The Changing Nature of Work and Old-Age Labor Supply

Daniel Giraldo Páez*

Job Market Paper - 1em October 28, 2023

Abstract

The labor force participation of older Americans has been increasing since the 1990s. The tasks and characteristics of American work have been changing for longer, moving away from the routine and physical and towards the social and cognitive. If these shifts in the nature of work make working less unpleasant and better paid, then they may have contributed to the observed old-age labor supply increase. I measure the contribution of the changing nature of American work to the increase in older men's labor force participation, its impacts on the distribution of welfare of older Americans, and implications for Social Security policy. Using the relationship in the Health and Retirement Study between occupation in men's early 50s and later labor force participation, I find that 10%–16% of the increase from 1990 to 2010 in labor force participation of 60-to-69-year-olds can be explained by changes in occupation characteristics. Exploiting differential changes in occupation characteristics across commuting zones and using the commuting zone's predicted routineness in 1950 as an instrument, I confirm there is a causal relationship between occupation characteristics and old-age labor force participation. Estimating a structural model of old-age labor supply with occupation differences across people, I find that the shifts in occupation led to welfare increases at all but the bottom quartile of lifetime income. Finally, I compare a policy that increases Full Retirement Age to one that achieves similar savings but but concentrates benefit reductions among higher earners. The former policy leads to large participation increases among men in the most physical occupations, while the latter does not. In terms of aggregate welfare among the elderly, the latter reform is preferable.

---

*Yale University. Email: william.giraldo@yale.edu. I am extremely grateful to my advisors Joseph Altonji, Jason Abaluck, and Cormac O'Dea for their guidance and encouragement. I also thank Jaime Arrellano-Bover, Orazio Attanasio, David Autor, Barbara Biasi, Zachary Bleemer, Richard Blundell, Mariacristina De Nardi, José Espín-Sánchez, Lucas Finamor, Eric French, Daniel Hamermesh, John Eric Humphries, Ilse Lindenlaub, Zachary Liscow, Arnaud Maurel, Costas Meghir, Bobby Pakzad-Huron, Fabien Postel-Vinay, Sarah Quincy, Amelia Ricketts, David Sturrock, Dmitry Taubinsky, Winnie Van Dijk, Seth Zimmerman, and participants in the Yale Labor/Public Prospectus Workshop for helpful comments. I thank the Yale Center for Research Computing for guidance and assistance in computation run on the Grace cluster. 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.

1 Introduction

Policymakers often propose increasing the Full Retirement Age (FRA) to reduce deficits in the Social Security program. But this change could burden older individuals who are in more unpleasant, physically demanding jobs and have low capacity for additional work. Perhaps allaying this concern, five decades of technological change have shifted American work away from physical and routine tasks and towards cognitive and social ones. Indeed, these changes in work, which moved work away from more unpleasant tasks, may have contributed to the increase in the labor force participation of older Americans since the 1990s. Figure **??** shows how American men and women, both high- and low-educated, have increased employment at old ages since the 1990s. If changes in tasks at work made work more pleasant and drove increases in participation, worries about Social Security reforms imposing large burdens on those in physical work may be tempered.

This paper measures the extent to which changes in occupation tasks and environment have increased the participation rate at older ages. It then builds and estimates a life-cycle model of old-age labor supply to assess the welfare impacts of these shifts and evaluate the effects of Social Security reforms on the participation of older men in more physical work. The analysis draws on data on the Census and American Community Study (ACS), occupation information from the Occupational Information Network (O*NET) database, and the Health and Retirement Study (HRS). The latter is a representative panel study of older Americans that follows them from ages 51–56 until death.

This work has two major parts. In the first, I evaluate whether and to what extent changes in work tasks and characteristics have increased old-age labor force participation. I begin by showing that someone in a more decision-, social-, or mathematical-intensive occupation in their 50s in the HRS is *more* likely to participate in the labor force at later ages, even when controlling for potential confounders such health, wealth, retiree insurance, and pension structure. Moreover, individuals in more physical, extreme, or routine work in their 50s are *less* likely to participate in the labor force at later ages. By focusing on the kinds of tasks that the task change literature has highlighted as experiencing the most change in the past decades (Autor, Levy, and Murnane 2003; Deming 2017, 2021), I am able to go beyond previous studies of the relationship between occupation characteristics and old-age participation (Hudomiet et al. 2020; Lopez Garcia, Mullen, and Wenger 2022) and explicitly connect changes in occupation characteristics and to observed changes in old-age participation.

Fixing the measured relationships between the occupation characteristics in one's early 50s and old-age labor force participation at ages 60–69, I calculate what changes in aggregate

Figure 1: Ages 65 and Older Employment Rate Over Time

Data are from the ASEC supplement of the March CPS. "High School Grad or Less" includes all individuals with at most a high school degree or equivalent. "Some College or More" includes all individuals with at least on year of education above a high school degree.

occupation characteristics imply about changes in old-age labor force participation. Using changes in the occupation characteristics of Americans in their early 50s from 1980 to 2000, as measured in the Census, I find that changing work explains between 10% and 16% of the increase in old-age labor force participation from 1990 to 2010 for men (4%–6% for women). While other work has considered, for example, the contribution of changes in spouse labor force participation (Schirle 2008), changes in Social Security (Mastrobuoni 2009; Blau and Goodstein 2010; Yu 2023), and changes in pension structure (Hurd and Rohwedder 2011; Coile 2018), this study is the first, to my knowledge, to measure the contribution of changes in work tasks and characteristics to the increase in old-age participation. I also augment previous studies showing that work characteristics have moved towards the stated preferences of older workers (Acemoglu, Mühlbach, and Scott 2022) by showing how occupation characteristics directly relate to old-age labor force participation and measuring the implied effect of changes in work on changes in later-life labor supply.

Even thought I control for a variety of potential confounders in the above analysis, doubt may remain that unobserved confounders are driving the measured relationship between occupation characteristics and old-age labor force participation. Addressing these concerns, I provide an analysis that uses changes in characteristics across commuting zones to test the relationship between occupation characteristics and old-age labor supply. I find that commuting zones with men in their 40s who have more cognitive occupations and less physically taxing occupations experience higher 60-to-69-year-old male labor force participation twenty years later.[1] In order to further purge this analysis of unobserved confounders, I instrument the change in a commuting zone's occupational characteristics using the commuting zone's predicted share of routine occupations in 1950 (Autor and Dorn 2013). The idea is that places with a higher share of routine occupations were more exposed to the computerization shock and IT revolution, which lead to larger subsequent increases in cognitive occupations and larger decreases in routine occupations. Previous work argued for the causal effect of occupation characteristics on retirement behavior with surveys using hypothetical occupations (Hudomiet et al. 2020); I build on that here by establishing a causal connection between observed occupation characteristics and observed old-age labor force participation.

Having established that the kind of work people do influences their participation in old-age and that this has had a sizeable effect on aggregate old-age labor force participation, in the second part of the paper, I examine the implications for welfare in old-age as well as how proposed Social Security reforms would impact those in the most physical occupations and in the poorest health. To do so, I write and estimate an old-age life-cycle labor supply model with health, savings, and Social Security that builds on existing models of old-age labor supply (French and Jones 2011; Yu 2023) but adds a novel ingredient: occupational differences. I model occupational differences as individuals having different, fixed types which impact their wages and disutility from work. In estimating the model, I take into account that individuals who arrive in their 50s with different kinds of work and health also arrive at that age with different levels of wealth and future social security benefits. Retirement arises endogenously as an individual weighs the benefits of work versus the utility cost of additional work, which varies by type.

Estimating this model using the HRS 1992 cohort, I confirm that individuals of different types have different disutility from work, with those in the most physical work having the highest disutility. With the model, I assess how changes in occupations across cohorts the 1992 and 2004 HRS cohorts shift welfare differently across the lifetime income distribution. I find households at all but the lowest quartile of lifetime income have benefitted from changes in the nature of work. The welfare of those in the lowest quartile declines as a result of the low-income group's decreasing attachment to the labor market. These results confirm that

[1] I perform this analysis for men only, as the rapidly changing labor market behavior of women in this time period makes the analysis fraught.

changes in work capacity have not led to gains in old-age welfare for everyone, one of the worries of policymakers and analysts contemplating increases in the Full Retirement Age (Konish 2023; SSA 1986).

Finally, I evaluate the impact of two different Social Security reform proposals on the labor force participation of workers in the most physical tasks and poorest health.[2] The first reform proposal is an increase in the Full Retirement Age from 67 to 69. This effectively cuts benefits by a similar percentage across all possible retirement ages. This reform induces the largest increases in labor force participation among those in the most physical work and in the poorest health. By contrast, an alternative reform that produces similar fiscal savings but concentrates benefit reductions largely among higher earners has little effect on participation among men in the most physical jobs. In terms of aggregate welfare, the latter reform is preferable to the former, both under the 1992 and 2004 HRS occupation distributions.

In most parts of my analysis, I explore the differences in labor market behavior of individuals based on the differences in their occupation characteristics in their 50s. The idea is that any future work they are likely to perform will be similar to that occupation, both because it is the kind of work that is available in the economy and because it is the kind of work for which they have accumulated the skills to perform.[3] In this sense, the analysis is agnostic about whether the changing nature of work is a demand or supply-driven phenomena. In the analysis measuring the contribution of changing work to changing labor force participation, this approach amounts to assuming that someone in 1990 with a given set of occupation characteristics in their 50s will have a similar labor market participation profile as someone in 2010 with that same set of occupation characteristics. In the model, I assign "type", the model analogue of access to different kinds of occupation, based on the occupation individuals hold in their early 50s in the HRS. Keeping type fixed allows me to keep the rich structure of previous structural retirement models that account for the complicated interplay of labor supply, saving, and social security benefits while keeping the model estimation tractable (e.g. French and Jones 2011).

This work contributes to four literatures. The first is the literature investigating the causes of the observed increase in old-age male labor supply. Previous work has looked at changes in the Delayed Retirement Credit (Pingle 2006; Duggan et al. 2023), changes in

[2]Both reforms are based on 2016 proposals from Rep. Sam Johnson which were scored as having similar impacts in terms of long-term aggregate benefits reduction by the Office of the Chief Actuary of Social Security (SSA 2016). These proposals formed the basis for more recent proposals from the Republican Study Committee (cite).

[3]Occupations later in life are very persistent. When people get new jobs in old-age, they are usually very similar to the kind of work they were previously doing (Johnson, Kawachi, and Lewis 2009; Sonnega, Helppie-McFall, and Willis 2016).

the Social Security earnings test (Song and Manchester 2007; Haider and Loughran 2008), increases in the FRA (Mastrobuoni 2009; Deshpande, Fadlon, and Gray 2021), changes in female labor force participation (Schirle 2008; Rogerson and Wallenius 2022), and changes in private pensions (Hurd and Rohwedder 2011).[4] My paper is the first in this literature to explicitly measure the contribution of the changing nature of work to increased labor force participation among older men. While many reviews of the trend in older employment suggested the changing nature of work as a cause (Maestas and Zissimopoulos 2010; Coile 2018), few papers have analyzed the link. Some studies found no evidence of shifts in occupation influencing older labor supply using broader occupation measures than the ones used here (Cajner, Fernández-Blanco, and Sánchez Marcos 2021; Yu 2023). Other studies found connections between changing levels of education and older labor supply and suggested job characteristics as a possible channel for this relationship (Blau and Goodstein 2010). The paper closest to mine in this literature is Acemoglu, Mühlbach, and Scott (2022). Using natural language processing techniques and the stated preferences of older workers elicited by Maestas et al. (2023), they created an index of the "age-friendliness" of jobs and showed that the age-friendliness of jobs in the economy had increased from 1990 to 2019. While that work showed that the occupation characteristics in the economy have shifted in the direction of older workers' stated preferences, this paper explicitly measures how changes work characteristics have led to concomitant increases in labor force participation among older individuals.

I also contribute to the literature on the relationship between occupation characteristics and retirement, begun by Filer and Petri (1988). Some recent papers have documented relationships between job characteristics, health, and employment in the HRS.[5] My paper augments this literature by examining the relationship between old-age labor force participation and decision-making, social, and routine inputs, which have been important elements of change over time in American work. The analysis using variation across commuting zones also innovates on this literature by employing methods that more directly test whether the relationship between occupation characteristics and older labor force participation is causal.

My work adds as well to the body of literature on the effects of the changing tasks in the labor market due to technological change. Much of this literature has examined the effects of task changes on the wage distribution (Autor and Dorn 2013; Acemoglu and Restrepo 2022). This paper points to an additional dimension for increasing inequality due to task changes. As work gets more cognitive- and social-intensive, individuals who gain access to

[4]For reviews of this literature, see Blundell, French, and Tetlow (2016) and Coile (2018)

[5]McFall et al. (2015); Hudomiet et al. (2017); Sonnega et al. (2018); Ameriks et al. (2020); Hudomiet et al. (2020); Lopez Garcia, Maestas, and Mullen (2020); Lopez Garcia, Mullen, and Wenger (2021); Lopez Garcia, Mullen, and Wenger (2022); Maestas et al. (2023).

these kinds of jobs not only experience higher earnings but also longer working lives, which increases lifetime income inequality.

Finally, I advance the literature on structural models of retirement.[6] My innovation is to study the influence of the *kinds* of work available to individuals on their old-age labor supply and savings decisions.[7] This allows me to estimate welfare changes from changes in occupation characteristics along three dimensions: 1) changes in wages, 2) changes in the disutility of work and 3) changes in life histories, which affect wealth and social security benefits. The papers most closely related to my approach here are French and Jones (2011) and Yu (2023). Both had individuals choosing employment and benefit claiming in an environment that took into account health, the effect of health on utility, wages, and expenditures, and also approximated social security benefit rules.

The paper proceeds as follows. Section 2 describes the data and task measures I use. Section 3 contains the main empirical evidence regarding the influence of occupational characteristics on old-age labor force participation. Section 4 describes the structural model, and outline its estimation. Section 5 presents the estimation and counterfactual results. Section 6 concludes.

2 Data and Trends in Occupation Characteristics

I study the changing nature of work and its impact on older employment using three datasets: the Health and Retirement Study (HRS), the Census and American Community Survey (ACS), and version 5.0 of Occupation Information Network (O*NET) occupation data. In this section, I describes the samples used, define the occupation tasks and characteristics variables used, and show the trends in these characteristics over time.

2.1 Samples

The core of my analysis utilizes the Health and Retirement Study (HRS). The HRS is a biennial survey of older individuals that began in 1992 by sampling individuals in the U.S. aged 51-61 and their spouses. These individuals are followed and re-interviewed every two years. Moreover, every six years, a new sample of 51- to 56-year-olds and their spouses are drawn from the population and permanently followed by the survey. The core of my

[6] These include Gustman and Steinmeier (1986b); Rust and Phelan (1997); French (2005); Blau and Gilleskie (2008); Klaauw and Wolpin (2008); De Nardi, French, and John B. Jones (2010); Haan and Prowse (2014); De Nardi, French, and John Bailey Jones (2016); Borella, De Nardi, and Yang (2023)

[7] Gustman and Steinmeier (1986a) estimated a simpler structural retirement model that allowed disutility of work to vary by blue-collar and white-collar work. They found that blue collar work provided higher disutility from work. My model allows for richer health dynamics and structure of occupations.

regression analysis uses 51- to 56-year-olds from the 1992, 1998, and 2004 cohorts in the HRS, while the structural model is estimated using only the 1992 cohort.

When examining the change in occupational characteristics over time, I used the 1950 and 1970 1% sample, the 1980, 1990, and 2000 5% Census samples, and the 2010–2019 ACS samples. I also used these surveys to exploit geographical variation across commuting zones and time to gauge the effect of occupation characteristics on old-age employment.

2.2 Occupations and Their Characteristics

As part of the HRS, respondents are asked about their current occupation if they are working, which is available in three-digit Census occupation coding in restricted versions of the HRS data. My analysis typically restricts attention to the first occupation individuals are observed to hold between ages 51 and 56. This is the point in the survey at which employment is likeliest. I am only unable to assign an occupation to 13.5%, 12.4%, and 14.6% of the 1992, 1998, and 2004 cohorts, respectively. Individuals without an assigned occupation are excluded from the regression analysis relating old-age labor force participation to occupation characteristics, but they are included in the structural model as workers with their own distinct type.

For data on the tasks and characteristics of occupations, I used the O*NET database. This dataset contains information on over 800 occupations. The information on occupations is provided as ratings along over 200 dimensions describing the kinds of skills, abilities, knowledge, work activities, work context, job interests, work values, and work styles that the occupation involves. While the original version of O*NET (and its predecessor, *The Dictionary of Occupational Titles*) based the occupational ratings on analysts' judgements, beginning in 2003 the database transitioned to basing the ratings on surveys of incumbent workers of the occupations as well as analysts' judgement of the requirements of an occupation based on incumbents' responses.

Periodically, O*NET updates the occupational information for a subset of the occupations in its database based on results from new surveys of incumbent workers. Because the database has been updated regularly since 2003, researchers have a choice of which version to use in their study. I used version 5.0 of the O*NET, released in 2003, because it is the earliest available instance of the modern O*NET database. This gives me access to a broader set of measures of occupational characteristics while minimizing the distance in time from the first cohort I examine in the HRS.

With the choice of O*NET version in hand, two issues emerge regarding how to measure occupational characteristics and its change over time in the Census and HRS. First, the occupation measures contained in O*NET are at the O*NET-SOC level, a more granular and different coding than three-digit Census codes used in the HRS, Census, and ACS. To deal with this, I created a crosswalk between O*NET occupations and 1980, 1990, and 2000 Census codes using the *occ1990dd* occupational classification (Autor and Dorn 2013). Details for the crosswalk construction are provided in Appendix XX.[8]

By linking all occupations to the O*NET 5.0 database, I hold the characteristics within three-digit occupation occupation constant across time. This means that when looking at change over time in the nature of work, I do not account for within-occupation change in characteristics. Studies have shown that within-occupation change is also a significant component of the changing nature of work (Autor, Levy, and Murnane 2003). Indeed, Atalay et al. (2020) find that a substantial portion of the movement from away from routine tasks and towards non-routine cognitive tasks between 1950 and 2000 occurred within occupation. Lopez Garcia, Maestas, and Mullen (2020) reach similar conclusions about the shift away from physical tasks and towards cognitive tasks between 2003 and 2018.

The second issue from the use of O*NET is that there are far too many ratings and measures to be tractably analyzed individually. To deal with this, I take two approaches. In the first, I average a select group of measures from O*NET to create six measures of job characteristics, which I call decision, social, mathematical, physical, routine, and extreme conditions. Specifically, for each of the six characteristics, I took two to five O*NET measures and re-scaled them so that they all ranged from zero to one.[9] Then, I averaged, within *occ1990dd* occupation, over the two-to-five chosen O*NET measures to create each of the six characteristic-intensity measures for each occupation. Table **??** details the O*NET measures over which I averaged to create the characteristic's measure. The column "Source" describes the source from which I drew the definition of the variable.

For interpretability, I followed Autor, Levy, and Murnane (2003) and re-scaled the occupational characteristic measures using the 1980 Census sample so that the value for each characteristic corresponds to the centile it would land on in the 1980 occupational distribution.[10] So, for example, if an occupation's decision-making value was 50, then its rating on this dimension was equal to that of the median 1980 occupation. If an occupation's score for decision-making was 80, then it had the decision-making intensity of the 80th percentile of decision-making in the 1980 occupational distribution.

I selected these six characteristics because previous literature showed them to have changed in importance in the past 40 years in the economy or to be of particular relevance for

[8][[Need some discussion here about the spread of the measures in those cases.]]

[9]O*NET scales have little cardinal interpretation (Lise and Postel-Vinay 2020), and the actual scale used varies from measure to measure. For example, some range from 0 to 7, and others range from 1 to 5.

[10]Autor and Dorn (2013), Deming (2017), and Deming (2021) also took this scaling approach.

older workers and their labor supply decisions. The O*NET measures chosen for decision-making, social, mathematical, and routine were drawn from Deming (2017) and Deming

Table 1: Occupation Characteristic Definitions

Characteristic	O*NET Measures	Source
Decision-making	Making Decisions and Solving Problems Developing Objectives and Strategies Planning, Organizing, and Prioritizing	Deming (2017)
Social	Social Perceptiveness Persuasion Coordination Negotiation	Deming (2017)
Mathematical	Math Knowledge Mathematical Skill Mathematical Reasoning	Deming (2017)
Routine	Importance of Repeating the Same Task Degree of Automation	Deming (2017)
Physical	Stamina Time Spend Bending Time Spent Standing Time Spent on Knees Crouching Trunk Strength	Own construction based on the findings of LMW (2021)
Extreme Conditions	Exposure to Whole Body Vibrations Exposure to High Places Exposure to Outdoor Weather Very Hot or Very Cold Temperatures Exposure to Hazardous Equipment Exposed to Contaminants Noise Levels are Distracting or Uncomfortable	Own construction based on the findings of LMW (2021)

The measure of intensity of each characteristic is created by averaging the corresponding O*NET measures within *occ1990dd* Census occupation. Because O*NET measures can have different scales and ranges, before averaging them, I first standardize the O*NET measures. After averaging across the measures, I then further rescale by measuring intensity in each characteristic in terms of centile of the 1980 Census occupational distribution, following Autor, Levy, and Murnane (2003). LMW (2021) refers to Lopez Garcia, Mullen, and Wenger (2021). Some of the O*NET names can refer to two different scales: one rating the *level* of the particular skill, ability, or knowledge needed in the occupation and one measuring the *importance* of the particular skill, ability, or knowledge to the occupation. In such cases, I always use the rating of the *level*.

(2021). Those two papers traced the growing importance of social and decision-making tasks in the economy, respectively. Together, the decision-making, social, and mathematical measures can be seen as a break-up of the larger category of non-routine cognitive or "abstract" tasks whose growing importance in the economy was highlighted by Autor, Levy, and Murnane (2003) and Autor and Dorn (2013).[11][12] By contrast, routine tasks have seen declining importance in the economy, as first documented by Autor, Levy, and Murnane (2003).

Studies have found the physical intensity of occupations is related to old-age labor supply. Maestas et al. (2023) found that older workers expressed a willingness to pay more for less physically-intense work (compared to younger workers). Hudomiet et al. (2017) showed that declines health predicted larger decreases in an individual's subjective probability of working past age 65 when the worker was in an occupation that relied on physical strength. Lopez Garcia, Mullen, and Wenger (2022) demonstrated that increased physical demands in early-life work were associated with a lower probability of employment in old-age. I picked O*NET measures to match the descriptors used by Lopez Garcia, Mullen, and Wenger (2022). I do the same for the extreme conditions measure, as that study also found it was correlated with old-age labor supply.

As a complement to my analysis with the six measures described above, I also analyzed occupations using the components from a Principal Components Analysis. Specifically, I applied the PCA algorithm to all of the O*NET ratings using the 1980 Census sample and extracted the first 20 components.[13] While interpretation is more difficult with PCA components, they have the benefit of capturing a lot of the variation in occupational characteristics parsimoniously. I also often focused only on the first principal component, which captured XX% of the variation in occupational measures in 1980, and was correlated with the six characteristics measures I constructed in a convenient way, as I explain in more detail below.

[11] The non-routine cognitive task measure in these papers was the average of two *Dictionary of Occupational Titles* measures: the extent to which the occupation involved Direction, Control, and Planning of activities (DCP), and GED-MATH, which measured the occupation's "quantitative reasoning requirements" (Autor, Levy, and Murnane 2003).

[12] Lopez Garcia, Mullen, and Wenger (2022) found that job autonomy/flexibility were associated with early retirement. While the decision, social, and mathematical measures here do not directly measure job autonomy or flexibility, they are likely to be correlated with both.

[13] This is the point at which the eigenvalue of the components falls below 1. The first 20 components capture close to 90% of the variation in the employment-weighted O*NET measures in th 1980 Census sample.

2.3 Other Variables

In the analyses performed, I brought in variables beyond labor force participation and occupation characteristics to control for potentially confounding factors. Some of these variables relate to other characteristics of occupations that are not captured in O*NET. For example, I observed in the HRS whether an individual had a defined benefit pension, a defined contribution pension, or retiree insurance in their initial job. Most of the additional variables are self-explanatory and I do not dwell on them here. I do, however, briefly detail the construction of the health variables used in the analyses.

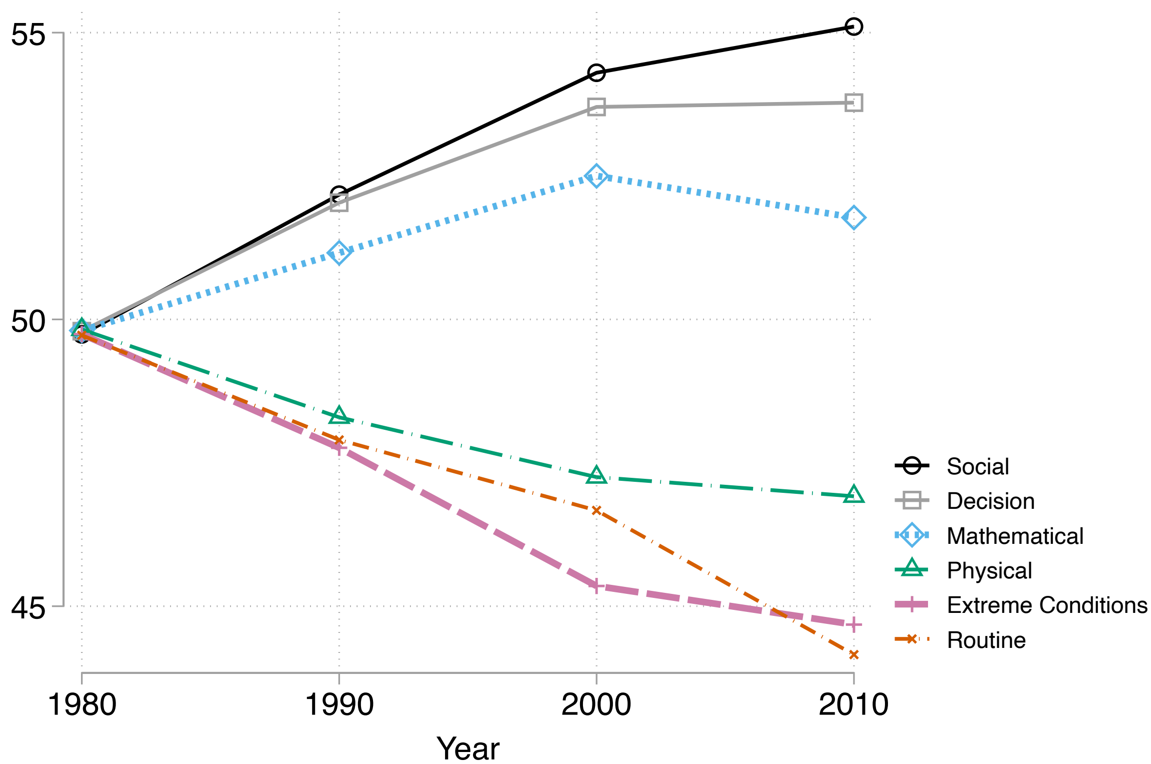
In the HRS data, I follow the method of Blundell et al. (2021) to create a single index of health. The health index variable is created in three steps. First, I extract the first principal component of the following self-reported measures of health: whether health limits work, health level, and whether the person has a mobility issue. Second, I regress this summary measure of subjective health on a natural cubic spline of age and indicators for the presence of various objective health issues such as diabetes, heart disease, and arthritis. Third, for each observation, I produce the predicted value from this regression. The health index is this predicted value. The procedure for its construction reduces measurement error and justification bias as the subjective measures are instrumented with the objective measures. And it is a single summary value of health that was shown to be significantly correlated with employment at old-ages. More details about the construction of the health index in the HRS and the health variable used for the Census are contained in Appendix XX.

2.4 Trends in Occupational Characteristics for Men

Figure **??** shows the evolution of average task intensity over time among the entire employed population in the United States. This includes people of all genders and all ages above 16. The figure shows that social, decision-making, and mathematical task input increased steadily from 1980 until 2000, with some slight plateauing in the 2000s. Conversely, routine and physical input as well as extreme conditions prevalence decreased steadily in the same time period. This figure replicates the findings of Autor, Levy, and Murnane (2003), Autor and Dorn (2013), Deming (2017), and Deming (2021) regarding the growing importance of non-routine cognitive tasks in the economy (particularly social and decision-making tasks) as well as the decreasing importance of routine tasks. To this I add the novel, to the best of my knowledge, contribution of the decline of extreme conditions and physical input in employment in the Census and ACS.[14]

[14] Johnson (2004) showed declining physical requirements for men under 60 in the HRS and Lopez Garcia, Maestas, and Mullen (2020) showed declines in physical demands of work using the CPS from 2003 to 2018.

Figure 2: Trends in U.S. Employment Task Intensity



Data are from 5% sample of the 1980, 1990, and 2000 Census and from the 2008-2010 multi-year sample of the American Community Survey. Tasks are O*NET scales explained in Section ??, rescaled so that they are expressed in centiles of the 1980 task distribution.

The trends in occupation characteristics in Figure ?? are very similar when looking at men only. They also hold when restricting to men older than 60, as well as when restricting to men ages 51–56. This latter group is the one I use for estimating how changes in work have affected old-age labor supply, as I have occupation at these ages in HRS. Appendix Figure ?? shows these patterns for men; Appendix ?? provides further discussion.

The trends in Figure ?? plateau in the 2000s. Lopez Garcia, Maestas, and Mullen (2020) looked at aggregate changes in occupation characteristics from 2003 to 2018 including both changes within-occupations and between-occupations. They found, using an index for cognitive demands and an index for physical demands, that cognitive demands increased in that time period while physical demands decreased; however, the vast majority of the change occurred *within-occupation*. Indeed, they found a *drop* in cognitive demands and an *increase* in physical demands when looking at changes *between-occupations*. Because of the dominant (and potentially "between-reversing") role of within-occupation shifts that Lopez Garcia, Maestas, and Mullen (2020) found after 2000, and because my occupation characteristics measures do not account for within-occupation shifts, I restrict myself to using shifts from before 2000 in my accounting of the role of occupation changes in the increase of old-age labor supply.[15] In future work, I plan to extend my measures to allow for within-occupation change. This would permit an extended accounting of the role of changing occupation characteristics on labor force participation at older ages and a projection of the impacts of trends in occupations on future labor force participation.

3 Occupation Characteristics and the Labor Force Participation of Older Men

In this section, I (i) show how my chosen task and characteristics measures relate to labor force participation at older ages in the HRS, (ii) use these relationships and the trends in aggregate occupation characteristics to predict increasing labor force participation for 60–69-year-old men, and (iii) provide evidence that the relationship between occupational characteristics and old-age labor supply is causal using variation in commuting zone occupational characteristics over time. I also show that (iv) occupation shifts conducive to longer work have been larger at higher levels of lifetime income.

3.1 Occupation Characteristics and Older Labor Force Participation in the HRS

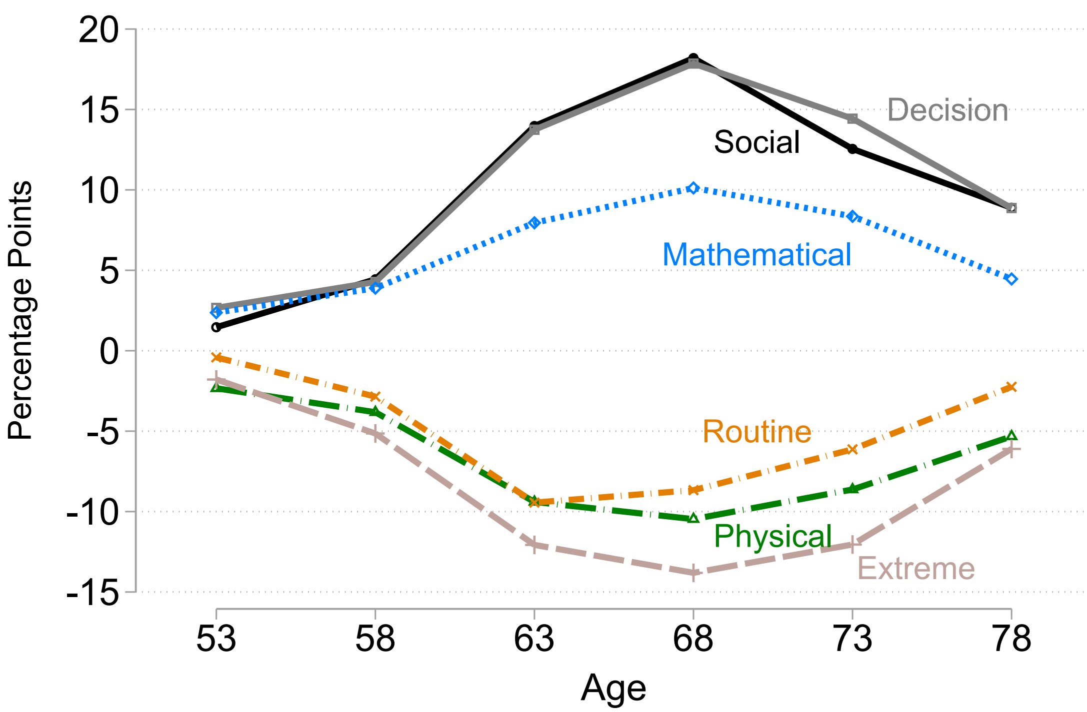
How do the tasks and characteristics of an individual's initial occupation relate to their probability of working at older ages? Figure **??** plots, at different ages and for each characteristic, the difference in labor force participation between individuals whose initial occupation was in the top tercile of that task's distribution in 1980 and individuals whose initial occupation was in the bottom tercile of the same distribution. The average difference is calculated over five-year age bins. For example, at ages 51–55, the average employment of men whose initial occupation was in the top tercile of social task intensity was only about 1 percentage point higher than men with an initial occupation in the bottom tercile of social task intensity. However, by ages 66–70 this gap has grown to be around 18 percentage points.

Figure **??** shows that there are dramatic relationships between a man's initial occupation task intensity and his employment probability in older ages. Men in initial occupations that are more decision-, social-, or mathematical-intensive are more likely to work at older ages;

[15]While Atalay et al. (2020) and Autor, Levy, and Murnane (2003) found that within-occupation shifts were also a contributor to changes in work before 2000, they were not the dominant force as they are in Lopez Garcia, Maestas, and Mullen (2020).

the opposite is true of men in more routine-, extreme-, or physical-intensive initial occupations. The differences in average employment across ages for a given task are statistically significant, as can be seen in Appendix Figure ??, which includes the standard error of each difference. As average employment at each age is also falling quite rapidly over these ages, the percentage difference in average employment between the bottom and top terciles is nearly monotone in age for each task (Appendix Figure ??).

Figure 3: Difference in Employment Rate Between Men in Top and Bottom Task Tercile



The figure plots the difference in the participation rate between individuals in the top tercile of a given task's intensity and the individuals in the bottom tercile of the same task's intensity. For a given task or characteristic, an individual falls in the "top" tercile if his initial occupation's value in that characteristic was larger than the 66.6th percentile of the 1980 distribution. Likewise, he falls in the "bottom" tercile if his initial occupation's value in that characteristic was lower than the 33.3rd percentile of the 1980 occupational distribution. The sample is men from the 1992, 1998, and 2004 of the HRS who were between 51 and 56 years old when they entered the survey and who had O*NET data linked via occupation available. Individuals are excluded from the sample if their first employment is observed after age 56. Employment averages are taken over five-year age bins starting with 51-55 and ending with 76-80. Point is plotted at the midpoint of the age bin.

Combining the insights from Figures ?? and ??, the aggregate tasks and characteristics of American work have shifted precisely towards those that are associated with longer work (decision, social, and mathematical), while shifting away from those associated with less work in old-age (routine, physical, and extreme conditions). But there could be other differences among individuals who hold different jobs at age 50 that may be driving this observed relationship between job characteristics and employment at older ages. For example, manufacturing and construction jobs might have more routine, physical, and extreme conditions content, but they may also have higher prevalence of defined benefit pensions. The incentive structure of defined benefit pensions could then be the source of some of the employment gaps observed in Figure **??** (Kotlikoff and Wise 1987).

As another example, better educated people are more likely to be in more decision- and social-intensive occupations. But this also means they are more likely married, which has been shown to be associated with higher retirement ages (Schirle 2008). Similarly, individuals with more education are also healthier on average (Coile, Milligan, and Wise 2017). Better health decreases disutility from work and increases wages (French and Jones 2011) which, in turn, increases the likelihood of employment.

To address this concern, I turn next to regression analysis to better isolate the contribution of work characteristics to retirement age and employment at later ages. In particular, I estimate models of the form

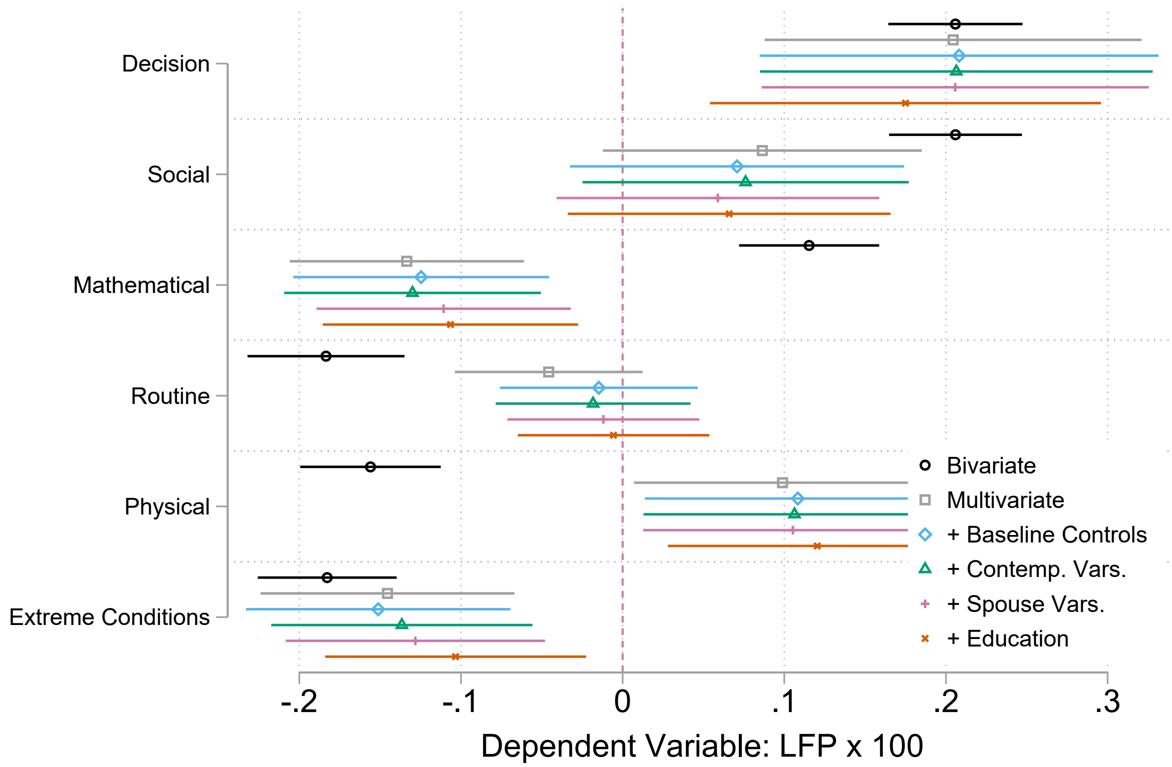
$$LFP_{i,t} = \alpha^{OccValue} OccValue_i + \beta_1 X_i^{initial} + \beta_2 X_{i,t} + \delta_t + \lambda_{age} + \varepsilon_{i,t}$$

where LFP_{it} is the labor force participation indicator for person i at time t and $OccValue_{i,initial}$ is person i's initial occupation value (that is, one of the six characteristics measures I have focused on). In different specifications, I control for the person's initial (that is, survey entry) covariates $X_i^{initial}$ and/or the covariates at time t: $X_{i,t}$. All models also include year and age fixed effects. I focus on labor force participation between ages 60–69; thus, the sample is person-year observations of men ages 60–69 for whom I was able to assign an initial occupation.

I begin by regressing labor force participation on each of the six task and characteristics measures separately. These regressions measure the bivariate relationship between labor force participation at ages 60 to 69 and each of the initial occupational characteristic measures. The black circles in Figure **??** plot the coefficients for each of the six measures, and the error bars represent 95% confidence intervals, clustered at the individual level. The signs and relative magnitudes of the coefficients are as expected, given Figure **??**. Entering ages 51 to 56 in an occupation with high decision or social intensity is associated with having higher labor force participation at ages 60 to 69. This also the case for mathematical intensity, though the point estimate is smaller. Entering the survey in an occupation with high physical, routine, or extreme-conditions intensity, on the other hand, is associated with a lower labor force participation at ages 60 to 69.

Including all six characteristics in a single regression shows how each occupational charac-

Figure 4: Labor Force Participation at Ages 60–69 and Initial Task Input



The figure displays the coefficients from a regression of an indicator for labor force participation (x 100) on initial occupation characteristics and additional control variables. The occupation characteristics measures are from the individual's first observed employment between ages 51 and 56. They are measured in centiles of the 1980 distribution of tasks. The sample includes all person-year observations between ages 60 to 69 of individuals from the 1992, 1998, or 2004 HRS cohort who were between 51 and 56 years old when they entered the survey, who were observed employed at least once between those ages, and for whom such employment can be linked to O*NET information. Standard errors are clustered at the individual level. 95% confidence intervals are displayed. All regressions include age and year fixed effects. The "bivariate" results display the coefficient on the occupation characteristics from a regression of LFP on only that characteristic. The "multivariate" results show the coefficients from a regression that includes all of the shown characteristics. "Baseline Controls" adds controls for the initial job having retiree insurance, the initial job having a defined benefit pension, initial health index value, initial wealth quintile, and marital status. "Contemp. Vars." further adds controls for the contemporary health index and wealth quintile. "Spouse Vars." further adds controls for spouse employment status (if married) and spouse age. Finally, "Education" further adds controls for years of education (up to 16) and whether the individual has schooling beyond college.

teristic relates to old-age employment holding the other five characteristics fixed. The results from that regression are plotted as gray squares in Figure **??**. These estimates are much noisier, and there are large shifts in the coefficients. This is to be expected as the measures are highly correlated. Decision and extreme conditions remain statistically significant and with the same sign as in the bivariate regressions. The social characteristic measure sees a fall in its positive relationship with employment probability at older ages; it is no longer statistically significant. This is also true of the routine measure.

By contrast, both the mathematical and physical measures see a flipped sign in their relationship with old-age employment when holding the other five characteristics fixed. For the mathematical measure, this result is in concordance with previous work that demonstrated that increased mathematical occupation content decreases retirement age holding other job characteristics fixed (Filer and Petri 1988). Increased physical tasks content holding the other five characteristics fixed now has a positive relationship with old-age labor supply. Finally, the coefficient on extreme conditions is still negative and of similar magnitude to that of the bivariate regression.

With this regression model, I can further exploit the rich nature of the HRS data to control for additional factors that could confound the relationship between occupation characteristics and old-age labor supply. The rest of the coefficients plotted in Figure **??** progressively add sets of controls to the multivariate regression. The controls include health, wealth, marital status, whether the initial job had a defined benefit pension, whether the initial job offered retiree insurance, and education. The point estimates of the coefficients are relatively stable to the addition of the extra controls. Appendix **??** contains a more detailed discussion of some of the movements produced by the additions of specific control sets.

3.2 Predicting Changes in Labor Force Participation

How has the changing nature of work contributed to the increase in labor supply for older men? The results discussed until now suggest that changing occupation characteristics indeed contributed to growing labor force participation for older men. The growth shown in Figure **??** has been in precisely the kind of job characteristics that are associated with longer work, while the characteristics associated with less work have decreased. However, the results from the multivariate regressions in Figure **??** do not provide a clear answer to this question. There, one of the job characteristics that has been shrinking in the economy (physical input) had a positive relationship with old-age labor force participation, while one of the growing characteristics (mathematical input) had a negative relationship.

To make sense of how the results from Figure **??** can speak to the change in old-age labor force participation, I take each coefficient estimate from that figure, multiply it by the change in that characteristic's intensity in the economy from 1980 to 2000 for 51- to 56-year-old men in the Census (shown in Appendix Figure **??** Panel D), and then sum up this value across all characteristics. In essence, I take the estimates from Figure **??** as estimates of the effect of occupational task intensity at ages 51–56 on labor force participation, and use the changes in occupational structure for that population to estimate how changes in the nature of work impacted the old-age labor supply.

The results are shown in Table ??.[16] The first column, "Main Tasks," focuses on the results from regressions in which only the six characteristic measures I have focused on so far are included. The first row, labeled "No Covariates" (which only includes age and year fixed effects as controls) shows the result from using the "Multivariate" regression in Figure ??. Changes in the six occupational measures among 51-to-56-year-old men from 1980 to 2000 predict an increase in the labor force participation rate of 60-to-69-year-olds of 1.46 percentage points. For comparison, the increase in labor force participation for men of those ages from 1990 to 2010 was about 7.8 percentage points.

Better interpretation of the result requires noting that about 14% of the men in the HRS were not assigned an initial occupation.[17] Assuming the labor force participation of those men is unaffected by the changing nature of work (a conservative assumption), then the predicted total change in labor force participation from the changing mean of the six characteristics is $1.46 \times 0.86 = 1.26$ percentage points. Thus, the multivariate regressions with only age and year controls suggest that the changing nature of work along the six characteristics discussed so far predicts about 16.2% of the increase in labor supply from 1990 to 2010 for 60-to-69-year-old men.

The successive rows in Table ?? show the predicted change in the labor force participation when using the corresponding coefficient estimates from Figure ??. Additional controls do slightly attenuate the effect attributable to the changing nature of work. The preferred specification, with all controls except for education, suggests that 13.9% of the change in the labor force participation of 60-to-69-year-olds from 1990 to 2010 came from the changing prominence of decision, social, mathematical, physical, routine, and extreme-conditions characteristics in work. Even including education in the specification leaves around 10% of the change in older labor force participation explained by the changing intensity of the six measures.

Of course, the six measures I have chosen do not capture all possible dimensions of work and changing occupation characteristics. Indeed, O*NET has over 200+ different scales measuring occupation characteristics. Perhaps these other characteristics have a different effect on labor force participation and have also had different trends over time. To address this concern, I add 7 additional measures considered in Deming (2017).[18] The results are

[16] The standard errors take into account the standard errors from the coefficients in Figure ??, but they do not take into account error from sampling variation in the Census, which is trivial.

[17] Recall that this means they were unlikely to have worked at all between the ages of 51 and 56 in the survey.

[18] These are interactive, coordination, service, finger dexterity, number facility, deductive inductive rea-

Table 2: Predicted Change in LFP x 100 from 1990 to 2010, Men Ages 60–69

	(1) Main Tasks	(2) All Tasks	(3) PCA Tasks
No Covariates	1.462	1.348	1.545
	(0.152)	(0.177)	(0.223)
Baseline Controls	1.380	1.451	1.576
	(0.164)	(0.190)	(0.240)
Add Contemp. Vars.	1.299	1.376	1.493
	(0.162)	(0.187)	(0.238)
Add Spouse Vars.	1.217	1.245	1.424
	(0.162)	(0.189)	(0.237)
Add Education	0.884	0.789	0.940
	(0.180)	(0.215)	(0.266)
LFP Change from 1990 to 2010		7.8	

The table displays the predicted change in the labor force participation (x100) from 1990 to 2010 for men ages 60 to 69. To produce the estimates in column 1, I take the coefficients from Figure ??, multiply them by the change from 1980 to 2000 in the mean occupational characteristics among employed men ages 51 to 56 in the Census, and then sum up all of the effects. The standard errors are based on the standard errors from Figure ??, which are clustered at the individual level. The standard errors presented here account for correlation in the coefficient estimates. They do not, however, take into account sampling error in the measure of the change in mean occupational content in the Census, which is small. Column 2 repeats the exercise including six additional occupational characteristic measures from Deming (2017). Column 3 repeats the exercise using the 20 first principal components extracted from a large set of O*NET scales using the 1980 Census. See Section ?? for more details on the PCA. See Figure ?? for an accounting of the control variables included in each of the rows.

shown in the second column of Table ??. Using this larger set of measures changes the results little.

I end by performing the same exercise with the 20 first principal components from the 1980 Census occupation O*NET characteristics distribution. Doing so allows me to capture a large fraction of the variation in occupational characteristics while keeping the precision of the exercise manageable.[19] The final column of Table ?? shows the results. Using the 20 principal components further increases the estimated contribution of the changing nature of work to the increase in old-age labor supply. The estimated effect increases across all specifications. The preferred specification indicates that changes in the PCA task measures among 51-to-56-year-old men from 1980 to 2000 predict about 15.7% of the increase in the labor force participation of men aged 60–69 from 1990 to 2010.[20]

soning, and information use.

[19]Recall that the 20 principal components capture about 90% of the variation in the 1980 Census O*NET characteristics.

[20]When controlling for education, the percent explained is 10.4%.

The relationship between initial occupation characteristics and labor force participation in old-age persists beyond ages 60–69. Appendix Table **??** shows the predicted changes in labor force participation for men ages 70–79 from 2000 to 2019 (ten years forward from the time frame for 60–69-year-old-men). The results suggest that changes in the nature of work can explain up to 44% of the increase in the 2.4 percentage point increase in labor force participation of this group in the at time period.

3.3 Estimating the Effect of Occupational Characteristics on Labor Force Participation Using Geographic Variation

I have demonstrated above that even when controlling for factors that could confound the relationship between occupation characteristics and old-age labor supply, initial occupation characteristics have a strong relationship to the likelihood of participating in the labor force at older ages. There could remain, however, unobserved factors correlated with both old-age labor force participation and occupational characteristics confounding the measured relationship. In this subsection, I exploit geographic variation in the kinds of work people perform and its change over time as an additional test for whether the relationship between occupational characteristics and older labor force participation posited in the previous subsection is causal. To simplify the analysis, I focus attention on a single measure for occupation characteristics: the first principal component of the 1980 Census O*NET occupational measures. I do this for several reasons. First, it simplifies exposition, as the focus is maintained on a single variable. Second, in the instrumental variable strategy, I only have a single instrument and so can only include one endogenous variable.

Third, in the HRS, an individual's initial occupation first component (from now on, I will refer to is as *Component 1*) has a strong relationship with the probability of being in the labor force at ages 60 to 69. In fact, it has by far the largest positive coefficient in the HRS regressions that include all of the first PCA 20 components in the analysis (see Appendix Figure **??**). *Component 1* also has a convenient correlation structure with six measures I had been focusing on until now.

Table **??** displays these correlations. *Component 1* is extremely positively correlated with the decision and social measures. It is slightly less correlated with the mathematical measure. By contrast, it is very negatively correlated with the physical and extreme conditions measures. Finally, it has a comparatively weak, negative correlation with the routine measure. Thus, *Component 1* captures an axis of occupation characteristic variation that lines up well with the characteristics that appear to promote longer work and the characteristics that discourage longer work. Moreover, it is also the PCA component measure that has seen the highest increase in average value in the economy since 1980 (show in Appendix graph XX).

Table 3: *Component 1* Correlations

	Decision	Social	Mathematical	Routine	Physical	Extreme
Component 1	0.921	0.887	0.729	-0.288	-0.691	-0.625

This table displays how the occupation characteristics measure *Component 1* correlates with the decision, social, mathematical, routine, physical, and extreme conditions occupation characteristics measures. *Component 1* is the first principal component of the employment-weight O*NET measures in the 1980 Census sample.

To assess the causal relationship between *Component 1* occupation characteristics and old-age labor supply, I model labor force participation rate of men aged 60–69 $LFP_{c,t}^{60-69}$ in commuting zone c at time t as t

$$LFP_{c,t}^{60-69} = \alpha Comp1_{c,t-20}^{40-49} + \beta X_{c,t} + \lambda_c + \delta_t + \epsilon_{c,t} \tag{1}$$

where $Comp1_{c,t-20}^{40-49}$ is the average Component 1 occupation value for 40-to-49-year-old men in commuting zone c twenty years before time t. The model includes commuting zone and year fixed effects. The analysis sample are the years 1990, 2000, 2010, and 2019. The ten-year gaps are to keep the same sample when I use a "first-differences" model below, as before 2005 data is only available every decade. I include 2019 instead of 2020 to avoid the onset of the COVID-19 pandemic. 1990 is the first year that can be used as 1970 is the first year for which $Comp1_{c,t-20}^{40-49}$ is available.

The idea behind Equation **??** is that the *Component 1* average value of men ages 40–49 twenty years prior captures the characteristics of the occupations that both (1) are likely to be available for men 60–69 in the current period and (2) those men are likely to have the skill and experience to perform. I go as far back as 40-to-49-year-olds twenty years prior, rather than, for example, 50-to-59-year-olds ten years prior in an effort to capture the kinds of occupations closest to main "career" of the men. Previous research has shown that occupations before ones 50s better predict effects on employment (Nicholas, Done, and Baum 2020), although the data limitations of the HRS prevented me from going this far back in the analysis in the previous subsection.[21]

The inclusion of the commuting zone fixed effects in Equation **??** means that α, the parameter of interest, is identified by changes across decades in the average value of *Com-*

[21] Going further back also gets closer to ages in which the individuals can react to occupation changes and invest appropriately in human capital. For example, if there is rapid occupation change in one's 50s, this might lead to obsolescence and quicker labor market exit in the near-term (Hudomiet and Willis 2021).

ponent 1 for men ages 40–49 within a commuting zone. This strategy controls for fixed unobservables across commuting zones that affect the labor force participation rate of men ages 60–69 and are correlated with $Comp1^{40-49}_{c,t-20}$.

Table ?? Panel A displays the results of the estimation of Equation ??. Column 1 presents the model with only year and commuting zone fixed effects. Confirming the results from the previous subsection, a higher average value of Component 1 among men ages 40–49 in a commuting zone twenty years prior increases the labor force participation of men ages 60–69 in the current period. The coefficient stays positive and statistically significant even with the inclusion of additional controls, which are discussed in more detail in Appendix ??.

One could still be unsatisfied with the strategy for estimating α in Equation ??. For example, there could be unobserved factors that are correlated with changes in the work characteristics of a commuting zone that also cause changes in labor force participation twenty years later, like long-lasting idiosyncratic shocks in labor demand in a particular commuting zone. To deal with this potential bias, I exploit the impact of computerization on job tasks (Autor, Levy, and Murnane 2003) and its differential impact across commuting zones to instrument for changes in the job characteristics of 40-to-49-year-olds in a commuting zone. The theory, from Autor, Levy, and Murnane (2003) and Autor and Dorn (2013), is that advent of computers and the IT revolution led to a decrease in routine tasks and an increase in nonroutine, cognitive tasks as computer capital substituted for the former and complemented the latter. The impact of the computerization shock is larger in commuting zones that initially had more routine jobs as those commuting zones had more jobs that could be substituted with computers.

Specifically, I use the Autor and Dorn (2013) instrument to purge Equation ?? of the aforementioned potential confounders. The instrument is the predicted share of routine jobs in commuting zone c in 1950. This prediction is constructed by using the commuting zone's industry composition in 1950 and each industry's share of routine jobs calculated at the national level (excluding commuting zone c's own state). For a given commuting zone c, one takes an industry's share of employment in 1950, multiplies by the industry's share of routine jobs in 1950 at the national level, and sums this value across all industries to obtain the prediction of share of routine jobs in the commuting zone in 1950.

Being determined far in the past makes the Autor and Dorn instrument a good candidate for instrumenting $Comp1^{40-49}_{c,t-20}$ in Equation ??. Its temporally distant determination means it is unlikely to be related to idiosyncratic shocks to supply, demand, and occupation characteristics in a commuting zone. At the same time, its connection to the "long-run, quasi-fixed component of the routine occupation share" (Autor and Dorn 2013) in a commuting zone means that it captures well how exposed each commuting zone was to the computerization

Table 4: Effect of Occupation Characteristics on Labor Force Participation Men 60–69

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Commuting Zone Fixed Effects					
Comp. 1 40-49 $t-20$	0.060***	0.060***	0.059***	0.045***	0.067***	0.045***
	(0.012)	(0.013)	(0.011)	(0.012)	(0.012)	(0.011)
Ratio 60-69 to 50-59 group		-0.094***				-0.084***
		(0.016)				(0.013)
Ratio 60-69 to 40-49 group		0.039**				0.042***
		(0.013)				(0.011)
Ratio 60-69 to 30-39 group		0.060**				0.028*
		(0.020)				(0.014)
Ratio 60-69 to 20-29 group		-0.047***				-0.027**
		(0.011)				(0.010)
Men Marriage Rate, 60-69			0.122***			0.028
			(0.037)			(0.036)
Men Avg. HH Size 60-69			0.038*			0.060***
			(0.015)			(0.013)
LFP Women Age 60-69			0.350***			0.329***
			(0.047)			(0.036)
Health Issue Share Men 60-69				-0.307***		-0.330***
				(0.034)		(0.029)
Men 60-69 Noncollege to College Ratio					-0.020**	-0.011*
					(0.006)	(0.005)
Observations	2888	2888	2888	2888	2888	2888
	Panel B: First-Difference IV					
Comp. 1 40-49 $t-20$	0.091	0.150**	0.097*	0.087	0.117*	0.131**
	(0.054)	(0.054)	(0.045)	(0.056)	(0.052)	(0.048)
Ratio 60-69 to 50-59 group		-0.058**				-0.064***
		(0.020)				(0.018)
Ratio 60-69 to 40-49 group		0.038				0.045**
		(0.021)				(0.017)
Ratio 60-69 to 30-39 group		0.080***				0.047*
		(0.024)				(0.021)
Ratio 60-69 to 20-29 group		-0.080***				-0.062***
		(0.014)				(0.013)
Men Marriage Rate, 60-69			0.192***			0.107*
			(0.046)			(0.048)
Men Avg. HH Size 60-69			0.010			0.025
			(0.016)			(0.016)
LFP Women Age 60-69			0.318***			0.274***
			(0.054)			(0.045)
Health Issue Share Men 60-69				-0.319***		-0.303***
				(0.053)		(0.048)
Men 60-69 Noncollege to College Ratio					-0.027**	-0.011
					(0.009)	(0.007)
Observations	2166	2166	2166	2166	2166	2166
First-stage Effective F-Stat	45.41	42.06	46.02	49.84	47.54	49.65

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Panel A errors are clustered at the commuting zone level. Panel B errors are clustered at the state level. The table presents the estimated effect of average Component 1 value among men ages 40 to 49 in the commuting zone 20 years before the current period (Comp. 1 40-49 $t-20$) on the labor force participation of men ages 60 to 69 in the current period. Years included are 1990, 2000, 2010, and 2019. 2000 is used as the "20 years before period" for 2019. All regressions contain year fixed effects. Panel A uses commuting zone fixed effects. Panel B is estimated using first differences and instruments Comp. 1 40-49 $t-20$ using the Autor and Dorn (2013) instrument. Specifically, the instrument is the commuting zone's predicted share of routine occupations in 1950 using the commuting zone's 1950 industry mix and each industry's national share of routine occupation workers in 1950 (excluding the commuting zone's own state). Panel A is weighted by population of 60-to-69-year-old men and Panel B is weighted by the initial (in the first difference) period's population of 60-to-69-year-old men. First-stage Effective F-Statistics from Montiel Olea and Pflueger (2013) are displayed.

revolution.

This instrument falls into the class of "exogenous shock" shift-share instruments analyzed by Borusyak, Hull, and Jaravel (2022). The shocks are each industry's routine-intensity in 1950, which proxies for the impact of the IT revolution. These industry-level shocks are aggregated to the commuting zone level using each commuting zone's 1950 industry shares. Identification requires that unobserved shocks to labor force participation (specifically that of older workers) in particular industries from the 90s onwards are uncorrelated with that industry's routineness in 1950. This seems quite plausible, but below I perform pretrend analysis to test the plausibility of this assumption.

Panel B of Table **??** displays the results from the instrumental variables model. Because the instrument is constant within commuting zone, I estimate the model in first (decadal)-differences. As in Autor and Dorn (2013), I allow the effect of the instrument on $Comp1^{40-49}_{c,t-20}$ to depend on the year, giving the instrument the flexibility to reduce its predictive power as the year gets further from 1950.[22] In all specifications, the coefficient on $Comp1^{40-49}_{c,t-20}$ increases, and in most of the specifications the coefficient remains statistically significant. Pre-trend checks, in which I replace the dependent variable in Table **??** Panel B with its lag and second lag, indicate the absence of substantial pretrends; the estimated coefficient on $Comp1^{40-49}_{c,t-20}$ in these regressions is close to zero and never statistically significant (See Appendix Table **??**).

Regardless, both the statistical significance of the estimate of α across most of the specifications in Table **??** as well as its consistent increase when compared to the results from the fixed effects estimator in Panel A support the existence of a causal link between the characteristics of people's occupations and their labor force participation at older ages. I can think of two major reasons why the IV estimates would be higher than the simpler fixed effects estimates. First, there is likely significant measurement error in the characteristics measures of O*NET. If this measurement error is classical, then the non-IV estimates of α would be attenuated. Second, there are some well known more recent labor market shocks in this time period that plausibly had a negative impact on labor force participation and a positive correlation with changes in $Comp1^{40-49}_{c,t-20}$. These are the China trade shock (Autor, Dorn, and Hanson 2013) and the replacement of jobs with robots (Acemoglu and Restrepo 2020). Both phenomena have been shown to have depressed employment. To the extent they eliminate jobs with lower values of decision, social, and mathematical content or higher values of extreme conditions, routine, or physical content, these phenomena could also increase the measured average of $Comp1^{40-49}_{c,t-20}$, biasing estimates of its relationship with old-age labor supply downwards.[23]

[22]This flexibility is achieved by interacting the instrument with the year. Theoretically one would expect that the 1950 industry shares are to be decreasingly predictive of the change in occupational characteristics as the year gets further way from 1950. This is indeed what happens.

[23]At first glance, the relationship between these shocks and average $Comp1^{40-49}_{c,t-20}$ value may seem to

3.4 Shifts in Occupation By Lifetime Income

Policymakers and analysts evaluating changes to Social Security benefits are interested not only in whether individuals have the capacity for work that can sustain decreases in benefits and increases in the retirement age, but also in how changes to that work capacity have been distributed across the income distribution. This comes up with regards to the distribution of changes in health (Konish 2023), but such concerns apply equally to work itself being conducive for work in old-age. Policymakers have shown such concern in the past, too. As part of the Social Security Amendments of 1983, Congress specifically mandated a study of of older workers in physical occupations and to what extent such occupations could be expected to persist (SSA 1986).

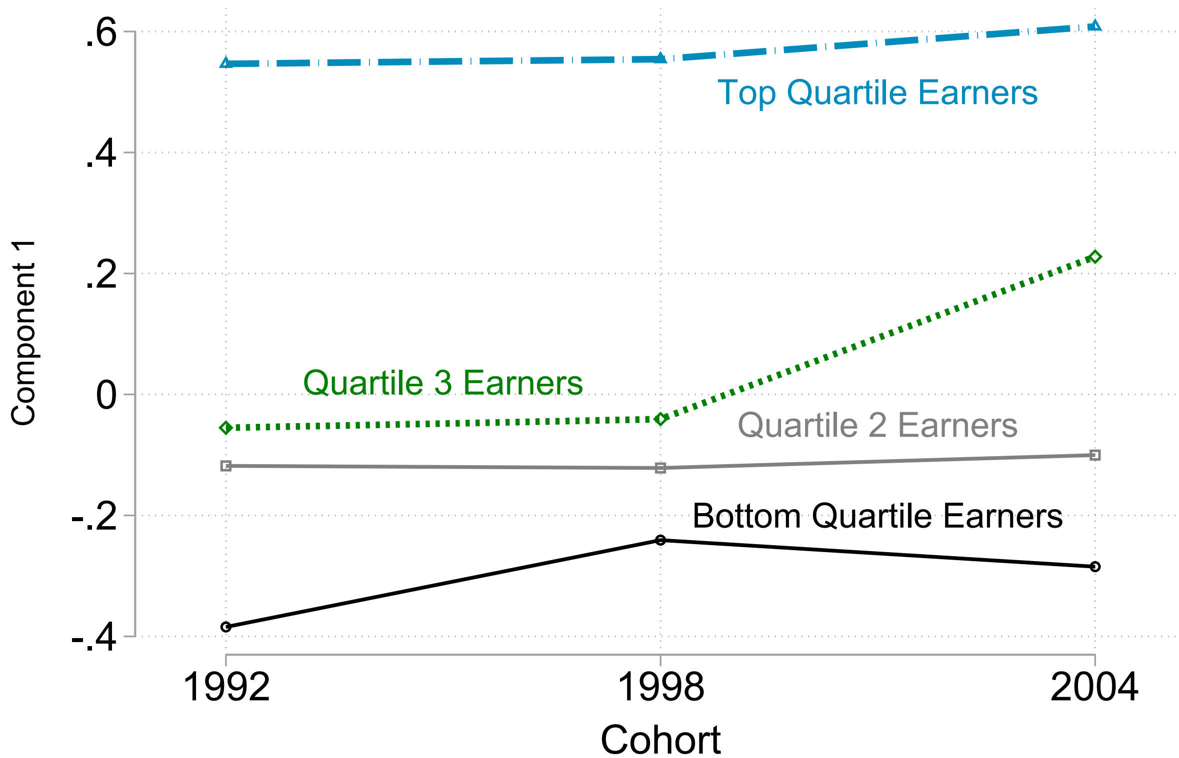
In this subsubsection, I examine how changes in occupation have been distributed across the lifetime income distribution. I focus on lifetime income distribution because this reflects differences in wealth people are likely to carry into old-age and because lifetime income is the concept that determines an individual's Social Security benefits. Specifically, I look at how the mean *Component 1* value of men's initial occupation has varied across HRS cohorts by quartile of lifetime income. Lifetime income is calculated by the HRS using the Detailed Earnings Record from Social Security administrative data.[24] I break up the first wave of each of the 1992, 1998, and 2004 HRS cohort by lifetime income at age 60 using this measure.

Figure **??** presents the results. All quartiles have seen an increase in the average value of Component 1, thought the increase for the second quartile has been very slight. This means that at all lifetime income quartiles, occupations in men's early 50s have gotten more decision- and social-intensive, while they have gotten less physical and extreme. While the sample sizes make the standard errors too large for a clear detection of trends across cohorts, when the sample is split into two quantiles, the increase in *Component 1* value is significant for those in the top half of the lifetime income distribution (Appendix Figure **??**).

threaten instrument validity. However, Autor, Dorn, and Hanson (2013) and Acemoglu and Restrepo (2020) find that contemporary occupation routineness does little to change the estimated effect of trade shocks or robots, respectively, on employment. This provides assurance that routineness in 1950 is unrelated to experiencing trade shocks or robot shocks later on.

[24]The HRS offers restricted data products in which HRS respondents are linked to administrative data from the Social Security Administration. Social Security administrative information is only available for individuals who consented to linking their HRS response to the admin data. The HRS imputes lifetime income measures for those individuals who did not consent to link to administrative data.

Figure 5: Mean of *Component 1* by Lifetime Income Quartile at Age 60 and Cohort



These figures displays the average value of *Component 1* by lifetime income quartile at age 60 and HRS cohort. Recall that occupation for individuals is defined as the first occupation in which they are observed at ages 51–56. Lifetime income is calculated by the HRS using tax records from the Detailed Earnings Record in Social Security administrative data. *Component 1* is described in more detail in Section ??.

4 Old-Age Labor Supply Model with Occupation Differences

In the previous section, I showed that shifts in occupation have been towards tasks and characteristics that induce longer work. I also showed that changes conducive to longer work have been larger at higher levels of lifetime income. Policymakers will be interested in how valuable these improvements in work capacity are and how they have differentially shifted welfare across the income distribution; debates and analyses on increases in the Full Retirement Age often focus on the differential trends in work capacity by income and how the poor may be particularly harmed by cuts in benefits, as a larger share of their income in retirement comes from Social Security benefits (Springstead 2011).[25]

[25]Note that a proposal to increase the Full Retirement Age without increasing the Early Retirement Age (currently 62) is essentially just a uniform (in percentage terms) cut in benefits at any given at age at which an individual claims benefits.

Proper measurement of the welfare effects of changes in occupation need to take into account not only that individuals have higher income from longer work and higher wages from better paid tasks, but also that, for any given amount of work they supply, they enjoy higher utility from the work being less unpleasant. Moreover, changes in work at age 50 likely reflect changes in work characteristics earlier in life, and so individuals may arrive at age 50 with different earnings histories and wealth. Finally, expected welfare in old-age depends on how social security benefits, savings and labor supply interact to provide individuals with insurance against health, wage, and longevity risks.

In this section, I build and estimate a model of labor supply, health, and differences in occupation to assess how people value changes in occupation across cohorts and how these welfare shifts differs by lifetime income. I build on French and Jones (2011), adding occupational differences across individuals. In the model, occupation is represented by individuals being of different types, which impacts their disutility from work, wages, and initial conditions. In representing occupational differences this way, I parsimoniously capture how the shifts in the kinds of work in the economy mean that people arrive at age 50 with different skills, job opportunities, and life trajectories, which affects their wealth and expected social security benefits at age 50 and gives them access to jobs that provide different disutilities and wages. Health evolves exogenously and affects time available for work, wages, and medical expenses. Retirement arises endogenously in the model.

4.1 The Model

The model begins at age 51 and ends at age 100. Individuals choose consumption in every period. Until age 81, individuals can work; if working, they also choose the number of hours. In accordance with the rules for Social Security, between ages 62 and 70, individuals can claim Social Security. Delaying claiming increases an individual's annual benefits received. After age 70, everyone automatically receives Social Security benefits.

4.1.1 Types and Preferences

Each individual i has a type $o_i \in \{1, 2, ..., O\} = \Theta$, which is fixed across time. Type affects the disutility from work and the wages individuals can earn. In the model estimation, it is also allowed to affect the distribution of initial conditions. These types are how I model occupational differences. The separate, unchanging types capture how individuals arrive at age 50 with distinct skills and experiences as a result of their different education and labor market trajectories. These distinct skills and experiences determine the kinds of jobs which they can hope to perform in the labor market and the wages they command. As the labor market changes the kinds of tasks demanded, the mix of types at age 50 also changes.

The per-period utility function at age t is (throughout, I suppress individual subscripts for simplicity):

$$u(c_t, l_t) = \frac{1}{1-\eta} \left(c_t^{\gamma} l_t^{1-\gamma}\right)^{1-\eta}. \tag{2}$$

Leisure l_t for a individual of type o is

$$l_t = L - n_t - (\alpha + \alpha_t t)\mathbb{1}\{n_t > 0\} - \sum_{h \in H} \alpha_h \mathbb{1}\{h_t = h\} - \sum_{o \in \Theta} \alpha_o \mathbb{1}\{n_t > 0\}\mathbb{1}\{o_i = o\} \tag{3}$$

where n_t is hours worked at age t, h_t is health state at age t, and L is total endowment of hours in a year. For each individual, there are two fixed leisure costs to working ($n_t > 0$). The first, $\alpha + \alpha_t t$, is a fixed leisure cost of employment common to all people, which is allowed to have a linear time trend.

The second, α_o, is common to all individuals of type o. This term captures how individuals of different types have access to different occupations. Some have access to more physical occupations, which will provide a higher disutility from work. Others will have access to more social- and decision-intensive occupations, which might provide less disutility. The inclusion of these parameters—and more broadly the inclusion of differences in people due to occupations—is one of the paper's principal modeling departures relative to the literature.

Health also affects leisure by subtracting from available leisure time (α_h). This effect occurs regardless of whether the individual works or not; still, because they have less available leisure time, less healthy individuals will be less likely to work and will also provide fewer hours when working.

Upon death individuals bequeath their remaining assets a_t and receive bequest utility. Bequest utility is an important force to include to capture the savings dynamics of the elderly (De Nardi and Fella 2017). The bequest function is of the form:

$$beq(a_t) = \psi \frac{(a_t + A)^{(1-\eta)\gamma}}{1-\eta} \tag{4}$$

ψ determines the intensity of the bequest motive, while A determines the extent to which bequests are luxury goods (De Nardi 2004).

4.1.2 Budget Constraint

An individual's income at time t depends on his assets a_t, his labor income $w_t n_t$, his spouse's earnings sp, which depends on health and age, and his social security benefits ss:

$$Inc_t = Y[ra_t + w_t n_t + ss(AIME_t, b_t, t) + sp(h_t, t)].$$

r is the rate of return on assets, while social security benefits depend on Average Indexed Monthly Earnings $AIME_t$, whether or not the individual has claimed social security benefits (in which case $b_t = 1$), and age. The ss function is described in more detail below. The function $Y[\cdot]$ applies taxes to an individual's income.

An individual who consumes c_t has next period assets of

$$a_{t+1} = a_t + Inc_t + tr_t - med(h_t, t) - c_t \tag{5}$$

where Inc_t is the person's income at age t, tr_t are government transfers received, and med are medical expenses, which depend on health and age. I constrain individuals so that they cannot carry negative assets into the next period before medical expenses are factored in.[26] Government transfers guarantee a consumption floor, as in Hubbard, Skinner, and Zeldes (1995):

$$tr_t = \max\{0, \underline{c} - (a_t + Inc_t)\}. \tag{6}$$

4.1.3 Wages and Spouse Earnings

An individual's wages at age t depend on his type, age, and an autoregressive component:

$$\ln w_t = W(h_t, t, o) + \omega_t \tag{7}$$

$$\omega_t = \rho\omega_{t-1} + \epsilon_t \tag{8}$$

$$\epsilon_t \sim N(0, \sigma_\epsilon) \tag{9}$$

The autoregressive component of wages allows for persistent differences in wages that are not captured by age, health, type, or hours.

4.1.4 Health, Medical Expenses, and Mortality

Health $h_t \in \{1, 2, 3, 4\} = H$ is a discrete variable where 1 is the worst level of health and 4 represents the best. Health evolves according to a Markov transition matrix that varies with age. Health can only get worse and is a completely exogenous process.

Mortality m_t is a person's probability of death at age t. It depends both on the health level, h_t, and age. At age 100, the final age in the model, $m_t = 1$.

[26] That is, individuals can have negative assets but only because of medical expenses: $c_t \leq a_t + Inc_t + tr_t$ (French and Jones 2011).

Medical expenditures med_t are all out-of-pocket medical expenditures a person has to pay. They are modeled as

$$\ln med_t = Med(h_t, t) + \xi_t \tag{10}$$

$$\xi_t \sim N\left(0, \sigma_\xi(h_t, t)\right) \tag{11}$$

where $Med(h_t, t)$ are mean out-of-pocket health expenditures at health h_t and age t, and ξ_t is an idiosyncratic expenses shock whose variance is allowed to depend on health and age.[27] In the estimation, I allow for discontinuities in both $Med(\cdot, \cdot)$ and σ_ξ at age 65 to account for eligibility for Medicare at that age.

4.1.5 Social Security

To appropriately capture the labor supply incentives of men in old-age, it is necessary to account for Social Security for it is both an important source of income in old-age (especially for the lower-income) and claiming social security benefits affects the returns to work done at certain ages. In the model, I capture, in a tractable way, the relationship between work, Social Security benefits, and the Social Security claiming decision. I describe the basic contours of both Social Security and how it I modeled it, but leave details for Appendix **??**.

Social security annual benefits, ss_t, depend on an individual's Average Indexed Monthly Earnings ($AIME_t$) and age at claiming. AIME is calculated by averaging over an individual's best 35 indexed earnings years.[28] AIME is converted into a Primary Insurance Amount (PIA) according to a progressive formula that gives higher replacement rates to those at lower levels of AIME.[29] Individuals who claim the claim Social Security at the Full Retirement Age (FRA) get $ss_t = PIA(AIME_t)$. That is, each year they get the PIA as determined by the replacement rate function applied to AIME. Men who claim Social Security before the FRA have their benefits reduced according to the years before the FRA, while men who claim after the FRA have their benefits increased according to the number of years since

[27] This is similar medical expenditures in French and Jones (2011), except I do not include an individual-specific persistent component of health expenses nor do I allow medical expenses to vary by health insurance type. I abstract from both health insurance and persistent differences in health expenditures for computational reasons, as, to be properly incorporated in the model, either feature would have to be carried as a state variable.

[28] The indexing here refers to the fact that earnings at a given age are indexed to the average earnings in the economy that year (this is called the Average Wage Index).

[29] Specifically, the formula has two bend points at which the replacement rate changes. AIME below the first bend point is replaced at a 90% rate, AIME between the first and the second bend point is replaced at a 32%, and AIME above the second bend point is replaced at 15%. Recall also that AIME is capped by the maximum covered earnings. Yearly earnings above this amount are not subject to payroll tax and are not included in the AIME calculation.

FRA. After age 70, all individuals who have not claimed Social Security automatically begin to receive the benefit.

In the model, it is straightforward to include the Social Security system's rules regarding reductions or increases to ss_t depending on age at claiming. It is also simple to include the formula for converting AIME to PIA. It is, however, intractable to model the evolution of AIME exactly as it is prescribed in law; doing so would require carrying all thirty-five best indexed earnings years as a state variable. Instead, I model the evolution of $AIME_t$ as in French and Jones (2011), carrying only a single number for $AIME_t$ at each age in the model. Details are in Appendix **??**.

One final component of Social Security that impacts labor supply is the earnings test. The earnings test applies to individuals who have labor earnings in years after they have claimed Social Security but before the FRA. Above a low threshold for earnings, a person loses one dollar of Social Security benefits for every two dollars of labor earnings. These benefits are not completely lost, however. The person's AIME is credited in such a way to boost ss_t in future years. In income tax function and the evolution of $AIME_t$, I account for the earnings test and the credit to $AIME_t$ from working when subject to the earnings test.

4.1.6 Recursive Formulation

Let $X_t = (a_t, h_t, o, AIME_t, \omega_t, b_{t-1})$ be the vector of state variables. These are: age, assets, health, type, AIME, the autoregressive wage component, and whether the individual has claimed social security benefits, b_{t-1}. The consumer picks consumption, hours, and whether to claim benefits[30] by solving the following problem:

$$V_t(X) = \max_{c_t, n_t, b_t} \left\{ u(c_t, l_t) + \beta(1 - m_t)\mathbb{E}\left[V_{t+1}(X_{t+1})|c_t, n_t, b_t\right] + \beta m_t beq(a_{t+1}) \right\}. \tag{12}$$

where the assets next period are determined by the budget constraint shown in (**??**). The rest of the state variables in X_{t+1} evolve as described above: health evolves exogenously, AIME evolves according to this period's earnings, and the autoregressive component of the wage draws an innovation. Individuals discount the next period by discount factor β, and they only receive the next period's expected value with probability $1 - m_t$, as they will die before next period with probability m_t and receive bequest utility $beq(a_t + 1)$.

[30]Note that this option is only available to those that have not yet claimed Social Security benefits.

4.2 Model Estimation: Parameters Set or Estimated Outside the Model

I estimate the model on the men who were 51–56-years-old in the first wave of the 1992 HRS cohort. Model estimation is split into two parts. In the first, I estimate some parameters directly using the HRS data (or set them to some fixed value). Most of these parameters are estimated using the men in 1992 HRS cohort ages 51–56, though some also include additional data points when estimating parameters for older ages. I estimate the remaining parameters, mostly preference parameters, using the Simulated Method of Moments (SMM). For the first group of parameters, I estimate them outside of the model using data from the HRS. I fix the interest rate r to be 4%, following De Nardi, French, and John Bailey Jones (2016).

4.2.1 Types

Following the empirical analysis in Section **??**, I use the first occupation I see individuals hold between ages 51 and 56 to assign type. Specifically, I break up the initial sample of men in the 1992 HRS into quartiles *Component 1*. I call these Type 2 through 5 in increasing intensity of *Component 1*. Those with the lowest values of *Component 1*, assigned to be Type 2, had physically-intense initial occupations with low nonroutine, cognitive input. Conversely, those with the highest values of *Component 1*, assigned to be Type 5, had decision- and social-intensive initial occupations with low physical input. I also include an additional type, called Type 1, for all the men who do not have a value of *Component 1* for their initial occupation because they were not employed when they were in the survey and between ages 51–56. This is a group with very low attachment to the labor force. At most ages for which they are observed in the survey, their employment rates are in the single digits.

4.2.2 Wages and Spouse Earnings

I estimate the wage profiles and process using the wages provided in the HRS RAND data (RAND 2023). Wages are total labor earnings divided by total hours worked. For the wages data, I only include the men who entered in the 1992 cohort aged 51–56. I estimate the model in four steps.

First, I must impute wages for cases in which they are not observed. This is especially necessary for obtaining wage profiles for those of Type 1, who are rarely employed and hence rarely have a reported wage. For all person-years for which I am missing wage data, I impute wages using an OLS regression of log real wage on a variety of variables.[31]

[31] These are a natural cubic spline in age, the health index, education, a marriage dummy, an indicator for an employed spouse if married, a cubic in work experience, and a quadratic in tenure.

Second, I estimate the following fixed-effects model on the reported and imputed wage data:

$$\ln w_{ti} = g(t;\theta) + g(t;\theta^o) \cdot \sum_{o\in\Theta} \mathbb{1}\{o_i = o\} + \mathbb{1}\{h_t = h\}\gamma_h + f_i + \varepsilon_{it} \tag{13}$$

where $g(t;\theta)$ is a natural cubic spline in age with parameters θ. The fixed effects estimator deals with bias in the estimates of the wage profiles coming from selection on the level of wages related to fixed characteristics of individuals. The model allows for health effects on wages as well as differences in the age profile of wages by type.[32]

Third, I calculate the wage intercept for each type, γ_o, by averaging the fixed effect over all individuals of that type. With these estimates and the estimates from Equation **??** in hand, I construct the mean wage profiles $W(t,h,o)$.

In the fourth step, I estimate the parameters of the residual wage process. Define the wage residual for each observation as

$$e_{it} = f_i + \varepsilon_{it} - \sum_{o\in\Theta} \gamma_o \mathbb{1}\{o_i = o\} \tag{14}$$

I model e_{it} as containing the AR(1) component described in Equation **??** and an i.i.d. measurement error me_{it}. This residual wage process is described by four parameters: the persistence of the AR(1) component (ρ), the variance of the innovation (σ_v^2), the variance of measurement error, and the initial distribution of the AR(1) component. I estimate this model using a minimum distance estimator as in O'Dea (2018). The results are show in Appendix Table **??**.

Spouse earnings are estimated using a natural cubic spline in age, health fixed effects, and interactions between the health cubic spline and age fixed effects. Spouse earnings are assumed to be zero after age 80.

4.2.3 Health, Mortality, and Medical Expenses

To assign the four health types, I begin with the health index variable described in Section **??**. Using the pooled panel of men from 1992–2020 who entered in either the 1992 HRS sample or the 1993 AHEAD sample, I calculate cutoffs for quartiles of the health index variable.[33] These cutoffs of the health index variable define the four health types, which I

[32] The latter occurs by differences in the the parameters θ^o of the age spline interacted with type.

[33] The AHEAD sample was a random sample of households of individuals aged older than 71 that was added to the HRS study in 1993. This group was also interviewed in 1995, and was merged into the biennial, even-year schedule of the rest of the HRS in 1996.

label: poor, fair, good, and excellent.

To calculate the probability of transitioning from one health type to another, I include individuals from 1992 HRS cohort (ages 51–61 to start) and AHEAD individuals (ages 71+ to start in 1993). I include the latter to capture the health dynamics of the very old, as the 1992 HRS sample has so far made it to, at most, 89. I use the share of individuals at each age that transitioned to a different health state as the probability of transition at a given age. Because health state *improvements* are rare, I assume that the probability of a health improvement is zero (scaling the rest of the empirical transitions shares so that they still add up to one). Finally, because I observe biennial transition probabilities, I assume that the observed biennial transition probabilities are created by annual transition probabilities that are equal over the two years. I calculate mortality in a similar way using the year of death information from the HRS.

Medical expenses are all out-of-pocket expenditures by households, a measure which is available in the HRS. I specify the medical expense model shown in Equation **??** and Equation **??** by allowing both the mean of log medical expenses and the variance in the medical expense shock to depend on a linear term in age, differences by health type, and intercept shifts for each health type if the person is over age 65. This latter set of four parameters accommodates the fact that the medical expense process for individuals may shift abruptly at age 65 as people become eligible for Medicaid.

To estimate these 18 parameters (9 each for the mean medical expense and for the variance of the idiosyncratic medical expense shock), I adapt the method from French and Jones (2011), using the method of moments to match the mean and 95th percentile of log medical expenses for five-year age bins from 51 to 91.

4.3 Model Estimation: Simulated Method of Moments

The remaining parameters are largely those governing preferences. First are the set of parameters in the leisure function: the leisure time cost of employment, the age slope of the time cost of employment, the leisure time cost of poor, fair, and good health, and the leisure time cost of the individual types. Second are the set of parameters in the utility function: the consumption weight and the risk aversion parameter. The final group are the bequest parameters and the consumption minimum. I estimate these parameters jointly using the Simulated Method of Moments.

Estimation proceeds as follows. First, for a given guess of the parameters θ, I solve the model using backwards-solving dynamic programming techniques. With policy functions describing the model solution in hand, I simulate 40,000 lives, drawing initial conditions according to the procedure described below. Then, I calculate moments, also detailed below, in the data and analogous ones in the simulated data. Finally, I calculate the distance between these two sets of moments, weighting according to the inverse variance of the data moment (Pischke 1995). Using optimization algorithms, I search for the $\hat{\theta}$ that minimizes this weighted distance between the data moments and the simulated moments.

In the rest of this section, I describe the procedure for determining the initial conditions of the simulated lives and detail the moments used in the estimation.

4.3.1 Initial Conditions

To simulate lives, it is necessary to draw type as well as initial health, wealth, AIME, and persistent wage component. I begin by drawing a health-type combination from the empirical distribution for the 1992 cohort. Initial wealth is determined by models of log household wealth as a function of health and type as well as probit models for the probability of holding zero wealth, which also depend on health and type. Initial AIME depends on health, type, a spline of wealth, and an initial idiosyncratic shock. Finally, I model the initial value of the persistent component of wages as depending on a wealth spline, AIME, health, type, and an initial idiosyncratic shock.

4.3.2 Targeted Moments

The estimator targets the following moments, which are calculated for five-year age groups: 56–60, 61–65, 66–70, 71–75, 76–80.

1. Wealth at the 25th, 50th, and 75th percentiles.
2. Participation by health group.
3. Log hours conditional on participation by health group.
4. Participation by wealth quartile.
5. Participation by type.

These amount to 100 moment conditions.

These moments were chosen with identification of the preference parameters in mind. The wealth profiles in old-age are important for identifying the patience, β, of individuals as well as the parameters of the bequest function, ψ and A. In particular, to the difference in wealth accumulation late in life across wealth quartiles will assist in determining the extent to which bequests are a luxury good.

The savings behavior and the differences in participation by wealth quartile identify the relative importance of consumption γ as well as the risk aversion η. How much participation and savings behavior varies by wealth level helps identify how risk-averse households are and the importance they put on consumption.

The hours moments and the participation moments contribute to the identification of the leisure function parameters. Hours worked help to pin down the leisure endowment, while common trends in hours inform the age slope of disutility from working. Differences in hours and participation by health contribute to the identification of the leisure costs of wealth. Finally, differences in participation by type inform the estimation of the fixed leisure costs of working by type.

5 Results and Counterfactual

5.1 Results

Table **??** displays the second-stage estimation results. The discount factor β estimate of 0.986 is on the higher side, yet still in line with previous estimates of life-cycle models (O'Dea 2018). The consumption weight γ estimate of 0.500 and the estimate of the coefficient of relative risk aversion of the consumption-leisure composite η of 5.77 imply a coefficient of relative risk aversion of consumption of 3, which is within the range of prior estimates.[34] While the curvature of the bequest function, A, has little interpretability, the estimate for ψ, the bequest weight, expressed as a marginal propensity to consume out of final-period (high) wealth is 0.0134. This is about half of that found in the HRS by French and Jones (2011), meaning that my estimates find larger bequest motives.

The estimates for the costs of leisure from health and the cost to working for different types are well behaved. Worse levels of health have higher leisure costs. Lower types have higher fixed leisure costs from work. Thus, individuals who have access to more physical and less cognitive occupations face higher disutility from work. Being a Type 2 worker (those with the most physical and least cognitive occupations) means that works costs 376 hours of leisure more than it does for a Type 5 worker. This is roughly comparable to the leisure hours loss when moving from excellent health to good health, or good health to fair health. Note that this comparison, however, is not completely clean; health costs are incurred whether an individual works or not, while the type costs only occur when the individual works.

The leisure costs of type and health are small relative to the fixed leisure cost of work

[34] See, e.g., the review in Attanasio and Weber (1995), Cagetti (2003), French (2005), French and Jones (2011)

Table 5: Parameter Estimates

Preference Parameters (Common to All)			
β: Discount rate	0.986	L: Leisure endowment	8700
γ: consumption weight	0.500	α: Fixed leisure hours cost of work	2056
η: coefficient of relative risk aversion	5.77	α_t: Leisure hours cost age trend	2.07
ψ: bequest weight	0.0134	A: bequest curvature	1.78m
Consumption floor	$\$4,579$		
Health Leisure Costs (in Hours)		Type Leisure Costs when Working (in Hours)	
Poor Health	1317	Type 1	1753
Fair Health	796	Type 2	376
Good Health	369	Type 3	253
		Type 4	64.3

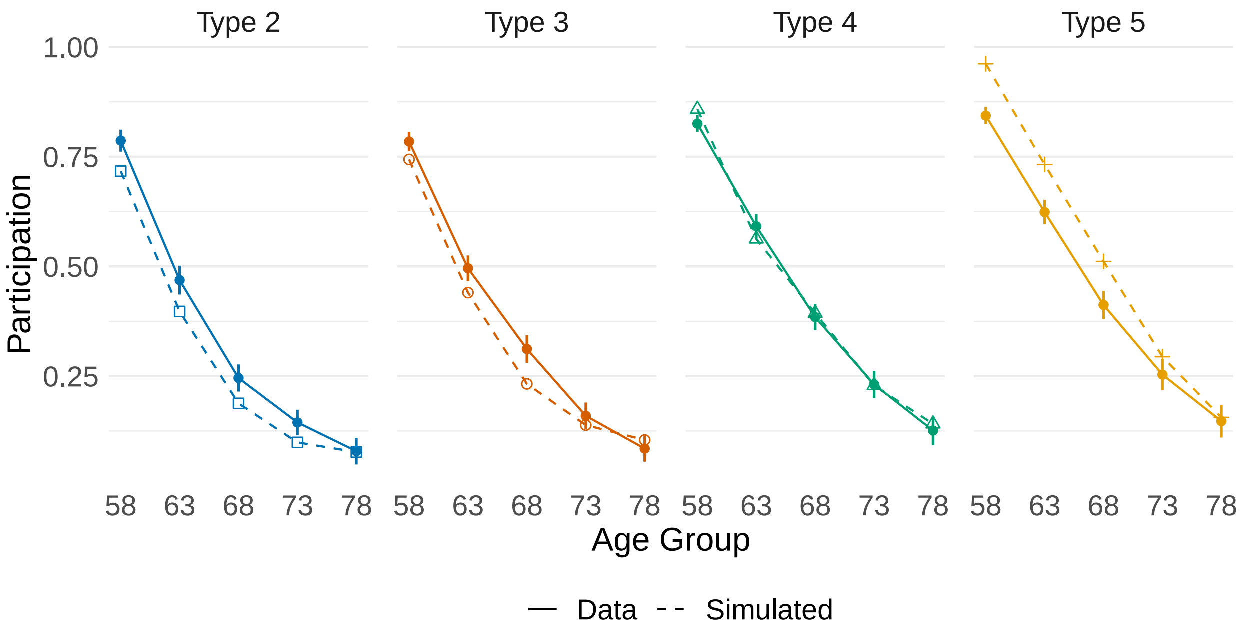
common to all individuals α, which is estimated to be 2056 hours. Only the health costs of those in poor health, 1317 hours, and the additional cost of work for those Type 1 (who have little attachment to the labor market) rival it in magnitude. Surprisingly, the model estimates find little scope for an increasing linear disutility of work with age. Previous estimates from French and Jones (2011) and Yu (2023) were about an order of magnitude higher than the estimate of 2.07 hours per year found here. Perhaps my richer health process, with four possible health states, reduces the need for the age slope of disutility parameter as aging naturally leads to worsening health and increasing costs to working.[35]

Figure **??** examines how well the model fits the age profile of participation by type. The model matches the participation profiles by type well. Although there is an overstatement of participation by those of type 5, particularly at ages 56-65, the model generally replicates the differences in participation between types at a given age, and how this gap increases with aging. There is a slight understatement of the participation of those of type 2.[36]

[35] French and Jones (2011) only had two health states while Yu (2023) allowed for three (but restricted the hours cost from bad health to be the same across the two "bad" states.)

[36] I do not display the results for Type 1 as this group has nearly no participation in the data and in the simulation.

Figure 6: Model Fit: Participation Moments by Type



5.2 Counterfactual Analysis

The data and simulated counterparts for the rest of the targeted moments are shown in Appendix Figures **??**–**??**. The model matches the wealth percentiles and participation by wealth percentile very well. The estimates also capture well differences in participation by health. The matching performance for the hours profiles is not as good. The model tends to produce many more hours of work for those in excellent health than the data.

In this section, I analyze two counterfactual scenarios to understand how shifts in occupations across cohorts affect labor force participation and differentially affect welfare along the lifetime income distribution. These are the "Just Types" counterfactual scenario and the "Types + Life History" counterfactual.

Just Types. In the first counterfactual, I shift the mix of initial types in the simulation so that the types distribution now matches that of the 2004 HRS cohort.[37] I leave all other initial conditions from the simulation intact. The idea is to examine how the different disutility from work and wages for the subset of individuals whose type changed affect labor force participation and the distribution of welfare.[38]

[37]To perform this reconfiguration while leaving the health distribution untouched, I randomly select the individuals whose type will be changed (these will be selected, in the appropriate proportions, from amongst types whose share declined across cohorts). Then, I randomly assign them, in appropriate proportions, to be from one of the types whose share increased across cohorts.

[38]Note that this assumes that the wage profiles in the 2004 cohort stay the same as in 1992.

Table 6: Types Distribution in the 1992 and 2004 HRS Cohorts

Cohort	Type 1	Type 2	Type 3	Type 4	Type 5
1992	0.122	0.214	0.219	0.226	0.219
2004	0.138	0.165	0.211	0.289	0.196

The table displays the distributions of types in the 1992 and 2004 HRS cohorts. Type is constructed by breaking up the 1992 sample assigned initial occupations into quartiles of *Component 1* values. Individuals in either cohort who were not assigned an initial occupation were designated as Type 1, a type intended to stand-in for men who enter the HRS with low levels of labor force attachment. Proportions were calculated using survey weights.

Table **??** shows the distribution of types in the two cohorts of interest. The 2004 cohorts saw a major rise (roughly 6 percentage points) in the share of Type 4 individuals along with a major decline in the share of Type 2 individuals. There was around a 1.5 percentage point increase in Type 1 individuals, and about a similar decline in the Type 5 share. Hence, there was a clear increase in *Component 1* across cohorts; this would be expected to increase labor force participation among older workers, as long as it overcomes the slight increase in men with weak attachment to the labor force (Type 1).

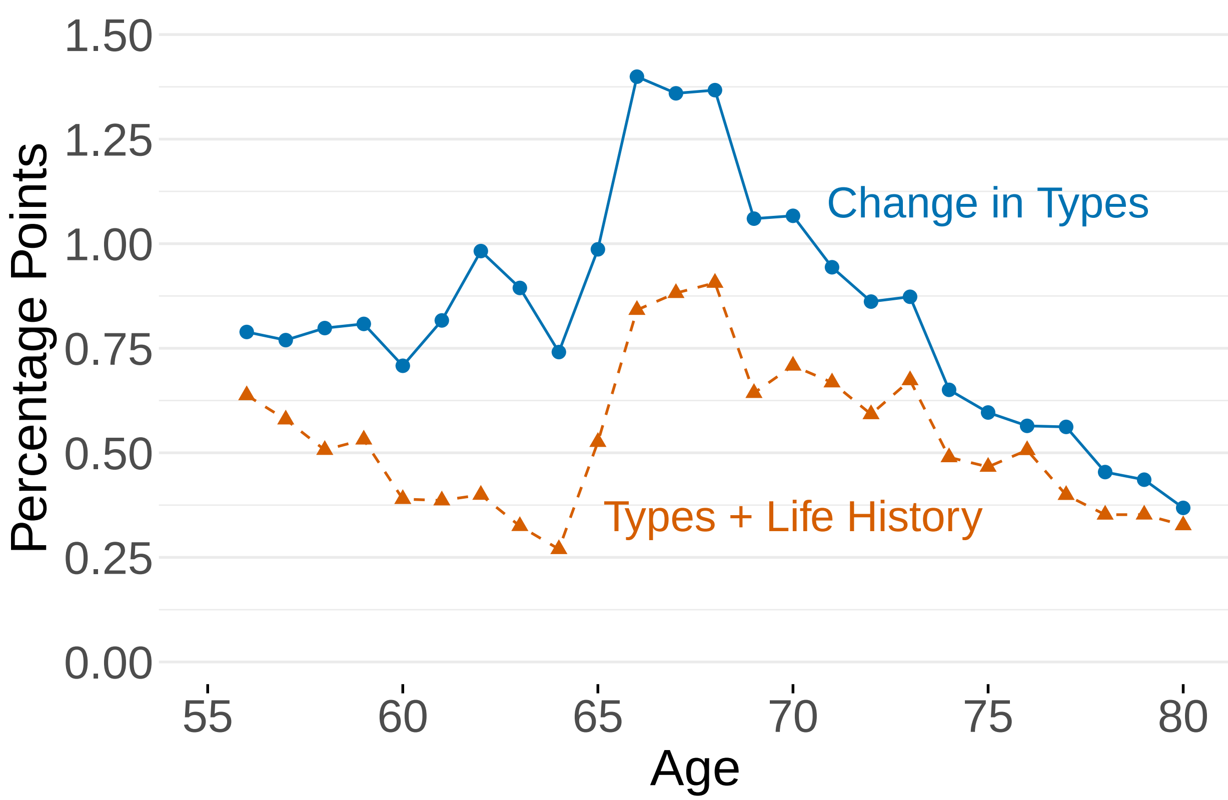
Types + Life History. Differences in occupations across cohorts are likely not experienced from age 50 onwards. Instead, the differential occupation mix at age 50 also reflects different occupation experiences earlier in life, which likely affect the wealth and AIME with which people arrive at age 50. To examine the effect of differences in life history across cohorts, the "Types + Life History" counterfactual re-draws initial wealth and AIME according to the new types of individuals. For example, individuals that were shifted from Type 2 to Type 4 now have their initial wealth and AIME drawn according to the models for Type 4 individuals. These new initial wealth and AIME replace the values used in the "Just Types" counterfactual, in which the initial wealth and AIME were still taken from the models for Type 2 individuals.

5.2.1 Counterfactual Employment Profiles

I begin by examining how the participation profile changes in the two counterfactual scenarios among individuals of Type 2 and above. Figure **??** shows the differences in participation by age between the each of the counterfactual scenarios and the baseline. Participation is higher at every age in both counterfactuals. The changes in disutility from work and the higher wages induce higher participation. Adjusting for life history, however, decreases counterfactual participation. The "Types + Life History" line is always below the line for just changes in types. The increases in wealth and AIME from the changes in types, therefore, produce income effects that induce lower labor force participation at older ages.

The differences in participation with respect to the baseline case spike in the years after age 65. This likely reflects the end of the social security earnings test lifting the 50% tax on labor earnings when Social Security had been claimed. Additionally, as was the case in the empirical findings from Section **??**, the average percentage point difference between ages 70–79 is similar to the average percentage point difference between ages 60–69, despite the fact that overall participation is much lower at ages 70–79 than at ages 60–69. The model's differences in wages and the differences in fixed costs of work across types are able to reproduce a pattern in the data.

Figure 7: Difference in Participation: Counterfactual Minus Baseline



The figure displays the average participation by age of the counterfactual scenarios minus the average participation by age at baseline. The "Just Types" counterfactual, in which only the type at age 51 is changed but not initial wealth and AIME, is displayed in the blue solid line. The "Types + Life History" counterfactual, in which the wealth and AIME are also redrawn, is shown by the dashed orange line. The sample is restricted to individuals of Type 2 and above.

5.2.2 Changes in Occupations and Welfare

How do changes in occupation characteristics affect welfare at older ages, and how has their effect differed along the lifetime income distribution? I evaluate this question by breaking up both the baseline simulation and the the counterfactual simulations into quartiles of AIME in the first period of the model (age 51). Within each quartile of AIME for the counterfactual simulations, I sum over the expected value of lifetime utility at age 51.[39] This provides a measure of aggregate welfare at each lifetime income quartile in each of the counterfactual scenarios.

To measure how welfare has changed at each lifetime income quartile relative to baseline, I calculate a measure of equivalent variation. Specifically, for a given quartile of lifetime income in the baseline simulation, I ask: what is the percentage change in consumption (in every state) needed to get the aggregate welfare of the baseline simulation to equal that of the considered counterfactual's?[40]

The results of this exercise are shown in Table **??**. The first row displays the results for the "Just Types" counterfactual. Reading from this row's first column, changes in just type, which lead to changes wages and in the leisure costs of work for a subset of the individuals in the simulation, improve welfare in the bottom quartile of age 51 AIME by 0.19% in consumption-equivalent terms. Similar welfare effects are seen for the second and third quartile. By contrast, the top quartile sees a very small reduction in welfare.

Table 7: Welfare Effects of Changing Occupations

	Consumption Equivalent Change			
	Initial AIME Quartile			
	Q1	Q2	Q3	Q4
Change in Types	0.19%	0.21%	0.14%	-0.04%
Change in Types + Life History	-0.33%	0.95%	1.61%	0.76%

This table shows the equivalent variation, expressed as a percent increase in consumption, needed to get aggregate welfare in the given quartile of AIME in the baseline simulation to equal aggregate welfare in the given quartile of AIME for the indicated counterfactual scenario.

The reasons welfare changes are distributed in this manner in the "Just Types" counterfactual are that (1) the share of Type 5s, which have the highest earnings and the lowest disutility from work, decreased, (2) Type 2s, the group with the biggest decrease, are present

[39]This is the expected value at age 51 of Equation **??**, the value function in the recursive formulation.

[40]This is the measure Low, Meghir, and Pistaferri (2010) use to measure welfare effects, and it is similar to that used by O'Dea (2018)

in every initial AIME quartile, and (3) Type 2s were most likely to be shifted to Type 4. As the wage and disutility from work differences are substantial between Type 2 and 4, this produces welfare gains across the board by lifetime income below the top quartile.

Hence, randomly changing the occupation possibilities at age 51 of the 1992 cohort to match those of the 2004 cohort produces gains at all lifetime income quartiles save for the top one. For reference, the welfare gain numbers for the bottom three quartiles in the "Just Types" counterfactual are of similar magnitude to the willingness to pay for a 1% increase in government unemployment insurance spending found by Low, Meghir, and Pistaferri (2010).[41]

As discussed above, arriving at age 50 with a different occupation is very likely not simply a reflection of having a different set of occupations available from age 50 onwards. Rather, it likely reflects that the individuals had a different life trajectory leading up to that point. To reflect this, the "Types + Life History" counterfactual redraws initial wealth and AIME for individuals whose type was changed. As a result, the people whose type changed can end up in different initial quartile of AIME. Those who were switched to be Type 1 will likely experience a fall in wealth and AIME, while those whose type was switched to Type 4 will experience increases in wealth and AIME on average.

The welfare changes by lifetime income quartile in the "Types + Life History" counterfactual are displayed in the second row of Table **??**. Now the welfare gains are positive and large for the highest three lifetime income quartiles. The shifts in occupation increase wealth and lifetime income for those with the "better" occupations, moving them up in the lifetime income rankings and greatly increasing the welfare of the quartiles above the bottom one. In contrast, the increase in the share of Type 1 households across cohorts means that there are declines in welfare among those with the lowest lifetime income.

The "Types + Life History" analysis provides evidence that changes in work and work capacity have benefitted higher income older individuals, but have not produced similar gains to low-income older individuals. This latter point has been made in the context of differential trends in mortality;[42] my contribution is to qualitatively and quantitatively show that changes in kinds of work people do during their life and old-age has contributed to widening inequality in welfare among older individuals.

[41] They found that high education individuals had a 0.19% consumption-equivalent willingness-to-pay for a 1% increase in unemployment insurance while low education individuals had a 0.24% willingness-to-pay.

[42] See, for example, Waldron 2007; Meara, Richards, and Cutler 2008; Bound et al. 2015; Hudomiet, Hurd, and Rohwedder 2019; Case and Deaton 2021.

6 Conclusion

In this paper, I measure how changes in work have contributed to the rise of old-age labor force participation that has been occurring since the 1990s. To do so, I use the relationship between occupation characteristics of individuals in their early 50s in the HRS and their later labor force participation and trends of aggregate occupation characteristics in the Census/ACS. I find that men in more decision- and social-intensive occupations tend to work longer, while the opposite is true of men in more physical and extreme occupations. Trends in the Census indicate that between 10%–16% of the increase in men's old-age labor force participation from 1990 to 2010 can be explained by changes in occupation. Using a novel model of old-age labor supply with occupation differences, I find that the observed shifts in occupation across cohorts in the HRS produce welfare increases for all but the bottom quartile of lifetime income, which experiences declines in welfare as a result of the increasing share of men with low attachment to the labor force.

These results have policy implications for potential changes in Social Security. They demonstrate that all but the lowest-income have benefitted from the changing nature of work, which allows people to work longer as a result of the less unpleasant work and better wages. To the extent the policymakers' motive for having a Social Security system is redistribution,[43] the results here add to growing evidence that inequality of welfare in old-age has been increasing. As policymakers evaluate options for closing the deficit in the Social Security Trust fund, when looking at options for reducing benefits they may prioritize cutting benefits for higher earners by, say, decreasing the replacement rates at high levels of AIME rather than cutting benefits across the board by, say, increasing the Full Retirement Age.[44]

Future work could extend the scope of years of occupational change considered here past 2000, especially in light of the finding in Lopez Garcia, Maestas, and Mullen (2020) that within-occupation changes in tasks and characteristics may have become by far the dominant force in occupation change. As artificial intelligence and automation change the landscape of the kind of work that is replaced or augmented by technological change, it will be important to monitor to what extent the work in the economy promotes or discourages longer working lives in the face of an aging population. Further work is also needed to incorporate women in the analysis, as women's increasing lifetime investment in careers means that the kind of work they hold at age 50 is indicative of their ability to work longer

[43] See Diamond (2005) and Michau (2014) for models in which a social planner's chief motive for creating a Social Security system is redistribution.

[44] A 2016 evaluation of the Social Security's Office of the Chief Actuary found that a gradual increase in the Full Retirement Age from 67 to 69 would have similar long-term benefits for the Social Security Trust Fund's deficit as a decline in the replacement rate at above-average levels of AIME from the current 15% to 2%-5% (SSA 2016)

with old-age. Moreover, assortative mating and differences in marriage rates by income may exacerbate the inequality-increasing impacts of the changing nature of work found in this paper.

References

Acemoglu, Daron, Nicolaj Søndergaard Mühlbach, and Andrew J. Scott. 2022. "The rise of age-friendly jobs." *The Journal of the Economics of Ageing* 23 (October 1): 1–13. Accessed May 21, 2023.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6). Accessed August 25, 2023.

———. 2022. "Tasks, Automation, and the Rise in U.S. Wage Inequality." _eprint: https://onlinelibrary.wile *Econometrica* 90 (5): 1973–2016. Accessed October 27, 2023.

Ameriks, John, Joseph Briggs, Andrew Caplin, Minjoon Lee, Matthew D. Shapiro, and Christopher Tonetti. 2020. "Older Americans Would Work Longer If Jobs Were Flexible." *American Economic Journal: Macroeconomics* 12, no. 1 (January): 174–209. Accessed March 31, 2021.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum. 2020. "The Evolution of Work in the United States." *American Economic Journal: Applied Economics* 12, no. 2 (April): 1–34. Accessed May 22, 2023.

Attanasio, Orazio P., and Guglielmo Weber. 1995. "Is Consumption Growth Consistent with Intertemporal Optimization? Evidence from the Consumer Expenditure Survey." Publisher: University of Chicago Press, *Journal of Political Economy* 103 (6): 1121–1157. Accessed October 13, 2023.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103, no. 5 (August): 1553–1597. Accessed June 14, 2021.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103, no. 6 (October): 2121–2168. Accessed August 25, 2023.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118, no. 4 (November 1): 1279–1333. Accessed June 14, 2021.

Blau, David M., and Donna B. Gilleskie. 2008. "The Role of Retiree Health Insurance in the Employment Behavior of Older Men." *International Economic Review* 49 (2): 475–514. Accessed May 29, 2023.

Blau, David M., and Ryan M. Goodstein. 2010. "Can Social Security Explain Trends in Labor Force Participation of Older Men in the United States?" *The Journal of Human Resources* 45 (2): 328–363.

Blundell, Richard, Jack Britton, Monica Costa Dias, and Eric French. 2021. "The Impact of Health on Labor Supply Near Retirement." Publisher: University of Wisconsin Press, *Journal of Human Resources* (January 19): 1217. Accessed March 17, 2021.

Blundell, Richard, Eric French, and Gemma Tetlow. 2016. "Retirement Incentives and Labor Supply." In *Handbook of the Economics of Population Aging,* redacted by John Piggott and Alan Woodland, vol. 1B, 457–566. Amsterdam: North-Holland.

Borella, Margherita, Mariacristina De Nardi, and Fang Yang. 2023. "Are Marriage-Related Taxes and Social Security Benefits Holding Back Female Labour Supply?" *The Review of Economic Studies* 90, no. 1 (January 1): 102–131. Accessed May 29, 2023.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-Experimental Shift-Share Research Designs." *The Review of Economic Studies* 89, no. 1 (January 1): 181–213. Accessed September 29, 2023.

Bound, John, Arline T. Geronimus, Javier M. Rodriguez, and Timothy A. Waidmann. 2015. "Measuring Recent Apparent Declines In Longevity: The Role Of Increasing Educational Attainment." Publisher: Health Affairs, *Health Affairs* 34, no. 12 (December): 2167–2173. Accessed October 16, 2023.

Cagetti, Marco. 2003. "Wealth Accumulation Over the Life Cycle and Precautionary Savings." *Journal of Business & Economic Statistics* 21, no. 3 (July 1): 339–353. Accessed October 13, 2023.

Cajner, Tomaz, Javier Fernández-Blanco, and Virginia Sánchez Marcos. 2021. "Widening Health Gap in the U.S. Labor Force Participation at Older Ages." *BSE Working Paper 1298* (November).

Case, Anne, and Angus Deaton. 2021. "Life expectancy in adulthood is falling for those without a BA degree, but as educational gaps have widened, racial gaps have narrowed." Publisher: National Academy of Sciences Section: Social Sciences, *Proceedings of the National Academy of Sciences* 118, no. 11 (March 16). Accessed May 13, 2021.

Coile, Courtney C. 2018. "Working Longer in the United States: Trends and Explanations." In *Social Security Programs and Retirement Around the World: Working Longer,* edited by Courtney C. Coile, Kevin Milligan, and David A. Wise. NBER International Social Security Series 8. Chicago: University of Chicago Press, November 28.

Coile, Courtney C., Kevin Milligan, and David A. Wise. 2017. "Health Capacity to Work at Older Ages: Evidence from the United States." In *Social Security Programs and Retirement Around the World: The Capacity to Work at Older Ages,* edited by David A. Wise, 359–394. National Bureau of Economic Research conference report. Chicago, IL: University of Chicago Press.

De Nardi, Mariacristina. 2004. "Wealth Inequality and Intergenerational Links." *The Review of Economic Studies* 71 (3): 743–768. Accessed May 17, 2021.

De Nardi, Mariacristina, and Giulio Fella. 2017. "Saving and wealth inequality." *Review of Economic Dynamics* 26 (October 1): 280–300. Accessed September 1, 2023.

De Nardi, Mariacristina, Eric French, and John B. Jones. 2010. "Why Do the Elderly Save? The Role of Medical Expenses." Publisher: The University of Chicago Press, *Journal of Political Economy* 118, no. 1 (February 1): 39–75. Accessed April 2, 2021.

De Nardi, Mariacristina, Eric French, and John Bailey Jones. 2016. "Medicaid Insurance in Old Age." *American Economic Review* 106, no. 11 (November): 3480–3520. Accessed April 21, 2021.

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *The Quarterly Journal of Economics* 132, no. 4 (November 1): 1593–1640. Accessed December 3, 2021.

———. 2021. *The Growing Importance of Decision-Making on the Job* w28733. National Bureau of Economic Research, May 3. Accessed May 13, 2021.

Deshpande, Manasi, Itzik Fadlon, and Colin Gray. 2021. "How Sticky Is Retirement Behavior in the U.S.?" *The Review of Economics and Statistics* (December 20): 1–55. Accessed June 19, 2023.

Diamond, Peter. 2005. *Taxation, Incomplete Markets, and Social Security.* Munich Lectures in Economics. MIT Press, January 14. Accessed May 21, 2023.

Duggan, Mark, Irena Dushi, Sookyo Jeong, and Gina Li. 2023. "The Effects of Changes in Social Security's Delayed Retirement Credit: Evidence from Administrative Data." *Journal of Public Economics* 223 (July).

Filer, Randall K., and Peter A. Petri. 1988. "A Job-Characteristics Theory of Retirement." Publisher: The MIT Press, *The Review of Economics and Statistics* 70 (1): 123–128. Accessed October 5, 2021.

French, Eric. 2005. "The Effects of Health, Wealth, and Wages on Labour Supply and Retirement Behaviour." *The Review of Economic Studies* 72, no. 2 (April 1): 395–427. Accessed April 5, 2021.

French, Eric, and John Bailey Jones. 2011. "The Effects of Health Insurance and Self-Insurance on Retirement Behavior." *Econometrica* 79 (3): 693–732.

Gustman, Alan L., and Thomas L. Steinmeier. 1986a. "A Disaggregated, Structural Analysis of Retirement by Race, Difficulty of Work and Health." *The Review of Economics and Statistics* 68 (3): 509–513. Accessed May 28, 2023.

———. 1986b. "A Structural Retirement Model." *Econometrica* 54 (3): 555–584. Accessed May 29, 2023.

Haan, Peter, and Victoria Prowse. 2014. "Longevity, life-cycle behavior and pension reform." *Journal of Econometrics* 178 (January 1): 582–601. Accessed May 29, 2023.

Haider, Steven J., and David S. Loughran. 2008. "The Effect of the Social Security Earnings Test on Male Labor Supply New Evidence from Survey and Administrative Data." *Journal of Human Resources* 43, no. 1 (January 1): 57–87. Accessed May 12, 2021.

Hubbard, R. Glenn, Jonathan Skinner, and Stephen P. Zeldes. 1995. "Precautionary Saving and Social Insurance." Publisher: University of Chicago Press, *Journal of Political Economy* 103 (2): 360–399. Accessed September 1, 2023.

Hudomiet, Péter, Michael D. Hurd, Andrew M. Parker, and Susann Rohwedder. 2020. "The effects of job characteristics on retirement." *Journal of Pension Economics & Finance:* 1–17. Accessed March 31, 2021.

Hudomiet, Péter, Michael D. Hurd, and Susann Rohwedder. 2019. *Trends in Health and Mortality Inequalities in the United States* MRDRC WP 2019-401. University of Michigan Retirement Research Center, September. Accessed March 30, 2021.

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.* Working Paper WP 2017-372. Ann Arbor, MI: Michigan Retirement Research Center, October. Accessed May 28, 2023.

Hudomiet, Péter, and Robert J. Willis. 2021. "Computerization, Obsolescence, and the Length of Working Life." *NBER Working Paper No. 28701* (April). Accessed July 1, 2021.

Hurd, Michael, and Susann Rohwedder. 2011. "Trends in Labor Force Participation: How Much is Due to Changes in Pensions?" *Journal of Population Ageing* 4, no. 1 (June 1): 81–96. Accessed May 12, 2021.

Johnson, Richard W. 2004. "Job Demands Among Older Workers." *Monthly Labor Review* (July): 48–56.

Johnson, Richard W., Janette Kawachi, and Erick K. Lewis. 2009. *Older Workers on the Move: Recareering in Later Life.* AARP Public Policy Institute, April.

Klaauw, Wilbert van der, and Kenneth I. Wolpin. 2008. "Social security and the retirement and savings behavior of low-income households." *Journal of Econometrics* 145, no. 1 (July 1): 21–42. Accessed May 29, 2023.

Konish, Lorie. 2023. "As Social Security's full retirement age moves to 67, some experts say it should not go higher." *CNBC.com* (February 12).

Lise, Jeremy, and Fabien Postel-Vinay. 2020. "Multidimensional Skills, Sorting, and Human Capital Accumulation." *American Economic Review* 110, no. 8 (August): 2328–2376. Accessed October 20, 2021.

Lopez Garcia, Italo, Nicole Maestas, and Kathleen J. Mullen. 2020. *The Changing Nature of Work.* MRDRC Working Paper 2020-415. Ann Arbor, MI: Michigan Retirement Research and Disability Center, November.

Lopez Garcia, Italo, Kathleen J. Mullen, and Jeffrey B. Wenger. 2021. *The Role of Physical Job Demand and the Physical Work Environment in Retirement Outcomes* MRDRC Working Paper 2021-437. Ann Arbor, MI: Michigan Retirement and Disability Research Center, November.

———. 2022. *The Role of Physical, Cognitive, and Interpersonal Occupational Requirements and Working Conditions on Disability and Retirement* MRDRC WP 2022-448. Ann Arbor, MI: Michigan Retirement and Disability Research Center, September.

Low, Hamish, Costas Meghir, and Luigi Pistaferri. 2010. “Wage Risk and Employment Risk over the Life Cycle.” *American Economic Review* 100, no. 4 (September 1): 1432–1467. Accessed October 23, 2023.

Maestas, Nicole, Kathleen J. Mullen, David Powell, Till von Wachter, and Jeffrey B. Wenger. 2023. “The Value of Working Conditions in the United States and Implications for the Structure of Wages.” *American Economic Review* 113, no. 7 (July).

Maestas, Nicole, and Julie Zissimopoulos. 2010. “How Longer Work Lives Ease the Crunch of Population Aging.” *Journal of Economic Perspectives* 24 (1): 139–160.

Mastrobuoni, Giovanni. 2009. “Labor supply effects of the recent social security benefit cuts: Empirical estimates using cohort discontinuities.” *Journal of Public Economics* 93, no. 11 (December 1): 1224–1233. Accessed May 12, 2021.

McFall, Brooke Helppie, Amanda Sonnega, Robert J. Willis, and Peter Hudomiet. 2015. *Occupations and Work Characteristics: Effects on Retirement Expectations and Timing* wp331. Michigan Retirement Research and Disability Center, October. Accessed March 30, 2021.

Meara, Ellen R., Seth Richards, and David M. Cutler. 2008. “The Gap Gets Bigger: Changes In Mortality And Life Expectancy, By Education, 1981–2000.” Publisher: Health Affairs, *Health Affairs* 27, no. 2 (March): 350–360. Accessed October 16, 2023.

Michau, Jean-Baptiste. 2014. “Optimal redistribution: A life-cycle perspective.” *Journal of Public Economics* 111 (March 1): 1–16. Accessed May 26, 2023.

Montiel Olea, José Luis, and Caroin Pflueger. 2013. “A Robust Test for Weak Instruments.” *Journal of Business & Economics Statistics* 31, no. 3 (July).

Nicholas, Lauren Hersch, Nicolae Done, and Micah Baum. 2020. “Lifetime job demands and later life disability.” *The Journal of the Economics of Ageing* 17 (October 1): 100184. Accessed August 3, 2023.

O’Dea, Cormac. 2018. “Insurance, Efficiency and the Design of Public Pensions.” *Working Paper* (March).

Pingle, Jonathan F. 2006. *Social Security’s Delayed Retirement Credit and the Labor Supply of Older Men* 2006-37. Washington, D.C.: Federal Reserve Board, August. Accessed May 12, 2021.

Pischke, Jörn-Steffen. 1995. “Measurement Error and Earnings Dynamics: Some Estimates from the PSID Validation Study.” *Journal of Business & Economic Statistics* 13 (3): 305–314. Accessed September 4, 2023.

RAND. 2023. *RAND HRS Longitudinal File 2020 (V1). Produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA,* March.

Rogerson, Richard, and Johanna Wallenius. 2022. "Shocks, Institutions, and Secular Changes in Employment of Older Individuals." In *NBER Macroeconomics Annual,* 36:177–216. University of Chicago Press, May. Accessed May 22, 2023.

Rust, John, and Christopher Phelan. 1997. "How Social Security and Medicare Affect Retirement Behavior In a World of Incomplete Markets." *Econometrica* 65 (4): 781–831. Accessed April 5, 2021.

Schirle, Tammy. 2008. "Why Have the Labor Force Participation Rates of Older Men Increased since the Mid-1990s?" *Journal of Labor Economics* 26, no. 4 (October 1): 549–594. Accessed May 12, 2021.

Song, Jae G., and Joyce Manchester. 2007. "New evidence on earnings and benefit claims following changes in the retirement earnings test in 2000." *Journal of Public Economics* 91, no. 3 (April 1): 669–700. Accessed April 5, 2021.

Sonnega, Amanda, Brooke Helppie-McFall, Peter Hudomiet, Robert J Willis, and Gwenith G Fisher. 2018. "A Comparison of Subjective and Objective Job Demands and Fit With Personal Resources as Predictors of Retirement Timing in a National U.S. Sample." *Work, Aging and Retirement* 4, no. 1 (January 1): 37–51. Accessed May 28, 2023.

Sonnega, Amanda, Brooke Helppie-McFall, and Robert J. Willis. 2016. *Occupational Transitions at Older Ages: What Moves are People Making?* Michigan Retirement Research Center (MRRC) Working Paper, WP 2016-352. Ann Arbor, MI: Michigan Retirement and Disability Research Center.

Springstead, Glenn R. 2011. *Distributional Effects of Accelerating and Extending the Increase in the Full Retirement Age.* Policy Briefs No. 2011-01. Social Security Administration.

SSA. 1986. "Increasing the Social Security Retirement Age: Older Workers in Physically Demanding Occupations or Ill Health." *Social Security Bulletin* 49, no. 10 (October): 5–23.

———. 2016. Letter to Representative Sam Johnson from the Office of the Chief Actuary, Social Security. December 8.

Waldron, Hilary. 2007. *Trends in Mortality Differentials and Life Expectancy for Male Social Security-Covered Workers, by Average Relative Earnings* Number 108. Social Security Administration, October.

Yu, Zhixiu. 2023. "Why Are Older Men Working More? The Role of Social Security." *Working Paper.*

Appendix

A Data Appendix

A.1 ONET Variables

I used the Occupational Information Network (O*NET) database 5.0 for occupation information. Over XX O*NET-SOC are given occupation ratings in XX different scales. To be able to use this information with the Census, ACS, and HRS data the O*NET-SOC codes must be cross-walked to Census Occupation codes.

Finally, I use Dorn (2011) [find actual cite] and Deming (2017) crosswalks to link all Census occupation codes from 1970, 1980, 1990, and 2000 as well as ACS occupation codes for 2010 to the *occ1990dd* occupational classification. Details for the crosswalk construction are provided in Appendix XX. In the end, some *occ1990dd* occupations are assigned to multiple O*NET-SOC categories. For these, I determine *occ1990dd* occupation's value in the O*NET measures by taking a simple average across the O*NET-SOC occupation ratings.[45]

A.2 Health Variable

B Trends in Occupation Characteristics

Figure **??** Panel B restricts attention to all employed men. It shows that men experienced similar trends in occupational characteristic intensity as all employed people (note the different axis scales in Panels A and B). Men's occupations also tend to have more extreme conditions and physical input than the population's occupations. By contrast, their occupations have slightly less decision-making and social input and less routine input.

Older men have also seen similar trends in occupational characteristics as the broader population. This can be seen in Figure **??** Panel C, which shows the evolution of mean occupation task intensity for men ages 60 and older. Notably, the increase in social and decision task intensity has been larger than that seen by all men in the population. For example, average social task intensity for men older than 60 grew from 49.2 in 1980 to 53.6 in 2000. The corresponding numbers for all men were 48.0 and 51.0, meaning that the increase in average social task intensity was 46% greater for older men. Looking at a task with declining intensity over time, average physical task intensity for older men decreased from 56.3 in 1980 to 50.9 in 2000. The corresponding numbers for all men were 56.1 to 53.9. Hence, the decline in physical intensity was 145% greater for older men than it was for all male employment.

[45] [[Need some discussion here about the spread of the measures in those cases.]]

Finally, I plot the change in occupational task and characteristic intensity in Panel D for men ages 51–56. I include this because the panel of men I focus on in the HRS enters the survey at these ages. Below, I use the trends shown in Panel D and results from the HRS to predict changes in retirement age and older employment coming from changes in job tasks and characteristics. This group of men has similar trends in occupational characteristics as did men ages 60 and older.

Figure **??** Panel B restricts attention to all employed men. It shows that men experienced similar trends in occupational characteristic intensity as all employed people (note the different axis scales in Panels A and B). Men's occupations also tend to have more extreme conditions and physical input than the population's occupations. By contrast, their occupations have slightly less decision-making and social input and less routine input.

Older men have also seen similar trends in occupational characteristics as the broader population. This can be seen in Figure **??** Panel C, which shows the evolution of mean occupation task intensity for men ages 60 and older. Notably, the increase in social and decision task intensity has been larger than that seen by all men in the population. For example, average social task intensity for men older than 60 grew from 49.2 in 1980 to 53.6 in 2000. The corresponding numbers for all men were 48.0 and 51.0, meaning that the increase in average social task intensity was 46% greater for older men. Looking at a task with declining intensity over time, average physical task intensity for older men decreased from 56.3 in 1980 to 50.9 in 2000. The corresponding numbers for all men were 56.1 to 53.9. Hence, the decline in physical intensity was 145% greater for older men than it was for all male employment.

Finally, I plot the change in occupational task and characteristic intensity in Panel D for men ages 51–56. I include this because the panel of men I focus on in the HRS enters the survey at these ages. Below, I use the trends shown in Panel D and results from the HRS to predict changes in retirement age and older employment coming from changes in job tasks and characteristics. This group of men has similar trends in occupational characteristics as did men ages 60 and older.

C Discussions of Additions of Controls and Robustness Checks

C.1 Figure ??

The additional set which produced the most movement was the "Baseline Controls" set. In particular, it increased the (negative) coefficient on the routine characteristic. This is expected given the preceding discussion. More routine jobs likely had higher incidence of defined pension benefits and retiree insurance. Not accounting for this could bias downward the measured relationship between routine characteristics and older labor force participation as defined benefit pensions and retiree insurance generally reduce the returns from working longer. The relative stability of the additional controls provides some comfort that the measured relationship between initial job characteristics and older labor supply reflects some true relationship.

The final set of controls included in Figure **??** show the coefficients on the initial job characteristics after further controlling for education. The inclusion of this variable could be considered conservative: if individuals obtain more education precisely in response to the changing nature of work, and education independently causes longer work, then controlling for education could erroneously remove some of the effect of the changing nature of work on old-age labor supply. Reassuringly, including education does not change much the estimated coefficients.

C.2 Table ??

Perhaps, as the United States population has aged, the changing mix of different ages has changed the relative supply and demand for older workers (CITE). If changes in this mix were somehow correlated with $Comp1^{40-49}_{c,t-20}$, this could bias the estimated coefficient. Column 2 controls for the log ratio at time t of 60–69 year olds to other age groups. These variables enter with coefficients similar to those from prior work (CITE again), but the point estimate for α barely changes.

In Columns 3, 4, and 5, I include controls similar to those I included in Figure **??**. In Column 3, I control for the time t marriage rate of men aged 60–69, the average household size of men aged 60–69, and the labor force participation of women aged 60–69. Column 4 controls for the share of men aged 60–69 at time t that had any health issue.[46] Column 5 controls for the log ratio of noncollege to college educated men aged 60–69 at time t. In all cases, the coefficient on $Comp1^{40-49}_{c,t-20}$ remains positive and highly significant. This remains true when all of the control variables are included, as in Column 6. Only the inclusion of the health control meaningfully attenuates the estimate of α, but this is not enough to blunt its statistical significance. The evidence from estimates of Equation **??** indicates, therefore, that changing occupational characteristics have caused increased participation from older workers.

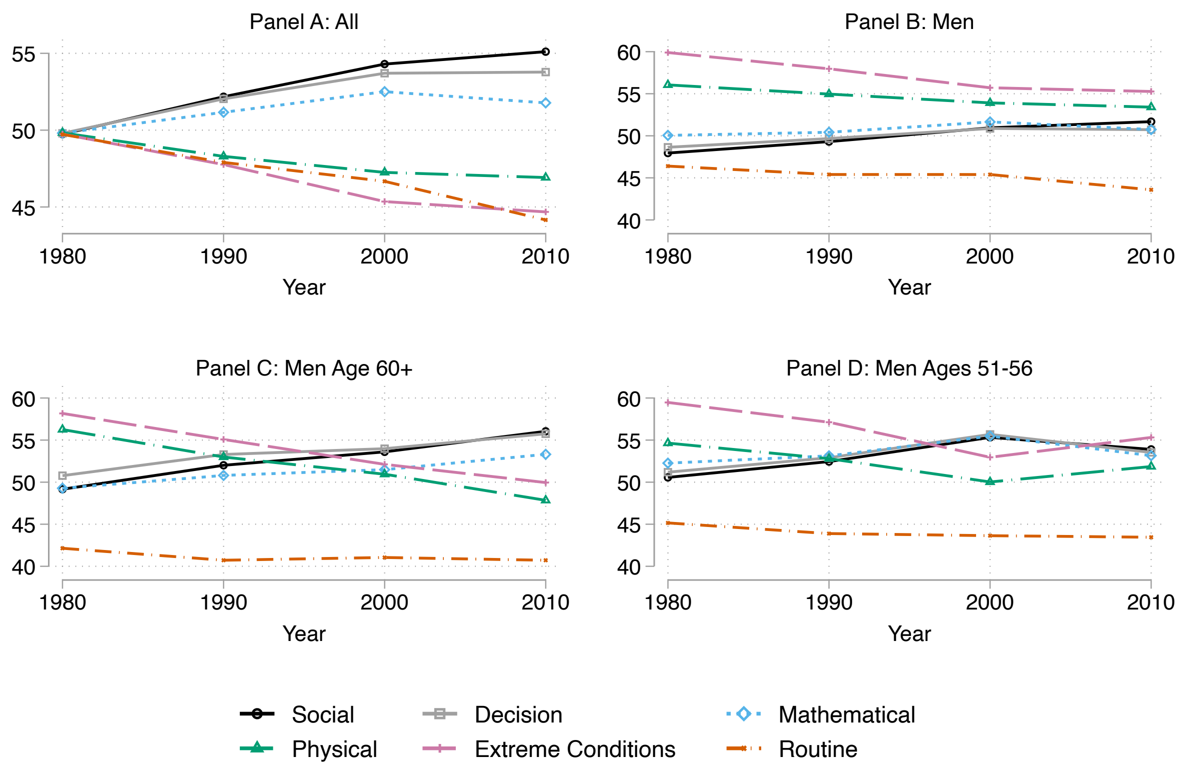
[46] I code an individual as having a health issue if they reported having at least one of: a work disability, a mobility difficulty, difficulty taking care of themselves, a vision or hearing difficulty, or a cognitive issue.

D Model Appendix

D.1 Taxes

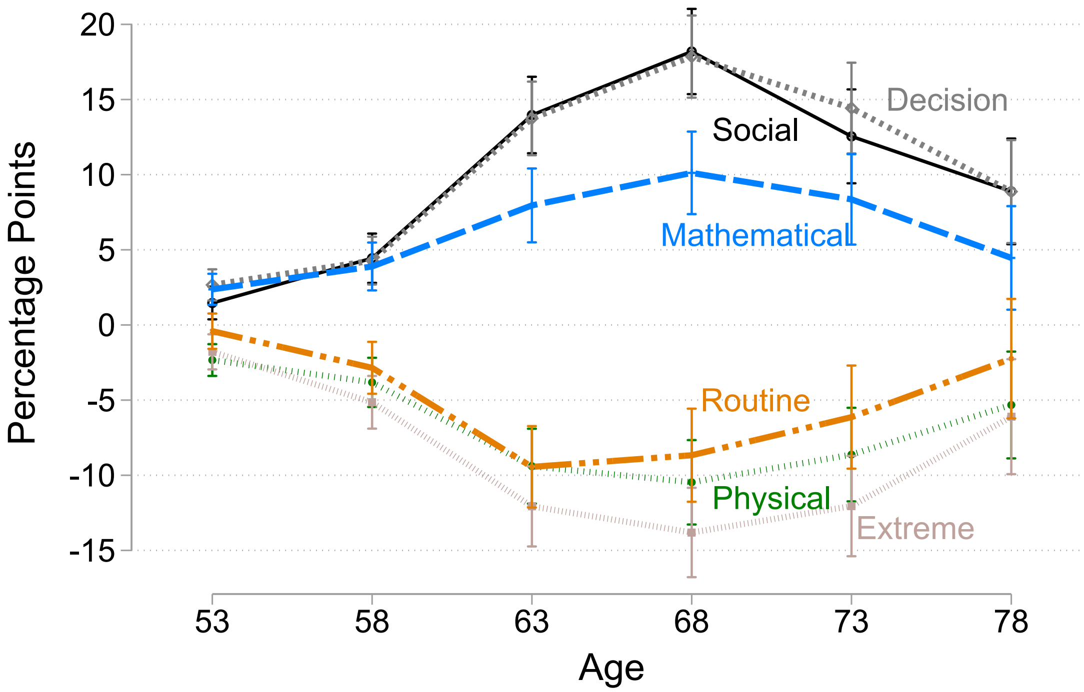
D.2 Evolution of AIME

Appendix Figure 1: Trends in U.S. Employment Task Intensity



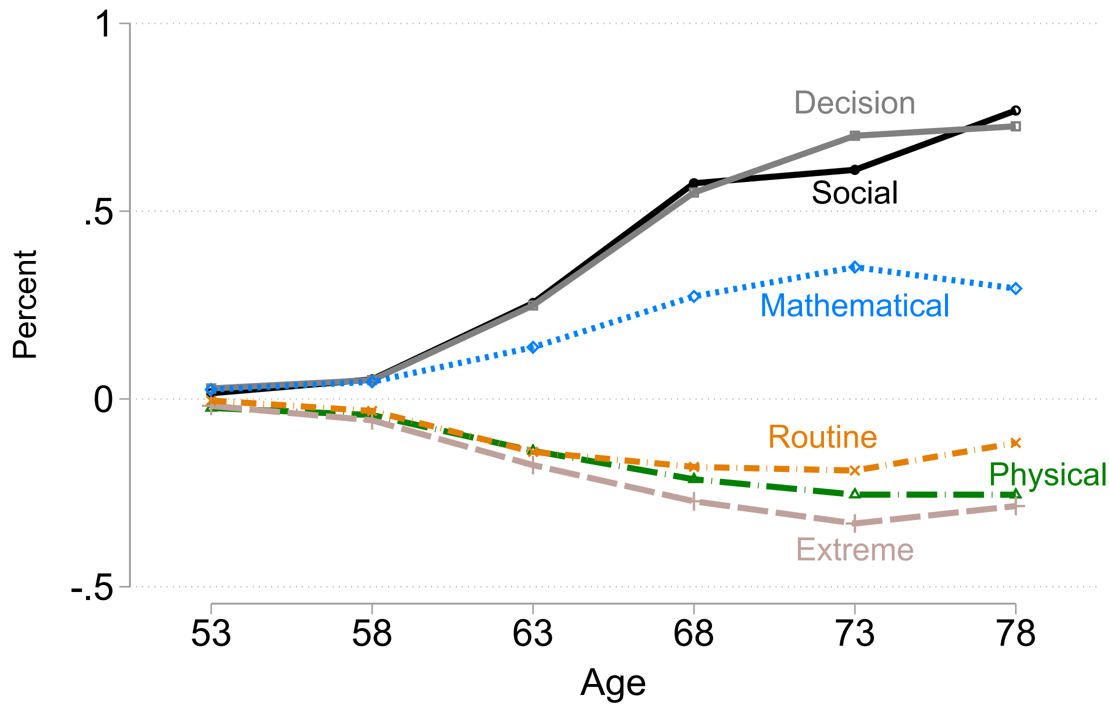
Data are from 5% sample of the 1980, 1990, and 2000 Census and from the 2008-2010 multi-year sample of the American Community Survey. Tasks are O*NET scales explained in Section **??**, rescaled so that they are expressed in centiles of the 1980 task distribution.

Appendix Figure 2: Difference of Employment Rate Between Men in Top and Bottom Task Tercile



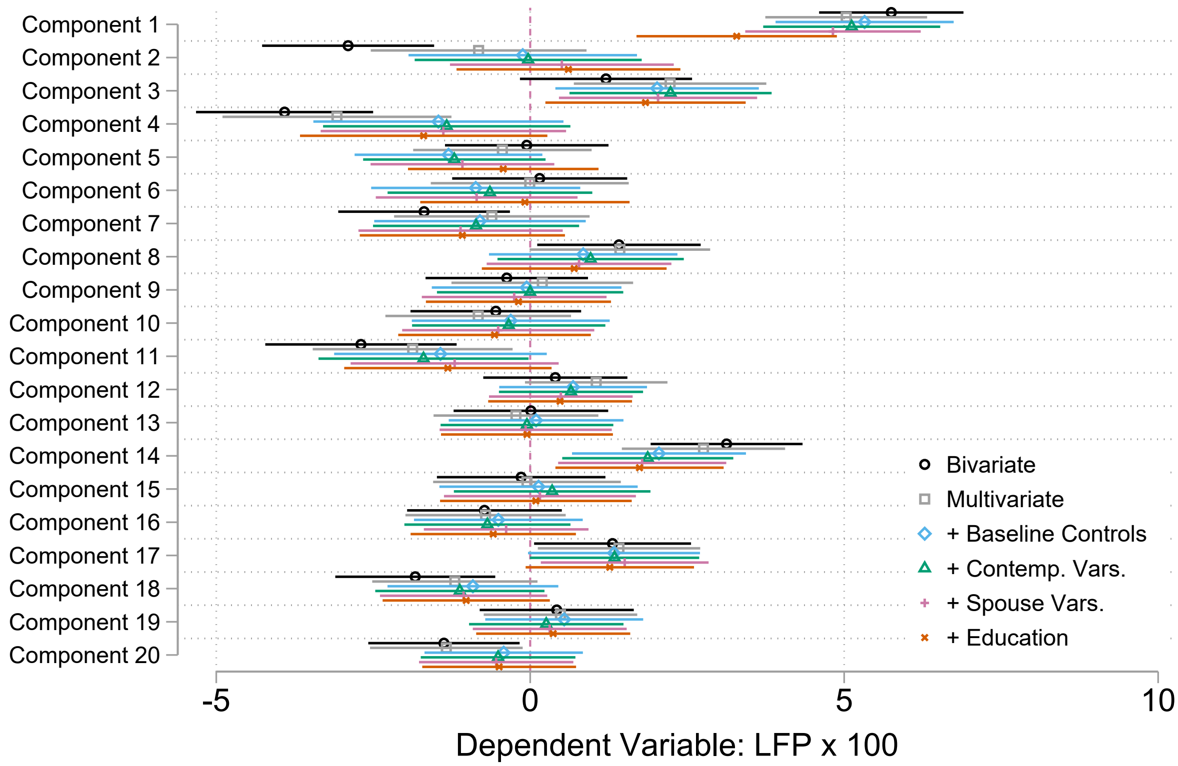
The figure plots the difference in the participation rate between individuals in the top tercile of a given task's intensity and the individuals in the bottom tercile of the same task's intensity. For a given task or characteristic, an individual falls in the "top" tercile if his initial occupation's value in that characteristic was larger than the 66.6th percentile of the 1980 distribution. Likewise, he falls in the "bottom" tercile if his initial occupation's value in that characteristic was lower than the 33.3rd percentile of the 1980 occupational distribution. The sample is men from the 1992, 1998, and 2004 of the HRS who were between 51 and 56 years old when they entered the survey and who had O*NET data linked via occupation available. Individuals are excluded from the sample if their first employment is observed after age 56. Employment averages are taken over five-year age bins starting with 51-55 and ending with 76-80. Point is plotted at the midpoint of the age bin.

Appendix Figure 3: Difference of Employment Rate Between Men in Top and Bottom Task Tercile Divided By Bottom Task Tercile Employment Rate



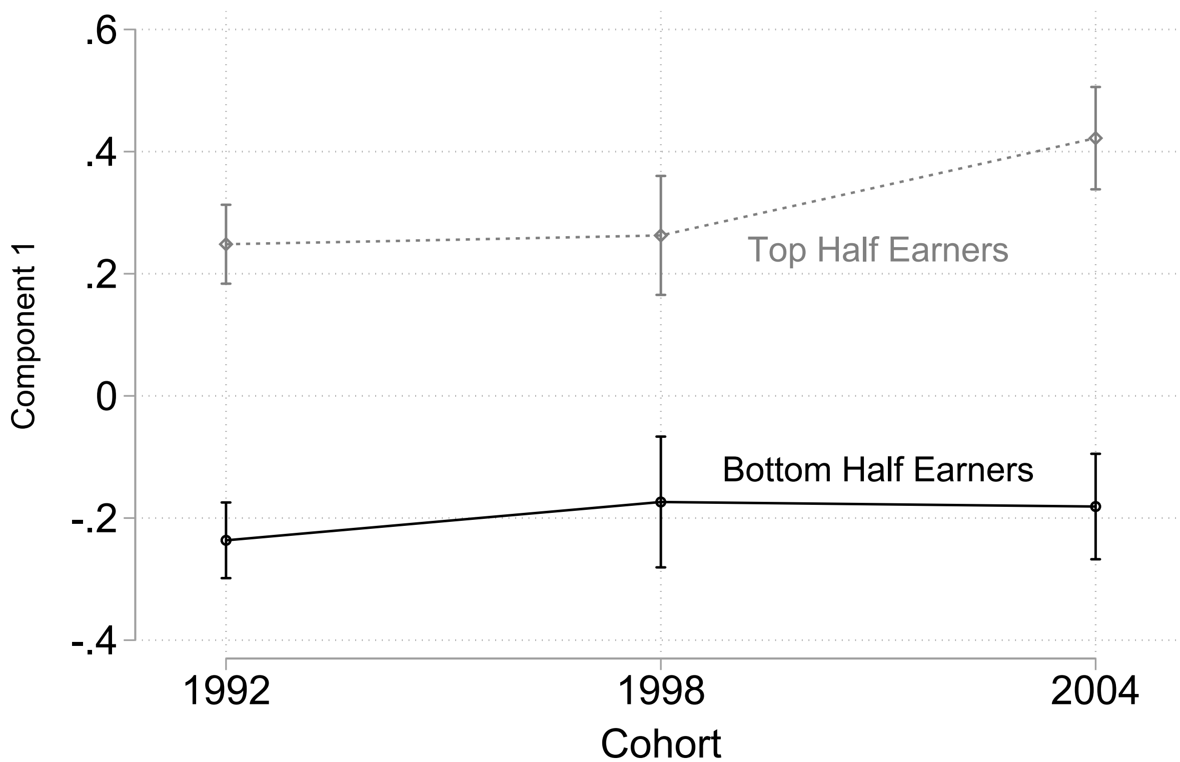
The figure plots the difference in the participation rate between individuals in the top tercile of a given task's intensity and the individuals in the bottom tercile of the same task's intensity. For a given task or characteristic, an individual falls in the "top" tercile if his initial occupation's value in that characteristic was larger than the 66.6th percentile of the 1980 distribution. Likewise, he falls in the "bottom" tercile if his initial occupation's value in that characteristic was lower than the 33.3rd percentile of the 1980 occupational distribution. The sample is men from the 1992, 1998, and 2004 of the HRS who were between 51 and 56 years old when they entered the survey and who had O*NET data linked via occupation available. Individuals are excluded from the sample if their first employment is observed after age 56. Employment averages are taken over five-year age bins starting with 51-55 and ending with 76-80. Point is plotted at the midpoint of the age bin.

Appendix Figure 4: Labor Force Participation at Ages 60–69 and Initial PCA Task Input



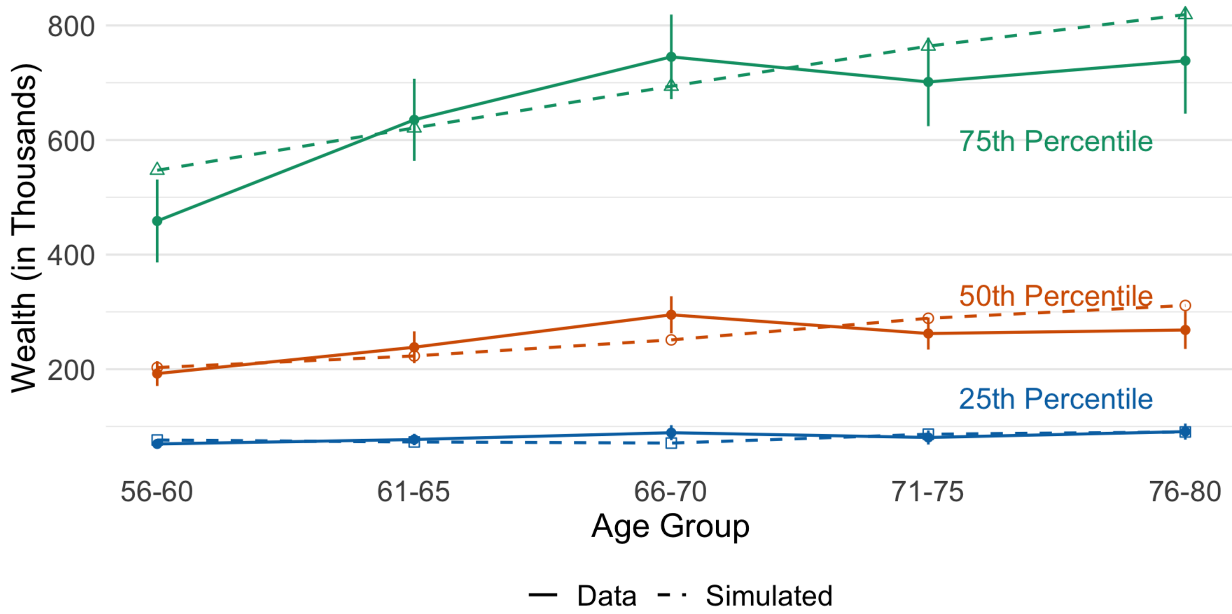
The figure displays the coefficients from a regression of an indicator for labor force participation (x 100) on initial occupation characteristics and additional control variables. The occupation characteristics measures are from the individual's first observed employment between ages 51 and 56. They are measured in standard deviations of the 1980 distribution of tasks. The sample includes all person-year observations between ages 60 to 69 of individuals from the 1992, 1998, or 2004 HRS cohort who were between 51 and 56 years old when they entered the survey, who were observed employed at least once between those ages, and for whom such employment can be linked to O*NET information. Standard errors are clustered at the individual level. 95% confidence intervals are displayed. All regressions include age and year fixed effects. The "Bivariate" results display the coefficient on the occupation characteristics from a regression of LFP on only that characteristic. The "Multivariate" results show the coefficients from a regression that includes all of the shown characteristics. "Baseline Controls" adds controls for the initial job having retiree insurance, the initial job having a defined benefit pension, initial health index value, initial wealth quintile, and marital status. "Contemp. Vars." further adds controls for the contemporary health index and wealth quintile. "Spouse Vars." further adds controls for spouse employment status (if married) and spouse age. Finally, "Education" further adds controls for years of education (up to 16) and whether the individual has schooling beyond college.

Appendix Figure 5: Mean of *Component 1* by Lifetime Income at Age 60 and Cohort



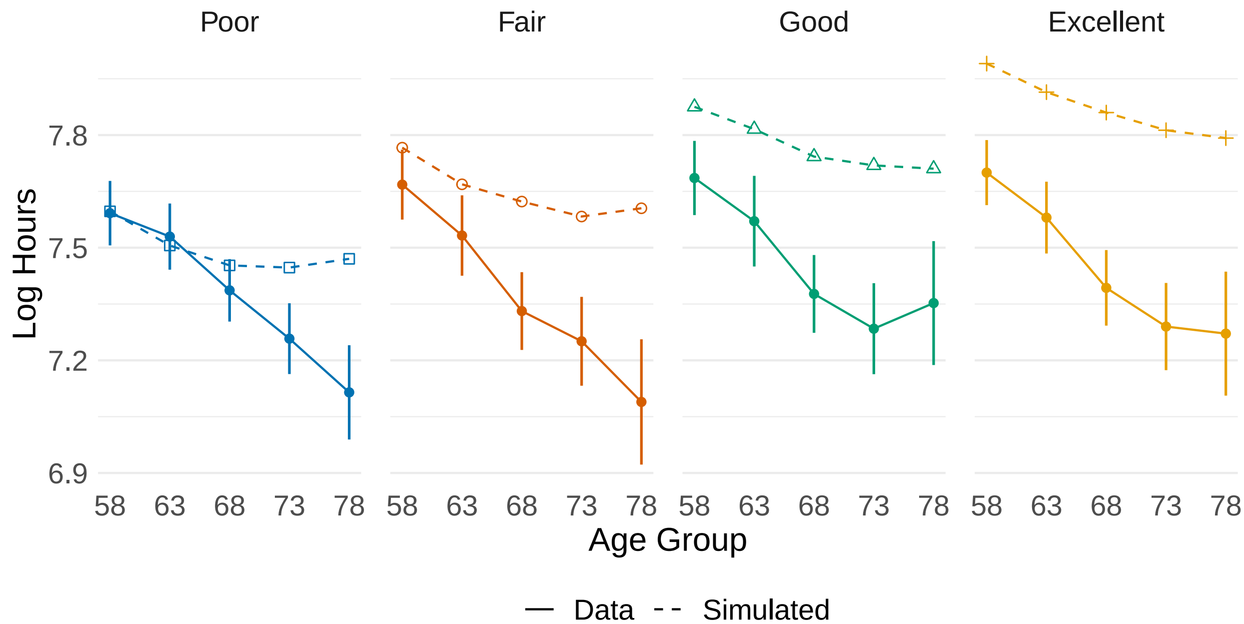
These figures displays the average value of *Component 1* by lifetime income quartile at age 60 and HRS cohort. Recall that occupation for individuals is defined as the first occupation in which they are observed at ages 51–56. Lifetime income is calculated by the HRS using tax records from the Detailed Earnings Record in Social Security administrative data. *Component 1* is described in more detail in Section **??**.

Appendix Figure 6: Targeted Wealth Moments and Simulation Counterparts



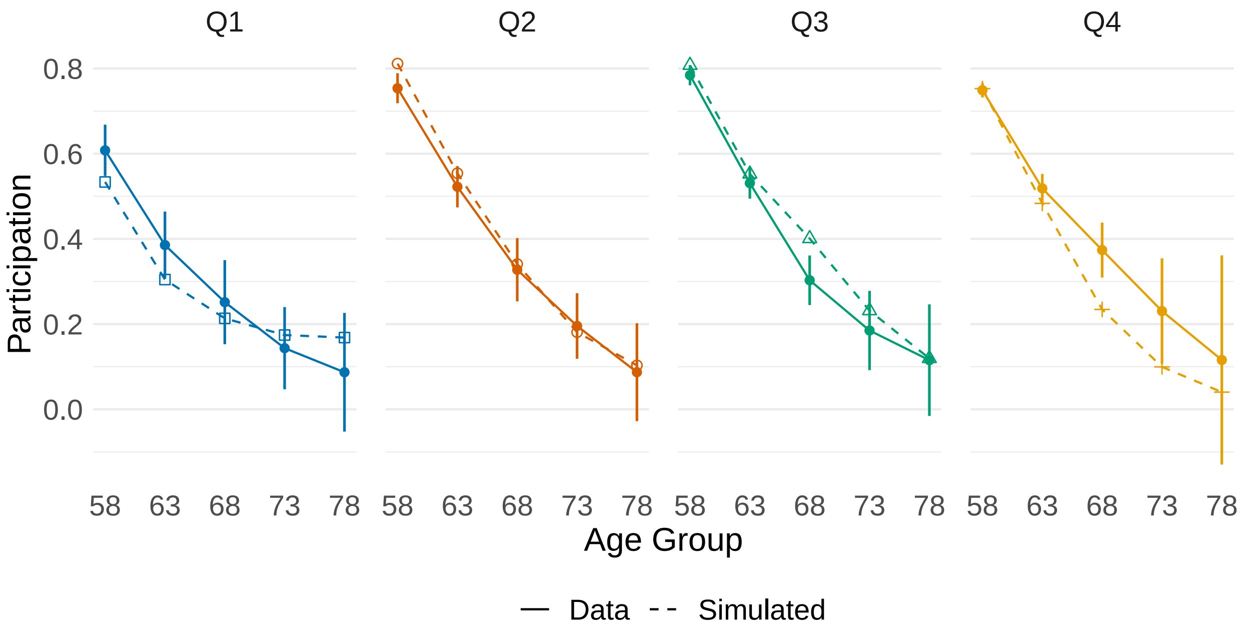
The figure plots the targeted data wealth percentile moments and the simulation counterparts.

Appendix Figure 7: Targeted Hours Moments and Simulation Counterparts



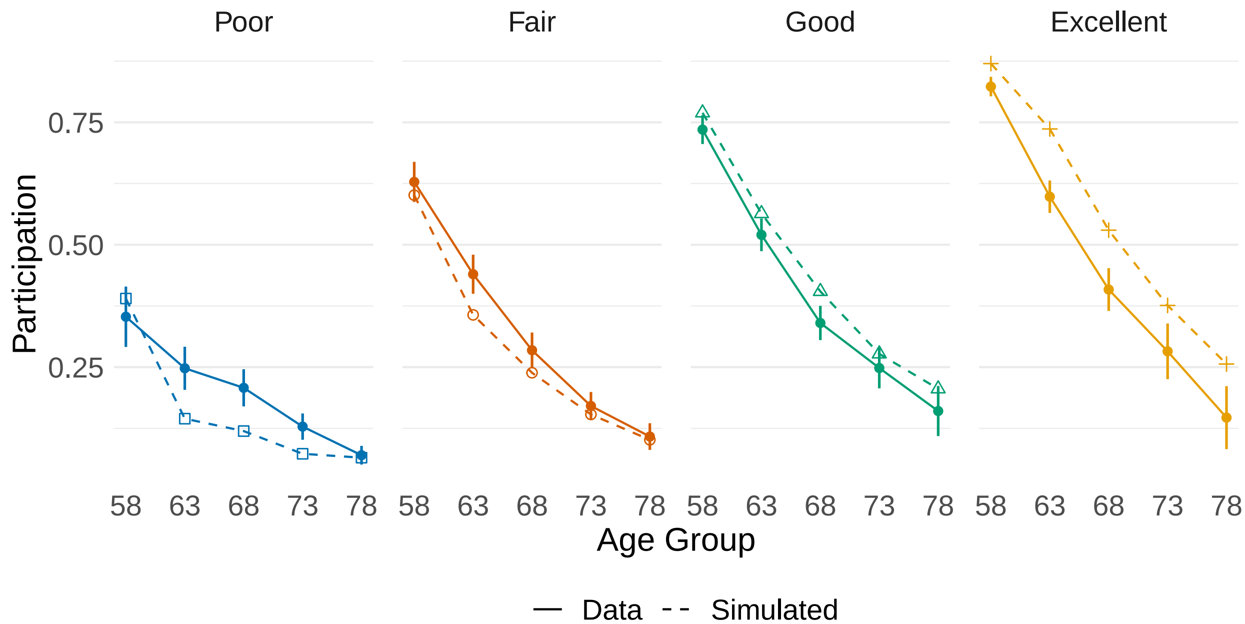
The figure plots the targeted log hours conditional on participation by health moments and the simulation counterparts.

Appendix Figure 8: Targeted Wealth Quartile Participation Moments



The figure plots the targeted participation by wealth quartile moments and the simulation counterparts.

Appendix Figure 9: Targeted Participation by Health Moments and Simulation Counterparts



The figure plots the targeted participation by health moments and the simulation counterparts.

Appendix Table 1: Predicted Change in LFP x 100 from 2000 to 2019, Men Ages 70–79

	(1) Main Tasks	(2) All Tasks	(3) PCA Tasks
No Covariates	1.145	0.973	1.291
	(0.202)	(0.241)	(0.289)
Baseline Controls	1.069	0.994	1.275
	(0.215)	(0.260)	(0.308)
Add Contemp. Vars.	0.999	0.926	1.187
	(0.215)	(0.259)	(0.308)
Add Spouse Vars.	0.992	0.917	1.226
	(0.213)	(0.255)	(0.301)
Add Education	0.859	0.736	1.150
	(0.232)	(0.289)	(0.339)
LFP Change from 2000 to 2019		2.4	

The table displays the predicted change in the labor force participation (x100) from 2000 to 2019 for men ages 70 to 79. To produce the estimates in column 1, I take the coefficients from the 70–79 analogue of Figure **??**, multiply them by the change from 1980 to 2000 in the mean occupational characteristics among employed men ages 51 to 56 in the Census, and then sum up all of the effects. The standard errors are based on the standard errors from Figure **??**, which are clustered at the individual level. The standard errors presented here account for correlation in the coefficient estimates. They do not, however, take into account sampling error in the measure of the change in mean occupational content in the Census, which is small. Column 2 repeats the exercise including six additional occupational characteristic measures from Deming (2017). Column 3 repeats the exercise using the 20 first principal components extracted from a large set of O*NET scales using the 1980 Census. See Section **??** for more details on the PCA. See Figure **??** for an accounting of the control variables included in each of the rows.

Appendix Table 2: IV Pretrend Tests

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Dep. Var.—Lagged Change in LFP Ages 60–69					
Comp. 1 40-49 $t-20$	0.039	0.003	0.025	0.039	0.036	-0.002
	(0.058)	(0.053)	(0.053)	(0.060)	(0.057)	(0.047)
Observations	2166	2166	2166	2166	2166	2166
	Panel B: Dep. Var.—Second Lagged Change in LFP Ages 60–69					
Comp. 1 40-49 $t-20$	0.005	0.040	-0.018	0.002	-0.014	0.008
	(0.068)	(0.073)	(0.056)	(0.066)	(0.063)	(0.056)
Observations	2166	2166	2166	2166	2166	2166

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Panel A errors are clustered at the commuting zone level. Panel B errors are clustered at the state level. The table presents the estimated effect of changes in average Component 1 value among men ages 40 to 49 in the commuting zone 20 years before the current period (Comp. 1 40-49 $t-20$) on the change in labor force participation of men ages 60 to 69 ten years and twenty years before the current period. Years included are 1990, 2000, 2010, and 2019. 2000 is used as the "20 years before period" for 2019. All regressions contain year fixed effects. The instrument is the commuting zone's predicted share of routine occupations in 1950 using the commuting zone's 1950 industry mix and each industry's national share of routine occupation workers in 1950 (excluding the commuting zone's own state). Regression are weighted by the initial (in the first difference) period's population of 60-to-69-year-old men.

Appendix Table 3: Wage Residual Process Parameters

Parameter	ρ	$var(e_{i1})$	σ_v^2	σ_{me}^2
Estimate	0.93858996	0.20974262	0.05788943	0.05386815

Displayed are the estimates of the residual wage process described by Equations **??**, **??**, and **??**. These are estimated using minimum distance methods, as in O'Dea (2018).

References

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *The Quarterly Journal of Economics* 132, no. 4 (November 1): 1593–1640. Accessed December 3, 2021.

O'Dea, Cormac. 2018. "Insurance, Efficiency and the Design of Public Pensions." *Working Paper* (March).