict measure and 56 percent according to the generous measure.

**Work capacity and current labor supply**

In this section, we investigate the extent to which work capacity, or the fraction of jobs individuals are able to do for a given education level, relates to current labor force participation compared with standard measures of health status. We study two labor supply outcomes: an indicator variable for whether the individual is currently in the labor force (i.e., working for pay, unemployed or on temporary layoff) and an indicator variable for whether the individual reports receiving Social Security Disability Insurance benefits.

*Labor force participation*

We begin by investigating the association between work capacity and labor force participation (LFP), both in comparison to and in concert with the effects of two standard measures of health status. Table 4 presents three sets of regression specifications. The first set, reported in column 1, shows coefficients from regressions of LFP on the standard

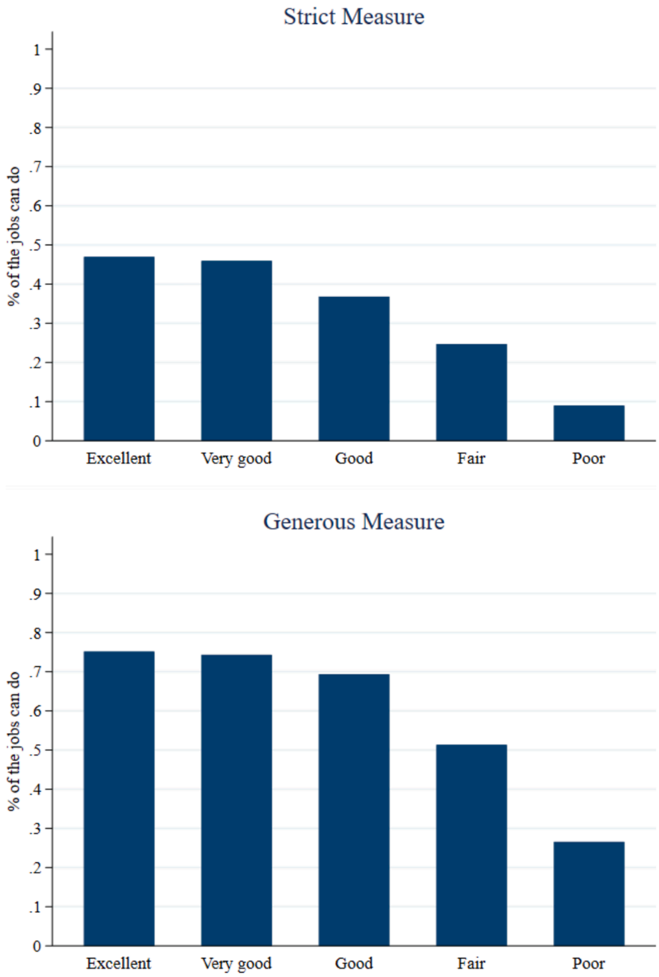


**Fig. 4.** Average Work Capacity by Self-Reported Health Status.

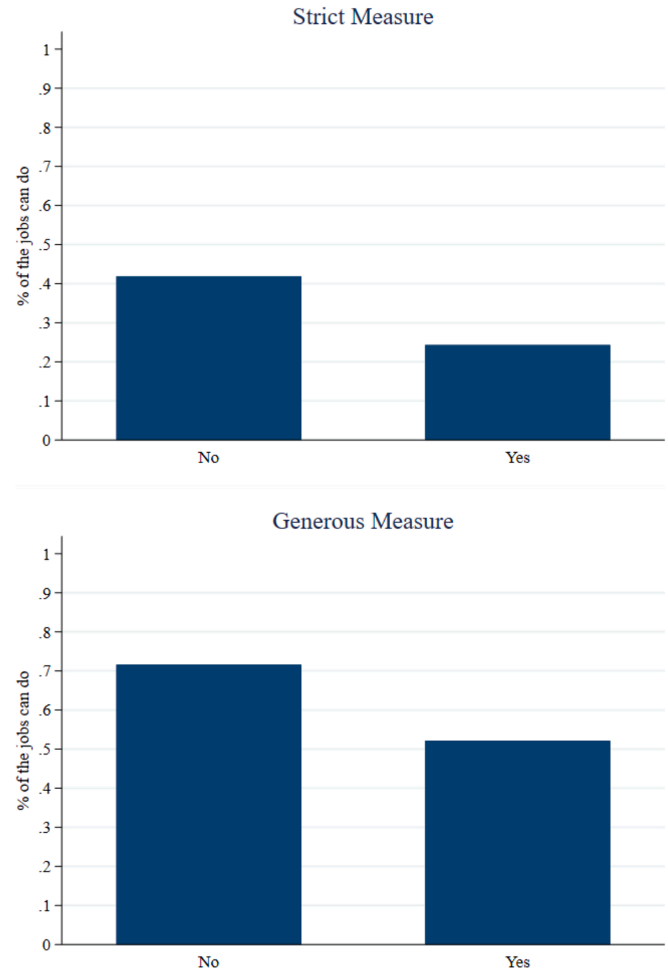


**Fig. 5.** Average Work Capacity by Work-Limiting Health Problem Status.

health variables, self-reported health status (with fair/poor as the baseline category) and absence of a work-limiting health problem. In the second set (columns 2–3) we regress LFP on our strict measure of work capacity, with and without additional controls for health. In the third set (columns 4–5), we regress LFP on our generous measure of work capacity, with and without additional controls for health. Both measures of work capacity can be interpreted as the fraction of jobs for a given education level that an individual can do based on their abilities relative to job demands. All regressions include controls for five-year age groups with ages 65–71 as the baseline category.[14] As such, the constant term can be interpreted as the predicted labor force participation rate of a 65–71 year old when other explanatory variables are set to zero.

In column 1, the labor force participation rate for an individual older than 65 years old in fair or poor health, with a work-limiting health problem, is not significantly different from zero (the constant term). Being in excellent/very good health is associated with a 12.8 percentage point increase in LFP, compared with being in fair/poor health. The differential association between LFP and excellent/very good health as compared to good health is statistically insignificant. Not having a work-limiting health problem is associated with a 30.3 percentage point increase in labor force participation compared with having a work-limiting health problem.

Columns 2 and 3 present results of regressions of LFP on the strict measure of work capacity, with and without controlling for health. In

**Table 4**
Regressions of Labor Force Participation on Health and Fraction of Jobs Individuals Can Do.

| | Only Health (1) | Strict Measure (T = 1) (2) | (3) | Generous Measure (T = 0.88) (4) | (5) |
|---|---|---|---|---|---|
| | coef/se | coef/se | coef/se | coef/se | coef/se |
| Fraction of jobs can do | | 0.173*** | 0.073*** | 0.232*** | 0.109*** |
| | | (0.027) | (0.026) | (0.027) | (0.027) |
| Health Status | | | | | |
| Excellent/Very Good | 0.128*** | | 0.114*** | | 0.103*** |
| | (0.028) | | (0.028) | | (0.028) |
| Good | 0.176*** | | 0.168*** | | 0.155*** |
| | (0.027) | | (0.027) | | (0.027) |
| No work-limiting health problem | 0.303*** | | 0.297*** | | 0.293*** |
| | (0.024) | | (0.024) | | (0.024) |
| Constant | −0.032 | 0.220*** | −0.043 | 0.129*** | −0.077** |
| | (0.028) | (0.025) | (0.028) | (0.029) | (0.030) |
| Number of observations | 1,934 | 1,934 | 1,934 | 1,934 | 1,934 |
| Adjusted R2 | 0.328 | 0.221 | 0.330 | 0.234 | 0.333 |

Note: All regressions control for age groups with baseline category age 65–71. The omitted (baseline) category for self-reported health status is fair/poor. Significance levels: 0.01 - ***; 0.05 - **; 0.1 - *.

[14] The results are robust to the inclusion of additional controls for gender and education (not shown).

Column 2, we estimate that the LFP rate of individuals aged 65–71 who are classified as unable to do *any* job for their education level is 22.0 percent (the constant term).[15] Those classified as able to do 100 percent of jobs for their education level are 17.3 percentage points more likely to work than those classified as unable to do any job—a 78 percent increase in labor force participation. Adding controls for health in column 3 reduces the coefficient on the size of the potential job set from 17.3 to 7.3 percentage points, reflecting the strong underlying (but not perfect) correlation between work capacity and health. However, work capacity remains a statistically significant, independent predictor of work status, even controlling for health.

In Columns 4 and 5 we perform the same analyses as in columns 2 and 3 but with the generous measure of work capacity instead of the strict measure. The constant term again gives the predicted labor force participation rate of an individual aged 65–71 who is classified as unable to do any job at their education level—in this case, 12.9 percent. A same-aged individual who is classified as able to do every job for a given education level has a predicted labor force participation rate of 36 percent, 23.2 percentage points higher or more than double the LFP rate as someone unable to do (a substantial enough fraction) of any job. As before, controlling for health reduces the independent effect of work capacity to 10.9 percentage points, but even so, work capacity remains a strong predictor of labor force participation.

Overall, these results suggest that the two measures of work capacity do have statistically significant relationships with current LFP that reflect underlying health to an important degree but also contribute explanatory variation that is independent of health alone. The underlying source of the additional variation in the work capacity measures is the (mis)match between abilities and job demands. The magnitudes of these relationships are economically relevant compared with standard health variables.

### *Receiving social security disability insurance benefits*

Federal disability insurance benefits are intended to replace lost earnings due to health shocks that prevent individuals from performing their own or any other job in the national economy to any substantial degree. The SSDI program uses disability criteria that implicitly link an applicant's remaining work capacity to the (predominantly physical) requirements of occupations at their level of education. The goal is to assess whether the applicant's ability profile is transferable to other occupations (with only a limited amount of retraining).[16] Since our measure of work capacity explicitly measures individuals' potential job prospects through the interaction of their health and occupational demands, it should both reflect underlying health and also add value over standard health measures in predicting SSDI receipt. Table 5 presents regression results examining this hypothesis. As in Table 4, we first present the associations of traditional health indicators with disability status, and then we add our measures of work capacity to the analysis. All regressions include controls for five-year age groups, but here, we set the youngest age group, ages 35–39, as the omitted (baseline) category. That way, the constant term can be interpreted as the predicted SSDI receipt rate of a 35–39 year old when other explanatory variables are set to zero.

The constant term in column 1 shows that 38 percent of individuals ages 35–39 with fair or poor health and a work-limiting health problem receive SSDI benefits. As expected, those in excellent, very good or good health, or who do not have a work-limiting health problem, are significantly less likely to receive SSDI benefits.

Columns 2 and 3 examine the role of work capacity using our strict measure. In column 2, the predicted rate of SSDI receipt among 35–39 year olds classified as unable to do any job for their education level is 10 percent. Being classified as able to do *any* job for a given education level reduces predicted SSDI receipt to essentially zero. When we include both work capacity and standard health measures in the same regression, both self-reported health status and presence of a work-limiting health problem remain predictive, but the strict measure of work capacity has only a marginally statistically significant association with SSDI receipt at the 10 % level. This suggests that the main channel through which this measure of work capacity relates to SSDI receipt is the variation in standard measures of health status that are relevant for determining SSDI qualification.

Finally, columns 4 and 5 repeat the same analysis using instead the generous measure of work capacity. In this case, 35–39 year olds classified as unable to do any job for their education level have a 19 percent probability of receiving SSDI benefits, almost twice as high as the rate classified as unable to work using the strict measure. As before, an increase in the size of the potential job set from being unable to do *any* job to being able to do any job at a given education level essentially eliminates one's chances of receiving SSDI. Moreover, when we add controls for health (column 5), the generous measure of work capacity remains a statistically significant predictor of SSDI receipt, suggesting that it includes additional information about the probability of SSDI receipt beyond standard measures of health alone.

## Work capacity and retirement expectations

We now turn to the association between work capacity and future labor supply decisions. First, we look at the subjective probability of working longer among individuals who are currently in the labor force. We do so by pooling together the subsample of workers younger than 65 that reported subjective probabilities of working past age 65 and the subsample of workers between 65 and 71 that reported subjective probabilities of working past age 70. Second, we study the subjective probability of returning to the labor force separately for individuals that report their current labor supply status as retired.

### *Expectation of working longer*

Table 6 presents coefficients from regressions of the probability of working longer (past age 65 for those younger than 65, and past age 70 for those in the 65–71 age range) on health and work capacity measures, separately and together. As in Table 4 above, we let age 65–71 be the omitted (baseline) category for the age group controls so the constant term can be interpreted as the predicted subjective probability of working longer for a 65–71 year old when other explanatory variables are set to zero. The constant in column 1 indicates that the expected probability of working longer among 65–71 year olds (who are currently working) is 55.4 percent. Having good, very good or excellent health, instead of fair/poor health, or having a work-limiting health problem does not significantly change the expectation of working longer.

Since we would expect older workers to have more accurate expectations about their probability of working at older ages than younger workers, we interact work capacity with indicators for the following age groups: age 65–71, age 55–64, age 45–55 and age 35–44. In columns 2 to 5 we observe that both measures of work capacity are strongly correlated with the self-reported probability of working longer, especially

[15] We measure the fraction of jobs one can do by relating individuals' abilities to average occupational requirements in the O*NET database. It is possible that some workers whose ability levels do not meet the occupational requirements of their current job may obtain workplace accommodations to address these limitations.

[16] Specifically, SSDI applicants in the U.S. are evaluated for whether they have one or more specific health conditions ("listed impairments") or they fall into certain categories under medical-vocational guidelines based on age, education, prior work experience and categorical rating of their overall residual functional capacity to perform physical work. The medical-vocational guidelines were originally based on the availability of entry-level jobs in each medical-vocational category. Except in specific cases, applicants are not evaluated for whether they are able to perform specific (current) jobs in the national economy. Moreover, not every person who might qualify applies for SSDI benefits.

**Table 5**
Regressions of SSDI receipt on the fraction of jobs individuals can do.

| | Only Health | Strict Measure (T = 1) | | Generous Measure (T = 0.88) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | coef/se | coef/se | coef/se | coef/se | coef/se |
| Fraction of jobs can do | | −0.121*** | −0.033* | −0.197*** | −0.094*** |
| | | (0.020) | (0.019) | (0.019) | (0.019) |
| Health Status | | | | | |
| Excellent/Very Good | −0.124*** | | −0.117*** | | −0.102*** |
| | (0.019) | | (0.020) | | (0.020) |
| Good | −0.143*** | | −0.139*** | | −0.124*** |
| | (0.019) | | (0.019) | | (0.019) |
| No work-limiting health problem | −0.240*** | | −0.238*** | | −0.232*** |
| | (0.017) | | (0.017) | | (0.017) |
| Constant | 0.384*** | 0.103*** | 0.392*** | 0.189*** | 0.425*** |
| | (0.023) | (0.020) | (0.023) | (0.023) | (0.024) |
| Number of observations | 1,925 | 1,925 | 1,925 | 1,925 | 1,925 |
| Adjusted R2 | 0.208 | 0.031 | 0.209 | 0.062 | 0.217 |

Note: All regressions control for age groups with baseline category age 35–39. The omitted (baseline) category for self-reported health status is fair/poor. Significance levels: 0.01 - ***; 0.05 - **; 0.1 - *.

**Table 6**
Regressions of Subjective Probability of Working Past Age 65 or Past Age 70 on the Fraction of Jobs Individuals Can Do.

| | Only Health | Strict Measure (T = 1) | | Generous Measure (T = 0.88) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | coef/se | coef/se | coef/se | coef/se | coef/se |
| Fraction of jobs can do | | | | | |
| Interacted with Age 65–71 | | 0.279** | 0.277** | 0.352*** | 0.346*** |
| | | (0.109) | (0.109) | (0.131) | (0.131) |
| Interacted with Age 55–64 | | 0.124** | 0.119** | 0.146*** | 0.145*** |
| | | (0.051) | (0.052) | (0.055) | (0.055) |
| Interacted with Age 45–54 | | 0.059 | 0.048 | 0.106** | 0.104** |
| | | (0.046) | (0.047) | (0.046) | (0.046) |
| Interacted with Age 35–44 | | 0.022 | 0.017 | 0.073 | 0.074 |
| | | (0.041) | (0.041) | (0.047) | (0.047) |
| Health Status | | | | | |
| Excellent/Very Good | 0.014 | | 0.001 | | −0.002 |
| | (0.030) | | (0.030) | | (0.030) |
| Good | −0.039 | | −0.044 | | −0.049* |
| | (0.029) | | (0.029) | | (0.029) |
| No work-limiting health problem | −0.006 | | −0.010 | | −0.011 |
| | (0.028) | | (0.028) | | (0.028) |
| Constant | 0.554*** | 0.431*** | 0.456*** | 0.285*** | 0.317*** |
| | (0.046) | (0.056) | (0.062) | (0.102) | (0.105) |
| Number of observations | 1,296 | 1,296 | 1,296 | 1,296 | 1,296 |
| Adjusted R2 | 0.012 | 0.015 | 0.018 | 0.021 | 0.025 |

Note: All regressions control for age groups with baseline category age 65–71. The omitted (baseline) category for self-reported health status is fair/poor. Significance levels: 0.01 - ***; 0.05 - **; 0.1 - *.

among older age groups. Consistent with the lack of association between standard measures of health and expectations of working longer (column 1), the coefficients on work capacity are not sensitive to inclusion of standard health measures. An increase in the size of the potential job set from being able to do *no* job to being able to do *all* jobs at a given education level according to the strict measure is associated with a 28 percentage point increase in the subjective probability of working at age 70 among those aged 65 and older, and the same increase in the size of the potential job set is associated with a 12 percentage point increase in the subjective probability of working at age 65 among those aged 55–64. The generous measure of work capacity is even more predictive of subjective expectations for working longer, for all age groups. An increase from 0 to 1 in the size of the potential job set using the generous measure increases the subjective probability of working longer by 35 percentage points among those aged 65–71, by 15 percentage points among those aged 55–64, by 10 percentage points among those aged 45–54, and by (a statistically insignificant) 7 percentage points among those aged 35–44.[17]

**Table 7**
Regressions of Subjective Probability of Returning to Work from Retirement on the Fraction of Jobs Individuals Can Do.

| | Only Health | Strict Measure (T = 1) | | Generous Measure (T = 0.88) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | coef/se | coef/se | coef/se | coef/se | coef/se |
| Fraction of jobs can do | | 0.133*** | 0.123*** | 0.103** | 0.094** |
| | | (0.041) | (0.043) | (0.042) | (0.044) |
| Health Status | | | | | |
| Excellent/Very Good | 0.026 | | 0.002 | | −0.002 |
| | (0.043) | | (0.044) | | (0.045) |
| Good | 0.017 | | 0.000 | | −0.006 |
| | (0.042) | | (0.042) | | (0.043) |
| No work-limiting health problem | 0.036 | | 0.031 | | 0.039 |
| | (0.035) | | (0.035) | | (0.035) |
| Constant | 0.156*** | 0.154*** | 0.137*** | 0.132*** | 0.116*** |
| | (0.031) | (0.021) | (0.031) | (0.031) | (0.036) |
| Number of observations | 387 | 387 | 387 | 387 | 387 |
| Adjusted R2 | 0.005 | 0.028 | 0.024 | 0.018 | 0.015 |

Note: All regressions control for age groups with baseline category age 65–71. The omitted (baseline) category for self-reported health status is fair/poor. Significance levels: 0.01 - ***; 0.05 - **; 0.1 - *.

### *Unretirement*

Finally, we are interested not just in exits from the labor force but also in potential reentry. Table 7 presents regression results of the probability of returning to the labor force among individuals who report that they are retired. For this analysis we dropped three respondents younger than 50 who reported themselves as retired. As in Tables 4 and 6 above, we let age 65–71 be the omitted (baseline) category for the age group controls so the constant term can be interpreted as the predicted subjective probability of returning to work for a 65–71 year old with other explanatory variables set to zero. In column 1, we see that the

[17] Kedzi and Shapiro (2023) relate individuals' work status at age 65 to their earlier subjective expectation of working at age 65 and find that an adjusted subjective probability of 0.2+0.5 times the self-reported probability is a more accurate predictor of an individual's actual probability of working at age 65. Even if we scale the coefficients on work capacity in Table 6 by 0.5, we find that work capacity remains predictive of the probability of working longer, especially at older ages.

average reported probability of "unretirement" is 15.6 percent among those aged 65–71 who report that they are in fair or poor health and who have a work-limiting health problem. This probability is statistically the same for same-aged individuals in excellent, very good or good health and those who do not have a work-limiting health problem. In other words, the standard health measures are not strong predictors of expectations about returning to work from retirement.

In contrast, in column 2, we see that the strict measure of work capacity is strongly predictive of expected unretirement. Whereas a 65–71 year old classified as unable to do any job for his education reports an average probability of unretirement of 15 percent, the same individual classified as able to do any job for his education nearly doubles his average probability of unretirement to 29 percent. Adding controls for health only slightly reduces the association between the strict measure of work capacity and the subjective probability of unretirement (column 3). Columns 4–5 show that the generous measure of work capacity is also predictive of unretirement independent of standard health measures, with a slightly smaller association between the set of potential jobs individuals can perform (from none to all jobs) and the expectation of unretirement: 10.3 percentage points without controlling for health, and 9.4 percentage points controlling for health.

## Robustness

In the analyses above, we assume that individuals accurately report their ability levels and hence we are able to accurately measure the fraction of jobs they can do in the national economy, conditional on their education. In this section, we test whether our results are robust to the inclusion of measures of individuals' personality traits, which have been found to predict overestimation of abilities (Moore and Healy, 2008, Schaefer et al., 2004). To do so, we use data from a previous RAND ALP survey that collected 26 items from the Big Five Inventory (John et al., 1991), and which is available for 64 % of our sample (N = 1,237). These items were designed to be aggregated into sub-scales representing five personality traits: conscientiousness, openness, neuroticism, agreeableness and extroversion, where each measure is standardized to have mean 0 and standard deviation 1.

Table 8 summarizes our regression results across all outcomes for the generous measure of work capacity (T = 0.88), when all five standardized measures of personality traits are included as controls. In the table, each horizontal panel represents a different outcome, and in columns we present three different specifications: (1) the benchmark regression of the outcome on the generous work capacity measure and age for the full sample, which we reproduce from columns 4 and 5 in Tables 4 through 8; (2) the same regression specification as (1), but estimated on the subsample of individuals with data on personality traits (matched sample); and (3) the same sample as (2) but adding standardized measures of personality traits as controls to the regression specification. We present specifications (1)-(3) without health controls in columns 1–3 and the same specifications (1)-(3) with health controls in columns 4–6.

Generally, we find that controlling for personality traits does not change the magnitude of the effect sizes nor the sign of the estimates, even after accounting for the difference in sample sizes. Comparing specifications (1) and (2), we find that our estimates of the associations between work capacity and outcomes in the restricted sample are equal to or slightly larger than those in the full sample. More importantly, when we compare specifications (2) and (3) in the restricted sample, we find that adding personality traits to the set of controls slightly reduces the estimated associations between work capacity and two outcomes (working for pay and SSDI receipt), but the magnitudes remain large and statistically significant. Estimates for the other three outcomes remain unchanged. These patterns are not altered by the inclusion of health controls. In Appendix Table A2 we present the same results for our strict measure of work capacity (T = 1) and show that controlling for personality traits makes no difference in the magnitude of the estimates in the restricted sample for any outcome.

## Discussion and conclusion

Declining health with age can limit individuals' work capacity, increasing the likelihood of mismatch between their abilities to perform certain tasks and the minimum demands of the jobs available to them. Traditional measures of health status are insufficient for understanding how labor force participation and retirement intentions are influenced by the match between individuals' abilities and job demands.

In this paper, we use new survey data harmonized with the O*NET database to create a new measure of individual work capacity, defined as the share of all jobs for a given education level in the national economy that the individual can do, and that is based on comparisons between individuals' own ability levels and the minimum levels required to perform a given occupation across 52 different abilities and for nearly 800 occupations in the economy. We use this information to construct a

**Table 8**
Regressions of Outcomes on Generous Measure of Work Capacity (T = 0.88) Controlling for Big Five Personality Traits.

| | Regressions Without Health Controls | | | Regressions With Health Controls | | |
|---|---|---|---|---|---|---|
| | Full Sample | Matched Sample | Matched Sample + Big Five Controls | Full Sample | Matched Sample | Matched Sample + Big Five Controls |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| a) Labor Force Participation | | | | | | |
| Coef. | 0.232*** | 0.293*** | 0.220*** | 0.109*** | 0.143*** | 0.124*** |
| SE | (0.027) | (0.036) | (0.037) | (0.027) | (0.036) | (0.037) |
| Number of observations | 1,934 | 1,237 | 1,237 | 1,934 | 1,237 | 1,237 |
| b) SSDI Receipt | | | | | | |
| Coef. | −0.197*** | −0.247*** | −0.193*** | −0.094*** | −0.125*** | −0.113*** |
| SE | (0.019) | (0.026) | (0.027) | (0.019) | (0.026) | (0.027) |
| Number of observations | 1,925 | 1,233 | 1,233 | 1,925 | 1,233 | 1,233 |
| c) Prob. Working After Age 65/70 | | | | | | |
| Coef. | 0.115*** | 0.190*** | 0.197*** | 0.114*** | 0.188*** | 0.196*** |
| SE | (0.028) | (0.038) | (0.041) | (0.028) | (0.038) | (0.041) |
| Number of observations | 1,296 | 764 | 764 | 1,296 | 764 | 764 |
| d) Prob. of Unretirement | | | | | | |
| Coef. | 0.103** | 0.086** | 0.085* | 0.094** | 0.093** | 0.094** |
| SE | (0.042) | (0.043) | (0.045) | (0.044) | (0.046) | (0.047) |
| Number of observations | 387 | 347 | 347 | 387 | 347 | 347 |

Notes: Columns 1 and 4 reproduce the coefficient on work capacity in columns 4 and 5, respectively, of Tables 4–7; Columns 2 and 5 estimate the same specification as the preceding column on the subsample of respondents with personality measures; Columns 3 and 6 add controls for personality traits to the specifications in the preceding columns.

one-dimensional summary measure of individuals' work capacity that we hypothesize is predictive of current labor force participation decisions, as well as of subjective expectations about the timing of retirement and about returning to the labor force among individuals who are retired. It is important to stress that our measure of work capacity is not the same as their employment prospects, which may depend on other factors such as an individual's skills, knowledge, experience, or other certification requirements beyond education level. Older individuals may also be subject to (illegal) employer discrimination on the basis of age or disability that our work capacity measure does not capture since it simply estimates the fraction of jobs in the national economy that an individual possesses the functional abilities to perform (conditional on education).

Our results can be summarized in three main findings. First, we find that average abilities overall and across different domains are high relative to average occupational demands. Second, age-related declines in abilities are modest, at least through age 70. Putting these elements together, individuals' work capacity is relatively stable with age. This conclusion is striking because there is an active debate about whether older workers are less productive than younger workers and the implications of population aging for economic growth (see e.g., Börsch-Supan 2003; Sheiner et al. 2007; Börsch-Supan and Weiss 2016; Maestas et al. 2023a). Our findings suggest that other factors, such as preferences, discrimination, employers' inaccurate perceptions of work capacity, employees' inaccurate perceptions of job requirements, and family caregiving responsibilities, likely play a larger role than potential productivity in observed declines in labor force participation over the life cycle (Berkman and Truesdale 2022).

Our third main finding is that our measures of work capacity are predictive of current and expected future labor supply outcomes. An increase in work capacity from being unable to do any job to being able to do all jobs is significantly associated with a 17–23 percentage point increase in labor force participation and a 12–20 percentage point decrease in the percentage receiving Social Security Disability benefits. Work capacity is also predictive of subjective expectations about future labor force participation. An increase in individuals' work capacity—-from being unable to do any job to being able to do all jobs at one's education level—is associated with a 28–35 percentage point increase in the subjective expectation of working past age 70 if the individual is age 65 or older, a 12–15 percentage point increase in the subjective expectation of working past age 65 if the individual is between ages 55 and 64, and a 10–13 percentage point increase in the chance that retired individuals will return to the labor force. These associations are robust to the inclusion of factors that have been found predictive of misestimation of own abilities, particularly personality traits.

Since these associations are significant over and above the associations between outcomes and health and are all economically relevant, we conclude that a measure of work capacity based on the (mis)match between a comprehensive set of abilities and job demands can increase understanding of labor force outcomes at older ages and inform the design of policies that would incentivize or even require individuals to extend their working lives.

Note that, for three out of four labor supply outcomes we examine, the strict measure of work capacity—requiring individuals to meet or exceed all important occupational ability requirements—is less predictive of labor supply than the generous measure of work capacity, which allows for some gaps in ability requirements. The exception is the subjective probability of unretirement, which unlike the other outcomes, largely reflects the *(re)entry* margin of work, as opposed to the *exit* margin. This suggests that the more conservative strict measure of work capacity is relatively informative of job prospects on the hiring margin, where it may be more important for an applicant to demonstrate qualification on all job requirements. In contrast, the more generous measure of work capacity, which gives partial credit for occupational requirements that are mostly (though not fully) met, may be relatively informative about the exit margin. It is likely that job incumbents may have more scope for compensating for any ability losses, by drawing on skills and experience, by using assistive technologies, or by obtaining work modifications or other accommodations from their employers, than potential new employees.

Another interesting finding is that work capacity is more predictive of the subjective expectation of working longer as individuals age. Some of this relationship may reflect the fact that older workers are likely selected differently than younger workers based on unobservable characteristics such as stronger preferences for work. However, previous research has also shown that older workers tend to have stronger preferences for certain types of working conditions (e.g., flexibility, lower physical demands) (Maestas et al. 2023b). Both findings are consistent with the idea that older workers place a higher premium than younger workers on avoiding jobs associated with a high disutility of work. Another reason work capacity could have a greater impact on expectations about working longer at older ages could be that workers anticipate that age discrimination could limit their employment prospects, resulting in stricter thresholds for hiring and retention (Farber et al. 2019).

Our findings have several policy implications. First, our findings suggest that age-related health decline does not substantially restrict the set of jobs individuals are able to perform, at least through age 70, on average. At the same time, roughly a quarter of Americans ages 35–71 are able to do less than 5 percent of jobs for their education level based on the strict measure, and only one in ten can do less than 5 percent of jobs for their education level based on the generous measure. This means a substantial fraction of Americans at any age could benefit from targeted policies to improve their health-related work capacity or compensate for work-related ability deficits. Our methodology can be used to identify which abilities have the biggest impact on work capacity, and therefore can be targeted in public health interventions; it can also be used to identify which occupational requirements have the biggest impact as well, which could be targeted in workplace regulations or policies affecting labor-saving technological advancements (e.g., automation, artificial intelligence, robotics). Finally, as noted above, the gap between work capacity and labor force participation at older ages indicates there may be substantial scope for retaining older workers in the labor force if we can identify and address the most important barriers to their ongoing participation.

## CRediT authorship contribution statement

**Italo Lopez Garcia:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Writing – original draft. **Nicole Maestas:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Writing – review & editing. **Kathleen J. Mullen:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Writing – original draft.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeoa.2025.100576.

## References

Belbase, Anek, Geoffrey Sanzenbacher, and Christopher M Gillis. 2015. "Does Age-Related Decline in Ability Correspond with Retirement Age?" *Center for Retirement Research at Boston College Working Paper.* (2015–24).

Berkman, L.F., Truesdale, B.C. (Eds.), 2022. *Overtime: America's Aging Workforce and the Future of Working Longer*. Oxford University Press.

Berger, Benjamin, Italo Lopez Garcia, Nicole Maestas, and Kathleen J. Mullen (2022). "The Link between Health and Working Longer: Differences in Work Capacity," In *Overtime: America's Aging Workforce and the Future of Working Longer*, Eds. Lisa Berkman and Beth C. Truesdale.

The Board of Trustees, Federal Old-Age And Survivors Insurance and Federal Disability Insurance Trust Funds. 2024. "The 2024 Annual Report of the Board of Trustees of the Federal Old-Age And Survivors Insurance and Federal Disability Insurance Trust Funds." https://www.ssa.gov/OACT/tr/2024/index.html.

Börsch-Supan, A., 2003. Labor market effects of population aging. *Labour* 17 (S1), 5–44.

Börsch-Supan, A., Weiss, M., 2016. Productivity and age: Evidence from work teams at the assembly line. J. Econ. Ageing 7, 30–42.

Coile, C., Milligan, K., Wise, D.A., 2017. Health capacity to work at older ages: evidence from the United States. In: Wise, D.A. (Ed.), Social Security Programs and Retirement around the World: the Capacity to Work at Older Ages. University of Chicago Press, pp. 359–394.

Cutler, D.M., Meara, E., Richards-Shubik, S., 2014. Health and work capacity of older adults: Estimates and implications for social security policy. SSRN.

Disney, R., Emmerson, C., Wakefield, M., 2006. Journal of Health Economics. "Ill health and retirement in Britain: A panel data-based analysis.". J. Health Econ. 25 (4), 621–649.

Farber, H., Herbst, C., Silverman, D., von Wachter, T., 2019. Whom do employers want? The role of recent employment and unemployment status and age. J. Labor Econ. 37 (2), 323–349.

Fleisher, M.S., Tsacoumis, S., 2012a. O*NET Analyst occupational abilities ratings: procedures update. Human Resources Research Organization, Alexandria, VA.

Fleisher, M.S., Tsacoumis, S., 2012b. O*NET® analyst occupational skills ratings: Procedures update. National Center for O*NET Development.

Fleishman, E.A., Costanza, D.P., Marshall-Mies, J., 1999. Abilities. In: Peterson, N.G., Mumford, M.D., Borman, W.C., Jeanneret, R.P., Fleishman, E.A. (Eds.), *An Occupational Information System for the 21st Century: the Development of O*NET*. American Psychological Association, Washington, DC, pp. 175–195.

Hudomiet, Péter, Michael D Hurd, Susann Rohwedder, and Robert J Willis. 2017. "The Effect of Physical and Cognitive Decline at Older Ages on Work and Retirement: Evidence from Occupational Job Demands and Job Mismatch.".

John, O.P., Donahue, E.M., Kentle, R.L., 1991. Big five inventory. J. Pers. Soc. Psychol.

Hurd, Michael D. "Subjective Probabilities in Household Surveys." *Annual Review of Economics* 1(1): 543-562.

Maestas, N., 2019. Identifying work capacity and promoting work: A strategy for modernizing the SSDI program. Ann. Am. Acad. Pol. Soc. Sci. 686 (1), 93–120.

Maestas, N., Mullen, K.J., Powell, D., 2023a. The effect of population aging on economic growth, the labor force, and productivity. Am. Econ. J. Macroecon. 15 (2), 306–332.

Maestas, N., Mullen, K.J., Powell, D., von Wachter, T., Wenger, J.B., 2023b. The Value of working conditions in the United States and implications for the structure of wages. Am. Econ. Rev. 113 (7), 2017–2047.

McGarry, K., 2004. Health and retirement: Do changes in health affect retirement expectations? J. Hum. Resour. 39 (3), 624–648.

Moore, D.A., Healy, P.J., 2008. The trouble with overconfidence. Psychol. Rev. 115 (2), 502.

Okonkwo, O.C., Wadley, V.G., Griffith, H.R., Belue, K., Lanza, S., Zamrini, E.Y., Marson, D.C., 2008. Awareness of deficits in financial abilities in patients with mild cognitive impairment: going beyond self-informant discrepancy. Am. J. Geriatr. Psychiatry 16 (8), 650–659.

Kedzi, Gabor, and Shapiro, M.D.. 2023. "Retirement Expectations." Chapter 10 in Bachmann, Rudiger, Giorgio Topa and Wilbert van der Klaauw, Eds. Handbook of Economic Expectations, Academic Press.

*O*NET Resource Center. 2017. "Content Model Reference." National Center for O*NET Development. Available from https://www.onetcenter.org/dictionary/22.1/excel/content_model_reference.html.

Peterson, N.G., Mumford, M.D., Borman, W.C., Jeanneret, P.R., Fleishman, E.A., Levin, K. Y., Campion, M.A., Mayfield, M.S., Morgeson, F.P., Pearlman, K., Gowing, M.K., 2001. Understanding work using the occupational information network (O* NET): Implications for practice and research. Pers. Psychol. 54 (2), 451–492.

Pollard, M.S., Baird, M.D., 2017. The RAND American life panel: Technical description. RAND Corporation, Santa Monica, CA https://www.rand.org/pubs/research_reports/RR1651.html.

Schaefer, P.S., Williams, C.C., Goodie, A.S., Campbell, W.K., 2004. Overconfidence and the big five. J. Res. Pers. 38 (5), 473–480.

Sheiner, Louise, Daniel Sichel, and Lawrence Slifman (2007). "A Primer on the Macroeconomic Implications of Population Aging." The Federal Reserve Board Finance and Economics Discussion Series 2007-1.

Tsacoumis, S., Willison, S., 2010. O*NET analyst occupational skill ratings: Procedures. Human Resources Research Organization, Alexandria, VA.

US Census Bureau, 2018. Projected age groups and sex composition of the population: Main projections series for the United States, 2017-2060. US Census Bureau, Population Division, Washington, DC.

US Census Bureau, 2023. 2020 Census demographic profile and demographic and housing characteristics file (DHC). US Census Bureau, Population Division, Washington, DC.

Vaupel, J.W., 2010. Biodemography of human ageing. Nature 464 (7288), 536–542.