The Changing Nature of Work, Old-Age Labor Supply, and Social Security

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Abstract

The labor force participation of older Americans has been increasing since the 1990s. The tasks and characteristics of American work have also been changing in the past few decades, 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, 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 labor force participation, its impacts on the distribution of welfare at older ages, and implications for Social Security policy. Using the relationship in the Health and Retirement Study between occupation in one's early 50s and later labor force participation, I find that 10–16% of the increase from 1990 to 2010 in the labor force participation of 60-to-69-year-old men can be explained by changes in occupation characteristics, while this amount is 5.8–9% for women. 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 male old-age labor supply with occupation differences, I find that the observed shifts in occupation characteristics led to welfare increases at all but the bottom quartile of lifetime income. Finally, I compare a policy that increases the Full Retirement Age to one that achieves similar savings 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 my model, raising the retirement age is especially harmful for low-income workers because it induces workers in the most physical jobs to continue working.

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1 Introduction

Five decades of technological change have shifted American work away from physical and routine tasks and towards cognitive and social ones. These changes away from more unpleasant tasks may have contributed to the increase in the labor force participation of older Americans since the 1990s. Figure 1 shows how American men and women, both higher- and lower-educated, have increased employment at old ages since the 1990s. Whether or not some kinds of work are more unpleasant and costly than others—and how shifts in these costs have been distributed across the income distribution—matters for policy. For example, 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 a low capacity for additional work. Shifts in occupation away from unpleasant tasks could allay such concerns, especially if lower-income individuals, for whom Social Security is a larger portion of old-age income, have benefitted from these shifts.

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 to evaluate the effects of Social Security reforms on the participation of older men in more physical work. The analysis draws on data from the Census, American Community Survey (ACS), 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 individuals from their early 50s until death.

The paper has two parts. In the first, I evaluate whether and to what extent changes in occupation tasks and characteristics have increased old-age labor force participation. I begin by showing that, in the HRS, someone in a more decision-, social-, or mathematical-intensive occupation in their 50s is *more* likely to participate in the labor force at later ages compared to someone in an occupation that is less intensive along those dimensions. This pattern holds even when controlling for potential confounders such as health, wealth, retiree insurance, and pension structure. Moreover, individuals with more physical, extreme, or routine work in their 50s are *less* likely to participate in the labor force at later ages compared to individuals in occupations that are less intensive along those dimensions.

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 the changes in aggregate 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 changes in work across cohorts explain between 10–16% of the increase in old-age labor force participation from 1990 to 2010 for men, and 5.8–9.0% of that for women. While other work has considered, for example, the contribution of changes in spousal 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 thus go beyond previous studies of the relationship between occupation characteristics and old-age participation (Hudomiet et al. 2021; Lopez Garcia, Mullen, and Wenger 2022) by focusing on the kinds of tasks (e.g., decision, social, and routine) that the task change literature has identified as having experienced the most change in the recent decades (Autor, Levy, and Murnane 2003; Deming 2017, 2021). I also augment previous studies showing that work characteristics have moved toward 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 though 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] 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 instrument's motivation is that places with a higher share of routine occupations were more exposed to the computerization shock and IT revolution, which led 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. 2021); I build on that research here by establishing a causal connection between observed occupation characteristics and observed old-age labor force participation. The first part of the paper thus establishes that the kind of work people do influences their participation in old age and that this relationship has had a sizeable

[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.

Figure 1: Employment Rate Over Time, Ages 65+

Data are from the Annual Social and Economic Supplement of the March Current Population Survey. "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 one year of education above a high school degree.

effect on aggregate old-age labor force participation as tasks and work characteristics have changed.

In the second part of the paper, I examine the implications of changes in the nature of work for welfare in old age, as well as how proposed Social Security reforms would impact those in the most physical occupations. To do so, I 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 occupations as individuals having different types. Different types have fixed differences in their mean wages and disutility from work. When estimating the model, I take into account that individuals who reach 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 1992 HRS 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 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 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 how the impact of two different Social Security reform proposals on the labor force participation of older men varies by their type of occupation.[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. I find that this reduction in Social Security benefits induces the largest increases in labor force participation among those in the most physical work, who are less wealthy and whose old-age income thus relies more heavily on Social Security. 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 physically intensive jobs. Because I find that work is more costly for those in the more physical occupations, raising the retirement age is especially harmful because it induces workers in the most physical jobs to continue working. 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. This strategy captures the empirical regularity that any future work respondents 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 phenomenon. 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 occupa-

[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 (RSC 2022).

[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).

tion characteristics. In the model, I assign "type," the model analog of access to different kinds of occupation, based on the occupation individuals hold in their early 50s in the HRS. Keeping type (and by extension, the general nature of the individual's occupation) fixed allows me to keep the rich structure of previous 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 the Social Security earnings test (Song and Manchester 2007; Haider and Loughran 2008), increases in the FRA (Mastrobuoni 2009; Deshpande, Fadlon, and Gray forthcoming), 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, my paper explicitly measures how changes in 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 partici-

[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. (2021); Lopez Garcia, Maestas, and Mullen (2020); Lopez Garcia, Mullen, and Wenger (2021); Lopez Garcia, Mullen, and Wenger (2022); Maestas et al. (2023).

pation 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 additionally augments the 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 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. My work adds differences in occupation that affect agents' disutility from work and wages.

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 outlines 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 the American Community Survey

[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 the 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.

(ACS), and version 5.0 of the Occupation Information Network (O*NET) occupation data. In this section, I describe the samples, 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 uses the HRS. The HRS is a biennial survey of older individuals that began in 1992 by sampling people in the U.S. aged 51-61 and their spouses. Respondents are followed and re-interviewed every two years. Additionally, 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 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 men from the 1992 cohort.[8]

When examining the change in occupational characteristics over time, I used the 1950 and 1970 1% Census samples, the 1980, 1990, and 2000 5% Census samples, and the 2010–2017 ACS samples. I also used these Census 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

The HRS asks respondents about their current occupation if they are working. Restricted versions of HRS data provide this occupation information information using three-digit Census occupation coding. My analysis typically concentrates on the first occupation individuals are observed holding between ages 51 and 56. This is the point in the survey at which employment is likeliest. Via this occupation assignment method, I am unable to assign an occupation to only 13.5%, 12.4%, and 14.6% of the 1992, 1998, and 2004 cohorts, respectively. The regression analyses relating old-age labor force participation to occupation characteristics exclude individuals without an assigned occupation, but I include them in the structural model as agents with a distinct type.

For occupation tasks and characteristics data, I used the O*NET database. This dataset contains information on over 800 occupations. The information 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

[8] I do, however, include spousal income in the model as well.

occupational ratings on analysts' judgments, beginning in 2003, the database transitioned to basing ratings on surveys of incumbent workers as well as analysts' judgment.

Periodically, O*NET updates the occupational information for a subset of the occupations 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. I used version 5.0 of O*NET, released in 2003, because it is the earliest available instance of the modern O*NET database. This gives me access to a broad set of measures of occupational characteristics while minimizing the distance in time between the first cohort in the HRS and the date of the O*NET release.

With the choice of the O*NET version in hand, two issues emerge regarding the measurement of occupational characteristics and their 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 coding scheme than the three-digit Census codes used in the HRS, Census, and ACS. To deal with this issue, I created a crosswalk between O*NET occupations and 1980, 1990, and 2000 Census codes using the *occ1990dd* occupational classification from Autor and Dorn (2013). Details for the crosswalk construction are provided in Appendix A.1.[9]

By linking all occupations to the O*NET 5.0 database, I hold the characteristics within a three-digit 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 away from routine tasks and towards non-routine cognitive tasks between 1950 and 2000 occurred within occupation categories. 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 with the use of O*NET is that there are far too many ratings and measures to analyze individually. To handle this, I take two approaches. In the first, I average a select group of measures from O*NET to create six measures of job tasks and characteristics, which I call decision, social, mathematical, physical, routine, and extreme conditions. Specifically, for each of the six characteristics, I first selected two to seven O*NET measures.[10] I based my selection of the measures on previous measures used by the task

[9] Some *occ1990dd* have more than one matched O*NET-SOC occupation assigned. In those cases, the O*NET measures for that *occ1990dd* are averages of the measures for the constituent O*NET-SOC occupations. 60% of *occ1990dd* occupations have only one match O*NET occupation, and an additional 18% have exactly two. See Appendix A.1 for further discussion.

[10] 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.

literature (Deming 2017, 2021) or on measures that previous work found were related to old-age labor force participation (Lopez Garcia, Mullen, and Wenger 2021). Then, I averaged, within *occ1990dd*-occupation, over the chosen O*NET measures to create each of the six measures for each occupation.[11] Table 1 details the O*NET measures over which I averaged to create the characteristic's measure. The column labeled "Source" describes the source from which I drew the definition of the variable.

For ease of interpretation, I follow Autor, Levy, and Murnane (2003) and re-scale 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.[12] So, for example, if an occupation's decision-making value is 50, then that means its decision-making rating is equal to that of the median 1980 occupation. If an occupation's score for decision-making is 80, then it has 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 older workers and their labor supply decisions. The O*NET measures chosen for decision-making, social, mathematical, and routine are drawn from Deming (2017) and Deming (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 Autor, Levy, and Murnane (2003) highlighted.[13] By contrast, routine tasks have declined in 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 health declines 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 (2021) demonstrated that increased physical demands in early-life work were associated with a lower probability of employment in old age. I picked

[11] Before averaging, I standardize each O*NET measure.

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

[13] 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). Lopez Garcia, Mullen, and Wenger (2022) found that job autonomy/flexibility was 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.

Table 1: Occupation Task 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 each task or 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 the intensity of each characteristic in terms of centiles 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*, following Deming (2017).

O*NET measures to match the descriptors Lopez Garcia, Mullen, and Wenger (2021) used. 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 using the six measures described above, I also analyzed occupations using the components from a Principal Components Analysis (PCA). Specifically, I applied the PCA algorithm to all of the O*NET ratings using the 1980 Census sample and extracted the first 20 components.[14] 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 focus only on the first principal component, which captures 41% of the variation in occupational measures in 1980 and has a convenient correlation structure with the six characteristics measures I constructed, as I discuss below in Section 3.3.

2.3 Other Variables

I incorporate additional variables in my analysis to control for potentially confounding factors. Some of these variables relate to other occupation characteristics that are not captured in O*NET and are not thought of as tasks or occupation requirements. For example, I observe 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 variable.

When using the HRS, I follow 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. This predicted value serves as my health index. This health variable construction mitigates measurement error and justification bias in self-reported health by instrumenting the subjective measures with objective health measures. It is a single summary value of health that Blundell et al. (2021) showed is significantly related to employment at older ages. Appendix A.2 contains details regarding the construction of the health index.

[14] 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 the 1980 Census sample.

2.4 Trends in Occupational Characteristics

Figure 2 shows the evolution of my six occupation tasks and characteristics over time among the entire employed population in the United States. This includes all ages above 20. 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 task input as well as extreme conditions prevalence decreased steadily during 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 regarding the decline of extreme conditions and physical input in employment in the Census and ACS from 1980 to 2000.[15]

The trends in occupation characteristics in Figure 2 are very similar when looking at men and women independently. They also hold when restricting to those older than 60, as well as when restricting to ages 51–56. This latter group is the one I use for estimating how changes in work have affected old-age labor supply. Appendix Figure 1 shows these patterns for men, and Appendix Figure 2 does so for women. Appendix B provides further discussion.

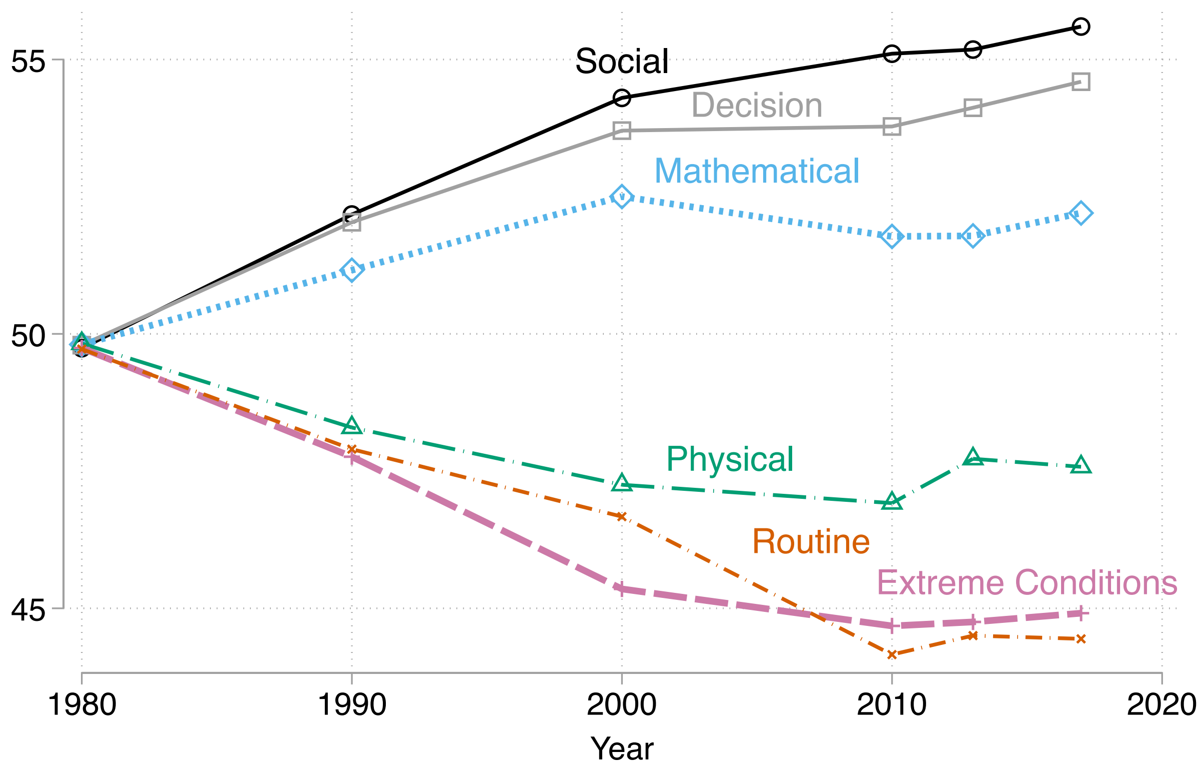
The trends in Figure 2 plateau from the 2000s onwards. Beaudry, Green, and Sand (2016) found that the rise in demand for cognitive tasks and skills halted around the early 2000s. Lopez Garcia, Maestas, and Mullen (2020) looked at aggregate changes in occupation characteristics from 2003 to 2018 including 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 during the 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 characteristic measures do not account for within-occupation shifts, I restrict myself to using shifts until 2000 in my analysis of the role of occupation changes in the increase of old-age labor supply.[16] In future work, I plan to extend my measures to allow for within-occupation change.[17] This would permit an extended

[15] 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.

[16] 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).

[17] This is challenging because the O*NET occupation coding scheme and measures change over time.

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



This figure shows the mean task intensity in the Census and American Community Survey over time among all workers ages 20 and older. Data are from the 5% sample of the 1980, 1990, and 2000 Census as well as the 2008-2010, 2011-2013, and 2013-2017 multi-year samples of the American Community Survey. Tasks are constructed from O*NET scales (see Section 2.2 and Table 1). The measures are rescaled so that they are expressed in centiles of the 1980 task distribution.

accounting of the role of changing occupation characteristics on labor force participation at older ages as well as a projection of the impacts of trends in occupations on future labor force participation.

3 Occupation Characteristics and Old-Age Labor Force Participation

In this section, I (i) show how the 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-olds, 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 his or her probability of working at older ages? Figure 3 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 grows to be around 18 percentage points.

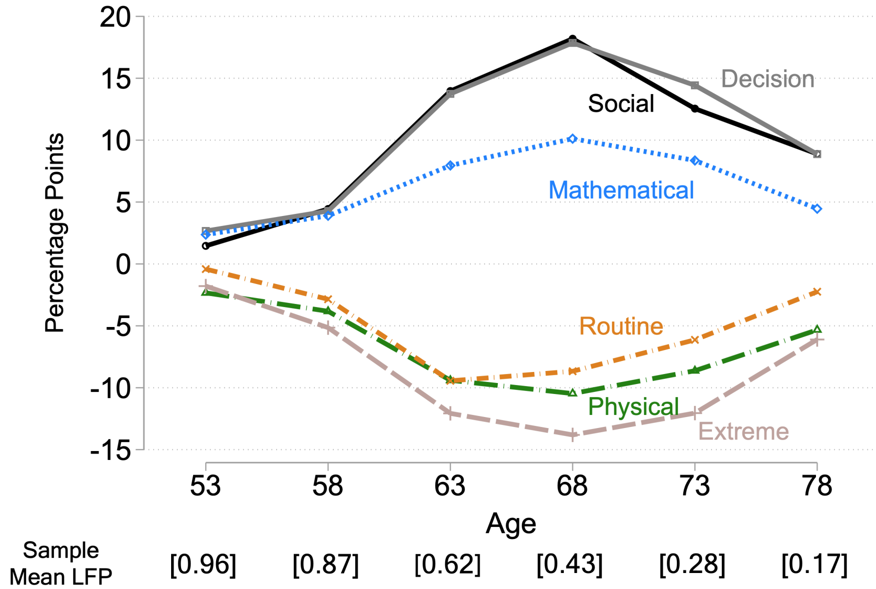
Figure 3(a) shows that there are dramatic relationships between a man's initial occupation task intensity and his participation probability at older ages. Men in initial occupations that are more decision-, social-, or mathematical-intensive are more likely to work at older ages; the opposite is true of men in more routine-, extreme-, or physical-intensive initial occupations. The differences in average participation across ages for a given task are statistically significant, as can be seen in Appendix Figure 4, which includes the standard error of each difference. As average employment 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 5).

Women have similar patterns as men. Figure 3 shows that women who enter the survey in more decision-, social-, or mathematical-intensive occupations are more likely to work in their 60s. The opposite is true for women who the survey in more extreme or physical occupations. Two differences with men stand out. First, differences in routineness have nearly no relationship with later labor force participation. Second, in most characteristics, differences in intensity wash away by the late 70s, perhaps reflecting women's lower attachment to the labor force in these cohorts. Appendix Figures 6 and 7 show these trends for women with standard errors and also in percentage terms, respectively.

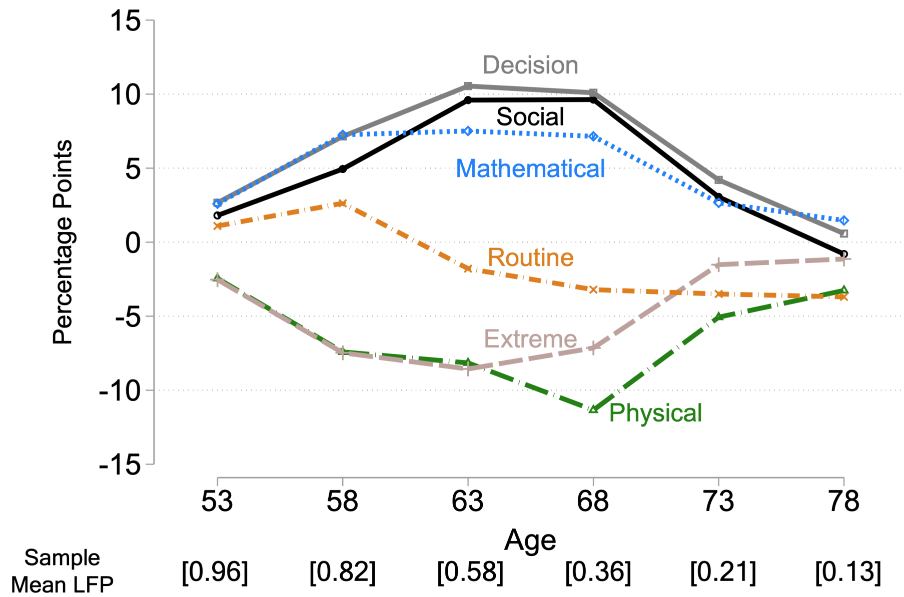
Taken together, Figures 2 and 3 evince that the aggregate tasks and characteristics of American work have shifted precisely towards those that are associated with longer work (decision, social, and mathematical), while they have shifted away from those associated with less work in old age (routine, physical, and extreme conditions). There could, however,

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

(a) Men



(b) Women



The figure plots the difference in the participation rate between individuals in the top tercile of a given task measure and the individuals in the bottom tercile of the same task measure. For a given task or characteristic, an individual falls in the "top" tercile if her initial occupation's value in that characteristic was larger than the 66.6th percentile of the 1980 distribution. Likewise, she falls in the "bottom" tercile if her initial occupation's value in that characteristic was lower than the 33.3rd percentile of the 1980 occupational distribution. The sample is respondents from the 1992, 1998, and 2004 HRS cohorts 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. The point is plotted at the midpoint of the age bin. The sample's mean labor force participation at each age bin is displayed below each graph.

be other differences among individuals who hold different occupations in their early 50s that may drive the observed relationship between occupation characteristics and participation at older ages. For example, manufacturing and construction jobs might involve more routine, physical, and extreme conditions tasks, but they may also have a 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 3 (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 to be married, which is associated with higher retirement ages (Schirle 2008). Similarly, individuals with more education are 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

$$LFP_{i,t} = \alpha_k OccValue_i^k + \beta_1 X_i^{initial} + \beta_2 X_{i,t} + \delta_t + \lambda_{age} + \varepsilon_{i,t} \tag{1}$$

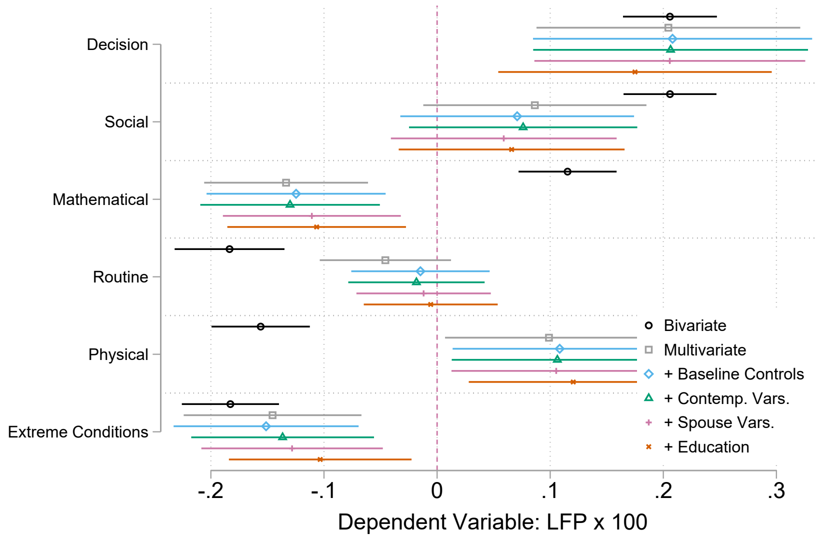
where LFP_{it} is the labor force participation indicator for person i at time t and $OccValue_i^k$ is person i's initial occupation characteristic value for characteristic k. In various specifications, I control for the person's initial (that is, survey-entry) covariates $X_i^{initial}$ and/or her covariates 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 either men or women 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 4 plot the coefficients for each of the six measures. The signs and relative magnitudes of the coefficients are as expected, given Figure 3. 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 is also the case for mathematical intensity, though the point estimate is smaller. Entering the survey in an occupation with high physical or extreme-conditions intensity, on the other hand, is associated with a lower labor force participation at ages 60 to 69. For men, but not for women, entering the survey in a more routine occupation is associated with lower labor force participation at older ages.

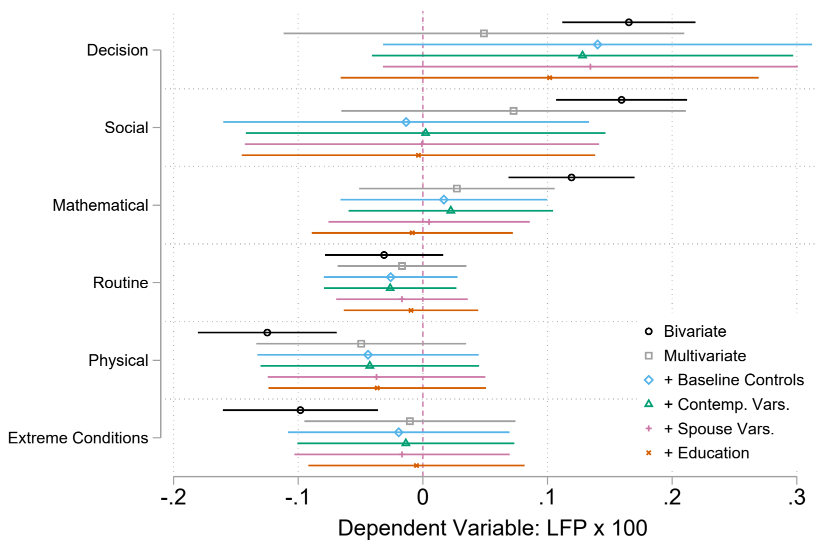
Including all six characteristics in a single regression shows how each occupational char-

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

(a) Men



(b) Women



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." 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.

acteristic relates to old-age participation when holding the other five characteristics fixed. The results from that regression are plotted as gray squares in Figure 4. These estimates are much noisier, and there are large shifts in the coefficients for men, shown in Panel (a). This result is expected because the measures are highly correlated. Decision and extreme conditions intensity remain statistically significant and with the same sign as in the bivariate regressions. The positive relationship between social task intensity and the probability of participation at older ages falls and is no longer statistically significant. The coefficient of routineness sees a similar attenuation.

By contrast, both the mathematical and physical measures see a flipped sign in their relationship with old-age participation 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.

For women, shown in panel (b), all task and characteristics coefficients move towards zero in the multivariate regression. Moreover, none of the coefficients are individually significant. The smaller sample size for women no doubt contributes to the imprecision. Only around 60% of women in the 1992 HRS cohort, for example, held an occupation between ages 51–56 (compared to 84% for men).

With this regression model, I can exploit the rich nature of the HRS data to control for additional factors that may confound the relationship between occupation characteristics and old-age labor supply. The rest of the coefficients plotted in Figure 4 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 stable across specifications. Appendix C.1 contains a more detailed discussion of some of the movements produced by the additions of specific control sets.

3.2 Explaining 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 contributed to growing old-age labor force participation. The growth shown in Figure 2 has occurred in precisely the occupation characteristics associated with longer work, while the characteristics associated with less work have decreased. However, the results from the multivariate regressions in Figure 4 do not provide a clear answer to this question. For men, one of the occupation characteristics that has been shrinking in the economy (physical input) has a positive relationship with old-age labor force participation, while one of the growing characteristics (mathematical input) has a negative relationship. For women, the multivariate coefficients have the expected signs, but the coefficients are individually imprecise.

To make sense of how the results from Figure 4 can speak to the change in old-age labor force participation, I adopt the following procedure. First, I calculate for occupation characteristic k, the change in the mean occupation value among 51-to-56-year-olds between the 1980 and 2000 Census:

$$OccChange^k_{1980-2000} = MeanOccValue^{51-56}_{2000} - MeanOccValue^{51-56}_{1980}. \tag{2}$$

Then, I take the coefficients α_k from the multivariate versions of Equation 1, multiply it by the corresponding $OccChange^k_{1980-2000}$ from Equation 2, and sum up across all six characteristics (let the set representing these containing all these characteristics be K):

$$LFP\Delta = \sum_{k \in K} \alpha_k \cdot OccChange^k_{1980-2000}. \tag{3}$$

$LFP\Delta$ is the estimate for the contribution of changes in the nature of work to changes in the labor force participation of 60-to-69-year-olds. The exercise assumes that an individual with a given set of occupation characteristics in 2000 has similar old-age participation behavior as someone with that same set of initial occupation characteristics in 1980. One way to test the validity of this assumption is to interact $OccValue^k_i$ in Equation 1 with cohort indicators. The coefficients on the cohort interaction variables in such regressions are not significant (not shown). This result is reassuring, along with previous work that found that occupations are very persistent in old age—that is, when individuals switch jobs in old age, they usually switch to occupations that are very similar to the one they were previously doing (Johnson, Kawachi, and Lewis (2009); Sonnega, Helppie-McFall, and Willis 2016). Hence, it is reasonable to assume that the occupation characteristics of someone's job at 50 are indicative of the kind of work they can and will do in the future. The occupation someone holds in their early 50s reflects the kinds of jobs for which the person has accumulated skills to perform, and it also reflects the occupations that are available in the economy.

One major threat to this assumption is that the returns to certain skills and tasks have been changing over this period (Deming 2017; Acemoglu and Restrepo 2022). If wage profiles for a given set of initial occupation characteristics are radically different across 1980 and 2000, it may be harder to believe that the relationship between initial occupation characteristics and later-life participation is stable. From a life-cycle labor supply model perspective, however, differences across individuals in the wage level are not very determinative of retirement decision differences; rather what matters most for each individual is how the offered wage compares to lifetime income (Filer and Petri 1988). This means that if the wage returns to a given task fell, but fell throughout a worker's life, then wage level differences across cohorts in the returns to those tasks are less of a threat to the strategy in Equation 3.

What is a greater threat to the strategy in Equation 3 is rapid contemporaneous changes to the wage returns to particular tasks or characteristics. For example, early in the computerization of the economy, older workers in occupations that were early and aggressive adopters of computer technology experienced sharp falls in wages and employment (Hudomiet and Willis 2021). The HRS cohorts examined, however, came later (1992, 1998, and 2004) and Figure 2 showed a relative slowdown in task changes after the 2000s, providing additional evidence that the relationships between characteristics and old-age participation found in Equation 1 are stable ones.

Estimates of $LFP\Delta$ from Equation 3 are shown in Table 2, separately for men and women.[18] 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 4. Changes in the six occupational measures among 51-to-56-year-old men from 1980 to 2000 would suggest an increase in the labor force participation rate of 60-to-69-year-olds by 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. The corresponding numbers for women are 1.67 and 14.0.

A better interpretation of the result requires noting that about 15% of the men and 40% of the women in the HRS were not assigned an initial occupation.[19] Assuming the labor force participation of those men and women 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 $1.46 \times 0.85 = 1.24$ percentage points (1 percentage point for women). 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 15.9% of the increase in labor supply from 1990 to 2010 for 60-to-69-year-old men (7.1% for women).

[18] The standard errors take into account the standard errors from the coefficients in Figure 4, but they do not take into account errors from sampling variation in the Census, which are trivial.

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

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

Panel A: Men

	(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	

Panel B: Women

	(1) Main Tasks	(2) All Tasks	(3) PCA Tasks
No Covariates	1.670	1.885	2.145
	(0.290)	(0.332)	(0.341)
Baseline Controls	1.732	2.118	2.269
	(0.321)	(0.366)	(0.377)
Add Contemp. Vars.	1.767	2.173	2.288
	(0.313)	(0.359)	(0.370)
Add Spouse Vars.	1.624	2.025	2.099
	(0.310)	(0.353)	(0.365)
Add Education	1.111	1.518	1.362
	(0.344)	(0.394)	(0.425)
LFP Change from 1990 to 2010		14	

The table displays the predicted change in the labor force participation (LFP) $\times$ 100 from 1990 to 2010 of men and women ages 60 to 69. These are estimates of $LFP\Delta$ from Equation 3. The standard errors are based on the standard errors from Figure 4, 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 measurements of the change in mean occupational content in the Census, which is small. Column 1 shows the LFP change implied by changes in the six main tasks and characteristics examined (see Table 1). Column 2 repeats the exercise including seven 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 2.2 for more details on the PCA. See Figure 4 for an accounting of the control variables included in each of the rows.

The successive rows in Table 2 show the predicted change in labor force participation when using the corresponding coefficient estimates from Figure 4. Additional controls slightly attenuate the effect attributable to the changing nature of work. The specification with all controls except for education suggests that 13.3% 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.

There are reasons for and against including education in the regression. On the one hand, individuals may get more education precisely to take advantage of the changing nature of work (e.g., higher prominence of and returns to cognitive tasks). If education has an independent effect on labor force participation, then it would make sense to attribute some of the effects of education on participation to occupation characteristics. On the other hand, education may be indicative of unobserved characteristics, such as work ethic, that might be correlated with occupation characteristics. It does not make sense to attribute the effect of differences in work ethic as being part of the effect of occupation characteristics on participation. Even including education in the specification, however, changes in occupation characteristics explain around 9.6% of the change in men's old-age labor force participation (4.8% for women).

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).[20] The results are shown in the second column of Table 2. Using this larger set of measures barely changes the results.

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 exercise's precision manageable.[21] The final column of Table 2 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. My preferred specifications are the rows "Add Spouse Vars." and "Add Education". They indicate that changes in the PCA task measures among 51-to-56-year-old men from 1980 to 2000 predict about 10–16% of the increase in the labor force participation of men aged 60–69

[20] These are interactive, coordination, service, finger dexterity, number facility, deductive inductive reasoning, and information use.

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

from 1990 to 2010.

For women, the corresponding figures are 5.8–9.0%. It is not surprising that the share of the change explained for women is lower than that for men. The 1992 HRS cohort of women is one of the last before Goldin's Quiet Revolution (Goldin 2006). Women's increasing attachment to the labor market and their increasing investment in careers have been powerful forces that explain a lot more of the changes for women.

The relationship between initial occupation characteristics and labor force participation in old age persists beyond ages 60–69. Appendix Table 1 shows the predicted changes in labor force participation at 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 41–43% of the 2.4 percentage point increase in labor force participation of this group in that time (9.9–16% of the 3.9 percentage point increase for women).

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

I demonstrated in the previous section that, even when controlling for potentially confounding factors, initial occupation characteristics have a strong relationship with 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 that confound the measured relationship between the two. In this subsection, I exploit geographic variation in the kinds of work people perform and its change over time as a test of the causal relationship between occupation characteristics and older labor force participation. 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, which I call *Component 1*. I do this for several reasons. First, it simplifies exposition: it maintains focus on a single variable. Second, in the instrumental variable strategy, I only have a single instrument, so I can only include one endogenous variable.

Third, in the HRS, an individual's initial occupation's first principal component has a strong relationship with the probability of being in the labor force at ages 60 to 69. 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 8). *Component 1* also has a convenient correlation structure with the six measures I have been focusing on until now.

Table 3 displays these correlations. *Component 1* is extremely positively correlated with the decision and social measures. It is less positively 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 findings in the previous section. The characteristics that I found are related to longer work contribute positively, while the characteristics that I found are related to shorter work lives contribute negatively. Moreover, it is the PCA component measure that has seen the highest increase in average value in the economy since 1980 (see Appendix Figure 3).

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 the labor force participation rate of men aged 60–69 $LFP_{c,t}^{60-69}$ in commuting zone c at time t as

$$LFP_{c,t}^{60-69} = \alpha Comp1_{c,t-20}^{40-49} + \beta X_{c,t} + \lambda_c + \delta_t + \epsilon_{c,t} \tag{4}$$

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, and the sample years are 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 are only available every decade. These ten-year gaps also focus attention away from short-run changes, as these can have deleterious short-run employment of older workers.[22] 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. Finally, I restrict attention to men because women's rapidly changing labor force participation and career behavior during this time riddle changes in $Comp1_{c,t-20}^{40-49}$ with selection effects.

The idea behind Equation 4 is that the *Component 1* average value of men ages 40–49 twenty years prior captures the occupation characteristics that (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,

[22] See Section 3.2 and the discussion of Hudomiet and Willis (2021)

for example, 50-to-59-year-olds ten years before, to capture the occupations closest to the men's main "career." Previous research has shown that occupations before one's 50s better predict effects on employment (Nicholas, Done, and Baum 2020), although the HRS's data limitations prevented me from going this far back in the analysis in the previous subsection.[23]

The inclusion of the commuting zone fixed effects in Equation 4 means that α, the parameter of interest, is identified by changes across decades in the average value of *Component 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 that are correlated with $Comp1^{40-49}_{c,t-20}$.

Table 4 Panel A displays the results from estimating Equation 4. 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 C.2.

One might still be unsatisfied with the strategy for estimating α in Equation 4. For example, there could be unobserved factors correlated with changes in the occupation characteristics of a commuting zone that are also correlated with changes in labor force participation twenty years later, such as long-lasting idiosyncratic shocks in labor demand. 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 occupation 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 the 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 4 of the aforementioned potential confounders. The instrument is the predicted share of routine jobs in the commuting zone c in 1950. This prediction is constructed using the commuting zone's industry composition in 1950 and each industry's share of routine jobs calculated at the national level (and excluding commuting zone c's state). For a given commuting zone c,

[23] 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, as previously discussed, 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).

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 the 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. The 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-decade" differences and instruments Comp. 1 40-49 $t-20$ using the Autor and Dorn (2013) instrument. Specifically, the instrument is a 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 the number of 60-to-69-year-old men in the commuting zone and Panel B is weighted by the initial period's population of 60-to-69-year-old men. The first-stage Effective F-Statistics from Montiel Olea and Pflueger (2013) are displayed.

one takes an industry's share of employment in 1950, multiplies it by the industry's share of routine jobs in 1950 at the national level, and sums this value across all industries to obtain the predicted 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 4. 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 revolution.

This instrument falls in the class of "exogenous shock" shift-share instruments analyzed by Borusyak, Hull, and Jaravel (2022). The shocks are each industry's routine share 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 routine share of jobs in 1950. This seems quite plausible, but below I perform a pre-trend analysis to test the assumption's plausibility.

Panel B of Table 4 displays the results from the instrumental variables model. Because the instrument is constant within commuting zones, I estimate the model in first (decadal)-differences. As in Autor and Dorn (2013), I allow the instrument's effect 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.[24] 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 4 Panel B with its lag and second lag, indicate that there is an absence of substantial pre-trends; the estimated coefficient on $Comp1^{40-49}_{c,t-20}$ in these regressions is close to zero and never statistically significant (See Appendix Table 2).

Both the statistical significance of the estimate of α across most of the specifications in Table 4 Panel B, as well as its consistent increase when compared to the results from the fixed effects estimator in Panel A, provide evidence for the existence of a causal link between the occupation characteristics and labor force participation at older ages. I can think of two major reasons why the IV estimates would be higher than the fixed effects estimates. First,

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

there is likely significant measurement error in the O*NET characteristics measures. 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 period that plausibly negatively impacted labor force participation and had 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 α downwards.[25]

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 work capacity to 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 whether occupations themselves are conducive to 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 older workers in physical occupations and to what extent such occupations could be expected to persist (SSA 1986).

I briefly 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.[26] 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.

[25] At first glance, the relationship between these shocks and $Comp1^{40-49}_{c,t-20}$ may seem to 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 reassures one that routineness in 1950 is unrelated to experiencing trade shocks or robot shocks later on.

[26] 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.

Appendix Figure 9 presents the results. All quartiles have seen an increase in the average value of Component 1, though 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 to detect significant trends across cohorts, when I split the sample into two quantiles, the increase in *Component 1* value is significant for those in the top half of the lifetime income distribution (Appendix Figure 10).

4 An 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 the value of these improvements in work capacity 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).[27] There are also concerns about Social Security reforms making individuals in very physical occupations work longer (SSA 1986; Steuerle and Kramon 2023).

When measuring the welfare effects of changes in occupation characteristics, it is not enough to account for the higher income from longer work and higher wages as a result of the more pleasant and better-paid tasks. One must also take into account that, for any given amount of work individuals supply, they enjoy higher utility from the work being less unpleasant. Moreover, changes in work across cohorts at age 50 likely reflect changes in work characteristics and tasks 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 differ by lifetime income. I restrict the analysis to men. I make this restriction

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

for practical reasons, as modeling an additional labor supply choice and marriage greatly increases computational intensity.[28] Because the findings in the previous section indicated that changes in occupation tasks and characteristics have had a greater impact on male old-age labor supply, and men were more likely to enter the HRS with an occupation, I choose to focus on men in this portion of the analysis.[29]

I build on French and Jones (2011), adding occupational differences across individuals. In the model, I represent occupation as 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 shifts in the kinds of work in the economy mean that people arrive at age 50 with different skills, job opportunities, and life trajectories. These differences, in turn, affect a person's wealth, expected social security benefits at age 50, and the kinds of occupations available to them in old age.

Health evolves exogenously and affects time available for work, wages, and medical expenses. Retirement arises endogenously.

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 can choose their hours, too. Under the rules for Social Security, between ages 62 and 70 individuals can claim their benefits. Delaying claiming increases an individual's annual benefits received. After age 70, everyone automatically receives Social Security benefits, reflecting current Social Security rules.

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. It also affects an agent's initial conditions. These types represent occupational differences. 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 they can 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.

[28] See Borella, De Nardi, and Yang 2023 for a structural model with singlehood, marriage, and a dual labor supply choice.

[29] Spousal labor earnings, though taken as given, are modeled.

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

$$u(c_t, l_t) = \frac{1}{1-\eta} \left(c_t^{\gamma} l_t^{1-\gamma}\right)^{1-\eta}. \tag{5}$$

Leisure l_t for a individual of type o is

$$l_t = L - n_t - (\alpha + \alpha_t t)\mathbb{1}\{n_t > 0\} - \sum_{h \in H} \alpha_h \mathbb{1}\{h_t = h\} - \sum_{o \in \Theta} \delta_o \mathbb{1}\{n_t > 0\}\mathbb{1}\{o_i = o\} \tag{6}$$

where n_t is hours worked at age t, h_t is health state at age t, and L is the 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 working common to all people. It is allowed to have a linear time trend to accommodate for an increasing disutility of work with age.

The second, δ_o, is common to all individuals of type o. This term captures how individuals of different types work in different occupations, and the different occupations provide different disutilities as a result of their different tasks and characteristics. Some types work in more physical occupations, which in theory provide a higher disutility from work. Others will work in more social- and decision-intensive occupations, which might provide less disutility. The inclusion of these parameters—and more broadly the inclusion of differences across people due to occupations—is one of the paper's principal modeling innovations relative to the literature.[30]

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:

$$beq(a_t) = \psi \frac{(a_t + A)^{(1-\eta)\gamma}}{1-\eta} \tag{7}$$

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

[30] Alternative specifications could allow for explicit interactions between health costs and types. For example, certain occupations might provide even more disutility from work in poor health states than they do in better states of health.

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 depend 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. Appendix D.1 discusses the tax function specification; it includes payroll, state, and federal income taxes.

An individual who consumes c_t has next-period assets of

$$a_{t+1} = a_t + Inc_t + tr_t - med(h_t, t) - c_t \tag{8}$$

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.[31] Government transfers guarantee a consumption floor, as in Hubbard, Skinner, and Zeldes (1995). If a person's income and assets are less than the consumption floor, transfers kick in to make sure the person can consume at least $\underline{c}$:

$$tr_t = \max\{0, \underline{c} - (a_t + Inc_t)\}. \tag{9}$$

4.1.3 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 exogenous.

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, $m_t = 1$.

Medical expenditures $med_t(h_t, t)$ are all of the out-of-pocket medical expenditures a person has to pay. They are modeled as a deterministic function of health and age. I allow for discontinuities in both $med(h_t, t)$ at age 65 to account for Medicare eligibility.

[31] 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).

4.1.4 Wages and Spouse Earnings

An individual's wage rate at age t depends on his health, occupation type, age, and an autoregressive component:

$$\ln w_t = W(h_t, t, o) + \omega_t \tag{10}$$

$$\omega_t = \rho\omega_{t-1} + \epsilon_t \tag{11}$$

$$\epsilon_t \sim N(0, \sigma_\epsilon) \tag{12}$$

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

4.1.5 Social Security

To appropriately capture the labor supply incentives of men in old age, the model includes important details of the Social Security program as 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 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 here the basic contours of Social Security and how I model it.

Social security annual benefits, ss_t, depend on an individual's Average Indexed Monthly Earnings ($AIME_t$) and age at claiming. Actual AIME is calculated by averaging over an individual's best 35 indexed earnings years.[32] A progressive formula dictates how AIME converts to actual benefits, called the Primary Insurance Amount (PIA). The formula gives higher replacement rates (of AIME) to those with low levels of AIME.[33]

Individuals who claim Social Security at the Full Retirement Age (FRA) get the yearly benefits dictated by the AIME-to-PIA formula. Those who claim Social Security benefits before the FRA have their benefits reduced by an amount that depends on the person's current distance to the FRA. The further away in age someone is from the Full Retirement Age at the time of benefits claiming, the larger the reduction in PIA. Once claimed, the PIA (and, therefore ss_t) remains constant in real terms for the rest of the person's life, save for some exceptions. Men who claim Social Security after the FRA receive the Delayed

[32] 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).

[33] 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% rate, and AIME above the second bend point is replaced at 15%. The maximum covered earnings amount caps AIME. Yearly earnings above this amount are not subject to payroll tax and are not included in the AIME calculation.

Retirement Credit; their benefits are increased in proportion to the number of years since the FRA at the time of claiming. 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 of the 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 D.2.

A 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 before their age has passed 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 as to boost ss_t in future years. I account for the earnings test in the income tax function and in the evolution of $AIME_t$.

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}. In every period, each agent picks consumption, hours, and whether to claim benefits, if that option is available, by solving the following problem:

$$V_t(X_t) = \max_{c_t, n_t, b_t} \left\{ u(c_t, l_t) + \beta(1 - m_t)\mathbb{E}\left[V_{t+1}(X_{t+1})|c_t, n_t, b_t\right] + \beta m_t beq(a_{t+1}) \right\} \tag{13}$$

where assets in the next period are determined by the budget constraint shown in (8). 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 the next period with probability m_t and receive bequest utility $beq(a_t + 1)$ instead.

4.2 Model Estimation: Parameters Set or Estimated Outside the Model

I estimate the model using the men who were 51–56 years old in the first wave of the 1992 HRS cohort. Model estimation proceeds in two parts. In the first, I estimate some parameters directly using the HRS data. Most of these parameters are estimated using the men in the 1992 HRS cohort aged 51–56, though some estimation procedures also include additional HRS sample members when estimating parameters for older ages. I estimate the remaining parameters, mostly preference parameters, using the Simulated Method of Moments (SMM).

4.2.1 Types

Following the empirical analysis in Section 3, I use the first occupation I see individuals hold between ages 51 and 56 to assign type. Recall that *Component 1* is the first principal component of all of the O*NET measures in the 1980 Census. As shown in Table 3, it is highly positively correlated with decision, social, and mathematical input, while it is quite negatively correlated with physical and extreme input. In this way, it is a convenient summary index of the age-friendliness of an occupation. The higher its value for an individual's initial occupation, the more likely that individual is to be working in old age.

I break up the initial sample of men in the 1992 HRS into quartiles of *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* 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 in the survey, their employment rates are in the single digits.

4.2.2 Wage Rate and Spouse Earnings

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

First, I 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.[34]

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

$$\ln w_{ti} = g(t;\theta) + g(t;\theta^o) \cdot \sum_{o \in \Theta} \mathbb{1}\{o_i = o\} + \mathbb{1}\{h_t = h\}\gamma_h + f_i + \varepsilon_{it} \tag{14}$$

where $g(t;\theta)$ is a natural cubic spline in age with parameters θ. The model allows for health effects on wages as well as differences in the age profile of wages by type.[35]

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 14 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

$$e_{it} = f_i + \varepsilon_{it} - \sum_{o \in \Theta} \gamma_o \mathbb{1}\{o_i = o\} \tag{15}$$

I model e_{it} as containing the AR(1) component described in Equation 11 and i.i.d. measurement error me_{it}. Four parameters, then, describe this residual wage process: 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. Appendix Table 3 shows the estimates.

Spouse earnings are estimated using a natural cubic spline in age, health dummies, and interactions between the age cubic spline and health dummies. I assume spouse earnings are 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 2.3. To capture the total variation in health at all ages above 51, I use the pooled panel of men from 1992–2020 from either the 1992 HRS sample or the 1993 AHEAD sample[36]

[34] 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.

[35] Differences in the parameters of the age spline interacted with type, θ^o, capture differences in the wage profiles by type.

[36] The AHEAD sample was a random sample of households of individuals ages 71 and up 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.

I calculate quartiles of the health index variable for this panel. These quartiles define the cutoffs for the four health types, which I label: poor, fair, good, and excellent.

I calculate the probability of transitioning from one health type to another using the same sample. 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 the biennial transition probabilities, I assume that the observed biennial transition probabilities are created by annual transition probabilities that are equal over the two years. With this assumption, I recover the annual transition probability. I similarly calculate mortality probabilities using year-of-death information from the HRS.

Medical expenses are all of a household's out-of-pocket expenditures, a measure available in the HRS. The log of medical expenses depends on a linear term in age, intercept shifts for each health type, and separate post-65 intercept shifts by health type. To estimate these 9 parameters, I match the mean 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:

$$\theta = \left(\alpha, \alpha_t, \{\alpha_h\}_{h=1}^{3}, \{\delta_o\}_{o=1}^{4}, \gamma, \eta, \psi, A, \underline{c}\right)$$

First is the set of parameters in the leisure function: the leisure time cost of employment (α), the age slope of the time cost of employment (α_t), the leisure time cost of poor (α_1), fair (α_2), and good health (α_3), and the leisure time cost of the individual types ($\{\delta_o\}_{o=1}^{4}$). The parameters in the utility function form the second set: the consumption weight (γ) and the risk aversion parameter (η). The bequest parameters (ψ, A) and the consumption minimum ($\underline{c}$) compose the final group.[37] I estimate these parameters jointly using the Simulated Method of Moments (SMM).

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 in the data and analogous ones in the simulated data. The specific moments are also detailed below. 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

[37] The other remaining parameter is the interest rate r. I set it to 3%, following French and Jones (2011).

the $\hat{\theta}$ that minimizes this weighted distance between the data moments and the simulated moments.[38]

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, I need 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 of 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, and 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 are 100 moment conditions in total.

These moments were chosen with the 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, differences in wealth accumulation late in life across wealth quartiles 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

[38] Specifically, I use Controlled Random Search global minimization search algorithm from the NLOpt library

and savings behavior vary 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, Counterfactuals, and Social Security Reform

5.1 Results

Table 5 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 (e.g., French 2005; 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 together imply a coefficient of relative risk aversion of consumption of 3.39, which is within the range of prior estimates.[39] While the curvature of the bequest function, A, has little interpretability, the estimate for ψ, the bequest weight, is 0.0134 in terms of marginal propensity to consume out of final-period (high) wealth. This is about half of that found in the HRS by French and Jones (2011), meaning that my estimates imply larger bequest motives.

The estimates for the costs of leisure from health and the cost of working for different types are as one would expect. Worse levels of health have higher leisure costs. Lower types have higher fixed leisure costs from work. Thus, individuals who have more physical and less cognitive occupations experience a higher disutility from work. Being a Type 2 worker (those with the most physical and least cognitive occupations) means that work 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.

The leisure costs of type and health are small relative to the fixed leisure cost of work common to all individuals α, which is estimated to be 2,056 hours. Only the health costs of those in poor health, 1,317 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

[39] See, e.g., the review in Attanasio and Weber (1995) as well as Cagetti (2003), French (2005), and French and Jones (2011). This is also close to the calibrated value in Ameriks et al. (2011)

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 the richer health process, with four possible health states, reduces the need for the age slope of the disutility parameter, as aging naturally leads to worsening health and increasing costs of working.[40]

Figure 5 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 also replicates how this gap increases with aging. There is a slight understatement of the participation of those of type 2.[41]

The data and simulated counterparts for the rest of the targeted moments are shown in Appendix Figures 11–14. The model matches the wealth percentiles and participation by wealth percentile very well. The estimates also capture differences in participation by health well. The matching performance for the hours profiles is not as good. The model tends to produce many more hours of work, conditional on participation, for those in excellent health when compared to the data, especially at older ages. In aggregate hours, the difference between the data and simulated profiles is smaller, though, because at older ages overall participation is low, and "excellent" health is the least prevalent type of health.

5.2 Counterfactual Analysis

In this section, I analyze two counterfactual scenarios to understand how the observed shifts in occupations across cohorts affect labor force participation and differentially affect welfare along the lifetime income distribution. I refer to these as 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 distribution of types now matches that of the 2004 HRS cohort.[42] I leave all other initial conditions from the simulation intact. The idea is to examine how the new values of disutility from work and wages for the subset of individuals whose type changed affect labor

[40] 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.)

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

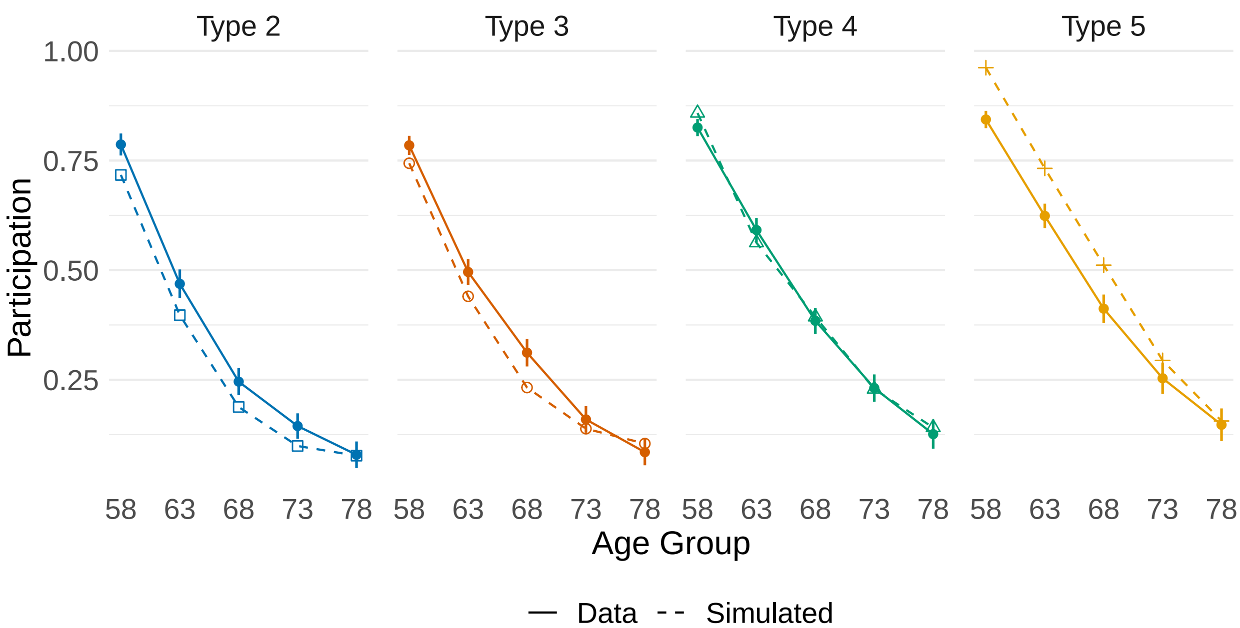
[42] To perform this reconfiguration while leaving the health distribution intact, I randomly select the individuals whose type will be changed (these are selected, in the appropriate proportions, from amongst types whose share declined across cohorts). Then, I randomly assign them, in appropriate proportions,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

Table 5: Parameter Estimates

Preference Parameters Common to All			
β: Discount rate	0.986	L: Leisure endowment	8700
	(0.0039)		(299)
γ: consumption weight	0.500	α: Fixed leisure hours cost of work	2056
	(0.016)		(73)
η: coefficient of relative risk aversion	5.77	α_t: Leisure hours cost age trend	2.07
	(0.62)		(0.98)
ψ: bequest weight	0.0134	A: bequest curvature	1.78m
	(0.00095)		(12.7k)
Consumption floor	$4,579		
	(451)		
Health Leisure Costs (in Hours)		**Type Leisure Costs when Working (in Hours)**	
Poor Health	1317	Type 1	1753
	(92)		(104)
Fair Health	796	Type 2	376
	(60)		(52)
Good Health	369	Type 3	253
	(66)		(51)
		Type 4	64.3
			(25)

This table displays the Simulated Method of Moments parameter estimates. Standard errors are displayed in parentheses.

Figure 5: Model Fit—Participation Moments by Type



This figure displays the mean participation by type and age group in the HRS data and the simulated data. Type is constructed by breaking up the 1992 sample with initial occupations values into quartiles of *Component 1* values. The value of *Component 1* is increasing from Type 2 to Type 5. That is, Type 2 individuals begin the survey in the most physically demanding and least cognitively demanding occupations. The opposite is true for Type 5 individuals. Type 1 individuals are those who were not employed in their early 50s and are thus not assigned an occupation. They have roughly single-digit participation rates at most ages and are omitted for space. Participation means are taken over five-year age bins. The points are plotted at the midpoint of the bin. See Section 4.2.1 for a description of the assignment of types as well as Section 3.3 for more details on the *Component 1* variable.

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. The value of *Component 1* is increasing from Type 2 to Type 5. That is, Type 2 individuals begin the survey in the most physically demanding and least cognitively demanding occupations. The opposite is true for Type 5 individuals. Type 1 individuals are those who were not employed in their early 50s and are thus not assigned an occupation. They have roughly single-digit participation rates at most ages. See Section 4.2.1 for a description of the assignment of types as well as Section 3.3 for more details on the *Component 1* variable. Proportions were calculated using survey weights.

force participation and the distribution of welfare.[43]

Table 6 shows the distribution of types in the two cohorts of interest. Notably, there is an increase in the share of Type 1 men. Recall that these are men who were not assigned an occupation because they were not employed from ages 51 to 56 during the HRS. This increase reflects the decrease in prime-age male labor force participation that has occurred over time.[44] Notwithstanding this decline, the 2004 cohorts saw a major rise (roughly 6 percentage points) in the share of Type 4 individuals along with a large decline in the share of Type 2 individuals. There was also around a 1.5 percentage point decline in the Type 5 share. On balance, there was an increase in *Component 1* across cohorts; one would expect labor force participation among older workers to rise as a result of these occupation shifts, as long as these participation gains overcome the slight increase in the share of men with weak attachment to the labor force (Type 1).

Types + Life History. It is unlikely cohorts experience differences in occupations purely from age 50 onwards. Instead, the differential occupation mix at age 50 likely also reflects different occupation experiences earlier in life, which in turn affect the wealth and AIME with which people arrive at age 50. As a way of examining the potential impacts of these differences in life history across cohorts, the "Types + Life History" counterfactual re-draws initial wealth and AIME according to each individual's new type. For example, individuals who were shifted from Type 2 to Type 4 in the “Just Types” counterfactual now also have a new 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"

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

[44] See Binder and Bound (2019) and Abraham and Kearney (2020) for reviews examining the reasons for this phenomenon.

counterfactual, which held constant the initial wealth and AIME values.

5.2.1 Counterfactual Employment Profiles

I begin by examining how the participation rate profile changes in the two counterfactual scenarios among individuals of Type 2 and above. Figure 6 shows the differences in participation by age between 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.

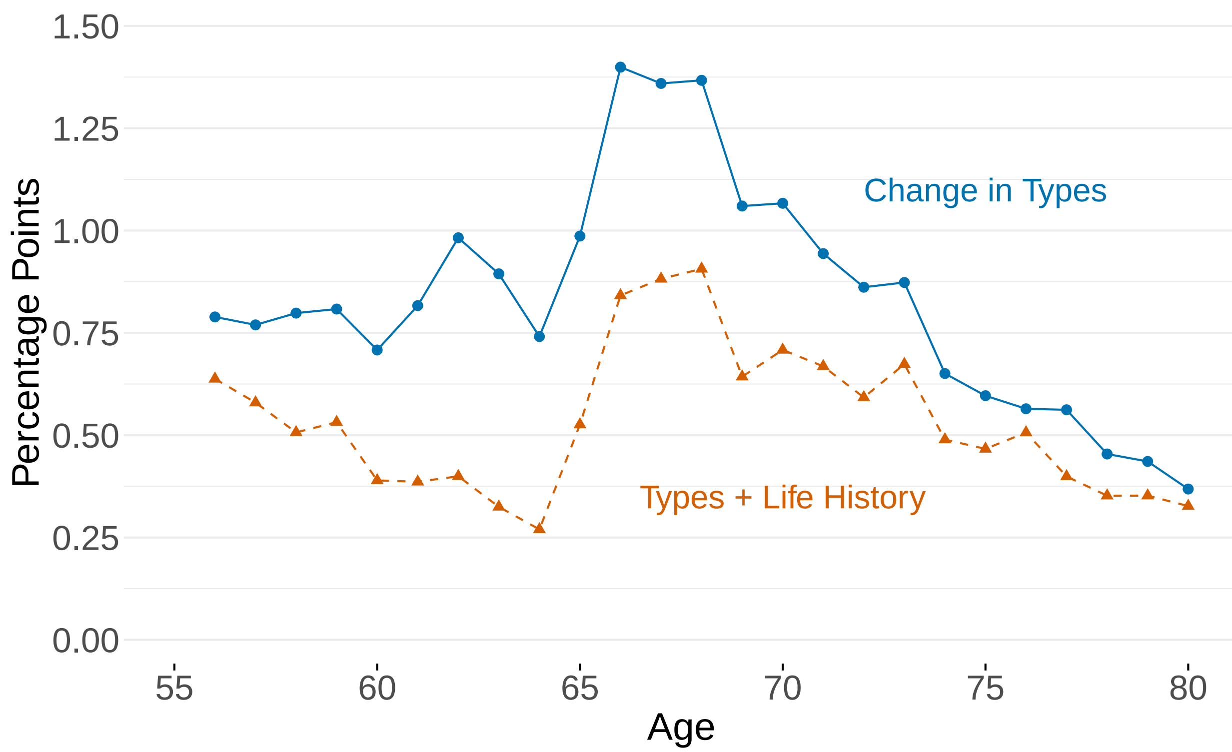
Two features of Figure 6 stand out. First, there is a larger increase in participation in the years after 65 in both counterfactuals. This is due to the earnings test, which, recall, is a (roughly) 50% tax on labor earnings for those who have claimed Social Security. In Figure 6, the earnings test only applies to agents between ages 62 and 65 who have claimed Social Security.[45] The individuals whose type changed for the better (i.e. who now experience a lower disutility from work) would like to work more, at any given age, all else equal. If they have claimed Social Security, however, they are incentivized to substitute some of this increased participation across age 65, as the returns to work are much higher after the earnings test is no longer in effect.

The second major feature of Figure 6 is that adjusting for life history decreases counterfactual participation relative to the “Just Types” scenario. The "Types + Life History" line is always below the line for “Just Types.” The change across the two scenarios is the redrawing of initial wealth and AIME according to the new types. Because the majority of type changes are improvements (in particular improvements from Type 2 individuals to Type 4), and higher types have life histories associated with higher wealth and lifetime income, the lower participation gains in the "Types + Life History" counterfactual are due to wealth effects. All else equal, individuals who are wealthier (be it liquid wealth or Social Security wealth) would like to work less since participation is costly in utility terms. These wealth effects coming from the changes in life history dampen, but do not reverse, the participation boosts from changes in types.

One final note is that, as was the case in the empirical findings from Section 3, the average percentage point difference between ages 70–79 is similar to the average percentage point difference between ages 60–69, even though overall participation is much lower at ages 70–79 than at ages 60–69. The model is thus able to reproduce this feature from the data.

[45] The model is estimated using the rules that were in effect for the 1992 HRS cohort. For this cohort, the Full Retirement Age was 65 and 2 months. See Section 4.1.5 for more details on the Social Security Program’s rules.

Figure 6: Difference in Participation: Counterfactual Minus Baseline



The figure displays the average participation by age in the counterfactual scenarios minus the average participation by age at baseline. The "Just Types" counterfactual is displayed in the blue solid line. This counterfactual changes only types at age 51 but leaves initial wealth and Average Indexed Monthly Earnings (AIME) intact. AIME determines Social Security benefits. The dashed orange line displays the results for the "Types + Life History" counterfactual. This counterfactual changes types and also redraws wealth and AIME among those who had their type changed. The sample is restricted to individuals of Type 2 and above. An individual is Type 2 and above if they had an occupation in their early 50s. Type 1 individuals are those with very low labor market attachment.

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.

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 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.[46] 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 the 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?[47]

The results of this exercise are shown in Table 7. 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 in wages and in the leisure costs of work for a subset of the individuals in the simulation, improve welfare at the bottom quartile of age 51 AIME by 0.19% in consumption-equivalent terms. The second and third quartiles experience similar welfare effects. By contrast, the top quartile sees a very small reduction in welfare.

The reasons welfare changes are distributed in this manner in the “Just Types” counterfactual are that (1) the share of Type 5s, who have the highest earnings and the lowest disutility from work, decreased; (2) Type 2s, the group whose share saw the biggest decrease, are present in every initial AIME quartile; and (3) most Type 2s whose type was shifted

[46] This is the expected value at age 51 of Equation 13, the value function in the recursive formulation.
[47] This is the measure Low, Meghir, and Pistaferri (2010) use to measure welfare effects.

became Type 4s. As the differences in wage and disutility from work between Types 2 and 4 are large, this shift produces welfare gains across the board by lifetime income below the top quartile. It fails to do so for the top income quartile because some Type 5s, who are prominent at the top of the initial AIME distribution, switched to lower types.

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).[48]

As discussed above, arriving at age 50 with a different occupation very likely reflects not only that the individual has a different set of occupations available from age 50 onwards. Rather, it also likely reflects that the individual had a different life trajectory leading up to that point. To model this difference in life trajectories, 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 a different initial quartile of AIME. Those who were switched to Type 1 will likely experience a fall in wealth and AIME, while those who were switched to Type 4 will experience increases in wealth and AIME on average.

The second row in Table 7 displays the welfare changes by lifetime income quartile in the "Types + Life History" counterfactual. Now the welfare gains are positive and large for the three highest lifetime income quartiles. The shifts in occupation increase wealth and lifetime income among those with "improved" occupations, moving them up in the lifetime income rankings and greatly improving 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.[49] My contribution is to qualitatively and quantitatively show that changes in the kinds of work people do during their lives as well as declines in men's attachment to the labor market have contributed to widening inequality in welfare among older households.

[48] 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.

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

5.3 Social Security Reform

When policymakers or analysts evaluate Social Security reforms, such as increasing the Full Retirement Age, they are often concerned that such changes will lead to longer work in physically demanding occupations (SSA 1986; Steuerle and Kramon 2023). In this section, I assess the impact of two Social Security reforms on the labor force participation of those in the most physically intensive occupations and the poorest health. Both reforms were scored by the Office of the Chief Actuary of the Social Security Administration as bringing similar long-term savings to the Social Security program (SSA 2016).[50] I briefly describe the policy changes. Appendix E includes the details. Reassuringly, in the model estimates I find that the reforms produce reductions in total Social Security benefits paid by the government.

Full Retirement Age (FRA) Increase from 67 to 69. This policy increases the FRA from 67 to 69. Individuals are still permitted to retire early starting at age 62. But they are only entitled to their "full" benefits (as determined by the formula converting AIME to benefits) if they retire at age 69, and benefit reductions from early retirement are done now in reference to age 69 instead of 67. This is roughly a retirement benefits cut of around 13% at any given age of benefits claiming. Functionally, it is a benefits cut that hits all individuals roughly the same in percentage-of-benefits terms.[51]

AIME to Benefits Formula Change. This policy keeps the FRA at 67 but drastically reduces the replacement rates of AIME at high incomes. Whereas the marginal replacement rates of AIME are currently 90%, 32%, and 15%, this policy changes them to 95%, 27.5%, and 2%. As a result, it reduces the benefits of high lifetime income individuals the most, and *increases* the Social Security benefits for some of the lowest lifetime income individuals.

Appendix Table 4 gives a sense of the benefits reductions from these policy changes and how these impacts differ across types. The table displays the percentage decrease in lifetime Social Security benefits received as a result of the policy changes. Reassuringly, the two reforms have similar total effects in the model. An increase in the FRA from 67 to 69 leads to a 12.8% total reduction in Social Security benefits paid, while the change in the AIME-to-benefits formula leads to a 12.2% total reduction.[52]

The policies' distributional impacts are, however, very different. When the FRA is increased, the percent reduction in total benefits is similar across types. By contrast, the reform that changes the benefits formula concentrates benefit reductions (in percentage terms) on higher types. In that policy change scenario, there is nearly no average reduction in benefits

[50] Both were taken from a 2016 proposal by Representative Sam Johnson (SSA 2016). A more recent set of Social Security reform proposals released by the Republican Study Committee, a conservative caucus in the House of Representatives, drew on Representative Sam Johnson's 2016 proposal (RSC 2022).

[51] Of course, individuals may change their date of benefits claiming in response to the change in policy.

[52] This is a pure summing of benefits across time. The values are not discounted depending on age.

for Type 1 agents (0.14%), a modest reduction for Type 2 agents (8.2%), and an increasing reduction in benefits as type increases, culminating with a 20% decrease in Social Security benefits received by Type 5 agents. Because higher types tend to have higher lifetime income and, hence, higher AIME, the change in the benefits formula affects higher types more (as a percentage of benefits) than lower types.

Note that for the reform that increases the FRA, I likely overstate the percent benefit reductions among the lower types, especially Type 1. This is because a significant chunk of this group will, in reality, depend on Disability Insurance (DI) benefits rather than Social Security benefits. As DI benefit amounts are unaffected by changes in the FRA, some individuals in this group will be insulated from changes in the FRA. Indeed, Springstead (2011) finds, using the Social Security Administration's Modeling Income in the Near-Term Model, that roughly 30% of people in the bottom two quintiles of lifetime income would not see benefit changes as a result of an increase in the FRA, while that amount is between 10 and 20% for the other three quintiles.[53]

Figure 7 displays the estimated participation effects of the policy reforms by age. It does so separately for each type.[54] The results are relative to the current policy; they display the average change in participation by person type and by age. Recall that Type 2 individuals are those in the most physically intensive and least cognitively intensive occupations. As type increases, the agents' occupations become less physically intense and more cognitively demanding.

Panels (a) and (b) of Figure 7 show the participation effects of the increase in retirement age. Type 2 men increase their participation rate at most ages in response to the increase in retirement age. Type 3 men display similar behavior, while Type 4 and 5 men only increase their labor force participation in their 70s. Thus, while all types increase participation in response to the negative Social Security wealth impact of the increase in retirement age, Type 2 men see the largest increases. This is especially evident in percentage terms, as shown in Figure 7(b). Type 2 men increase their participation the most in percentage terms at all ages in response to the retirement age increase. Because Social Security is a larger share of old-age income for poorer individuals, and Type 2 individuals tend to have lower wealth, lifetime income, and wages, it is thus individuals in these most physical and unpleasant occupations who increase participation the most in response to an increase in the FRA.

By contrast, the policy that keeps the FRA at 67 and instead reduces the AIME replace-

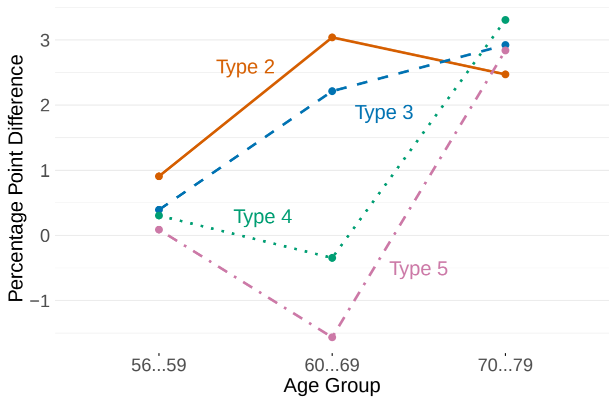
[53] Note that the Springstead (2011) figures are for lifetime income quintiles. DI collection is likely to be even more skewed among Type 1s compared to income quintiles because Type 1s are those who had no employment in their early 50s and so might be classified as Type 1 precisely because they were collecting DI payments.

[54] I ignore Type 1 in these participation figures since policy changes have little effect on their participation.

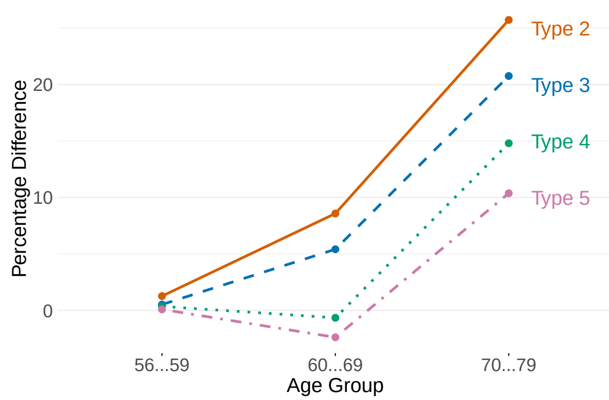
Figure 7: Participation Effects of Policy Changes Relative to Current Policy

Policy 1: Increasing Retirement Age from 67 to 69

(a) Percentage Point Effect

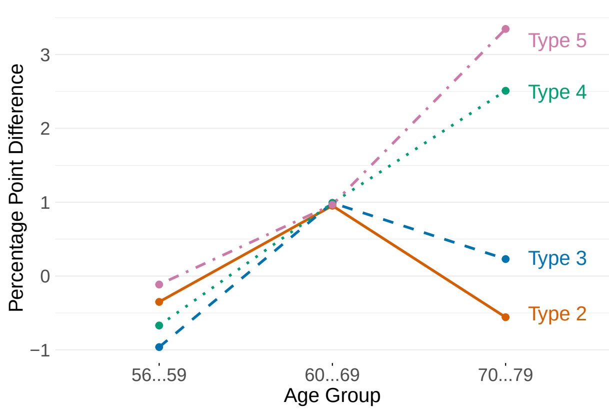


(b) Percentage Effect

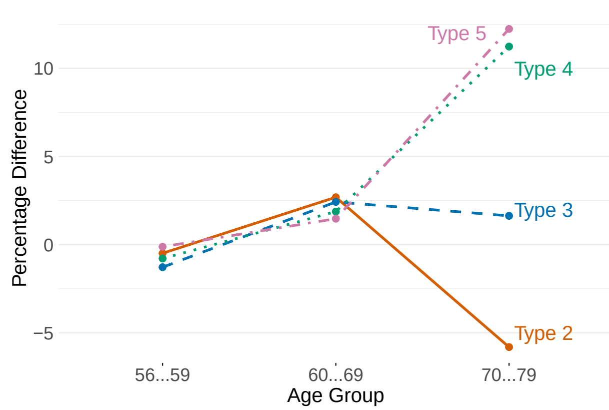


Policy 2: Progressive Change in AIME-to-Benefits Formula

(c) Percentage Point Effect



(d) Percentage Effect



These figures display the difference in participation between the policy reform counterfactual and current policy. Panels (a) and (b) display the participation difference from a policy that increases the Full Retirement Age from 67 to 69. Panels (c) and (d) display the participation difference from a policy with similar fiscal savings that concentrates benefit reductions among the highest earners. Type is constructed by breaking up the 1992 sample with initial occupations values into quartiles of *Component 1* values. The value of *Component 1* is increasing from type 2 to type 5. That is, type 2 individuals begin the survey in the most physically demanding and least cognitively demanding occupations. The opposite is true for type 5 individuals. See Section 4.2.1 for a description of the assignment of types as well as Section 3.3 for more details on the *Component 1* variable.

ment rates of those with the highest lifetime income does not induce similar increases in the participation of Type 2 men. Panels (c) and (d) of Figure 7 show the participation changes due to this policy change. There is a weak participation response among all types to the policy change at ages 56–69. At ages 70–79, only Type 4 and 5 men increase labor force participation relative to the current policy, and Type 2 men slightly decrease participation. This policy change concentrates benefit cuts among higher lifetime income individuals, who are disproportionately of higher types. Hence, it is Type 4 and 5 individuals who experience a large reduction in Social Security wealth and work more in response.

The policy counterfactuals show that the kind of Social Security reform implemented affects who works more in response. When the reform cuts benefits at all lifetime incomes roughly equally in percentage terms, those in the most physical and lowest earnings jobs significantly increase labor force participation. The effect is particularly large in percentage terms, as individuals in those jobs had lower participation rates at those ages in the baseline policy.[55]

In the model, inducing more work among those in the most physical occupations is costly as, all else equal, individuals in these occupations would rather retire earlier than individuals in other occupations. To assess which policy for reducing the Social Security deficit is preferable in light of differences in the cost of work across types, I compare aggregate welfare under the two counterfactual policies.

The results are displayed in Appendix Table 5. I express the welfare difference in terms of the percentage consumption increase needed to get aggregate welfare under the Full Retirement Age increase reform to equal aggregate welfare under the reform that changes the AIME-to-benefits formula. I find that, indeed, the aggregate expected utility at age 51 under the Social Security reform that changes the AIME-to-benefits formula is larger than the aggregate expected utility at age 51 under the FRA increase. This is both because it is costly to have Type 2 (and, to a lesser extent, Type 3) workers increase their participation and because Types 1, 2, and 3 individuals are poorer and, hence, have a higher marginal utility of income.

One might be concerned that the poorest and with the least attachment to the labor market, Type 1 individuals, drive the aggregate welfare conclusions. But aggregate expected utility at age 51 is also higher under the reform that changes the AIME-to-benefits formula even when restricting only to Types 2 through 5 in the aggregation. It is also higher under the AIME-to-benefits formula change when the aggregation is done using the 2004 HRS type distribution. The aggregate welfare difference between the two policies, though, does

[55] Appendix Figure 15 shows that the FRA also induces those in poor and fair health to work more, but the effects are not monotonic in health.

fall slightly when using the 2004 HRS type distribution, as the number of type 2 individuals decreased and hence additional work is less costly in aggregate.

6 Conclusion

In this paper, I measured how changes in work have contributed to the rise in old-age labor force participation that has been occurring since the 1990s. To do so, I used the relationship between the occupation characteristics of individuals in their early 50s in the HRS and their later labor force participation. I found that people in more decision- and social-intensive occupations tend to work longer. The opposite is true for people in more physical and extreme occupations. Combining this relationship with aggregate trends in occupation tasks and characteristics in the Census/ACS, I found 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, while this number is 5.8–9.0% for women. Using a novel model of old-age labor supply with occupation differences, I found that the observed shifts in occupation across cohorts in the HRS for men produce welfare increases for all but the bottom quartile of lifetime income, which experienced declines in welfare as a result of the increasing share of men with low attachment to the labor force. Moreover, an increase in the Full Retirement Age from 67 to 69 induces large increases in the participation of individuals in the most physically intensive occupations. This is particularly costly in my model, as this kind of work brings higher disutility than other kinds of work.

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 more pleasant work. To the extent policymakers see a redistributive motive for Social Security, the results here add to the growing evidence that inequality of welfare in old age has been increasing.[56] As policymakers evaluate options for closing the deficit in the Social Security Trust Fund, they may prioritize cutting benefits for higher earners rather than cutting benefits across the board by, for example, increasing the Full Retirement Age. I find that the former reform better insulates those in the most physical occupations from participation increases.

Future work could extend the time period 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 the dominant force in occupation change by far. As artificial intelligence changes the kind of work that is replaced

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

or augmented by technological change, it will be important to monitor the extent to which the kind of work in the economy promotes or discourages longer working lives—especially in the face of an aging population. Further work is also needed to incorporate women into the model or analyze them independently. Women's increasing lifetime investment in careers means both that they are increasingly important contributors to couples' incomes and that their lifetime earning dynamics have a greater impact on a household's Social Security benefits in 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.

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Appendix

A Data Appendix

A.1 ONET Variables and Occupation Crosswalks

The HRS's restricted-access data reports the three-digit Census occupation of almost all individuals who are working in each wave. Moreover, occupations in the Census and ACS, which I use to measure trends in tasks and occupation characteristics, are reported at the three-digit Census occupation code level.[57] Occupational Information Network (O*NET) data, my source for the task intensity and characteristics of occupations, contains data on occupations at the O*NET-SOC level, a much finer classification system than the Census's occupation coding scheme. To crosswalk O*NET-SOC codes to the three-digit Census occupational coding scheme used in the HRS sample, I proceeded as follows. First, I linked O*NET 5.0 eight-digit O*NET-SOC codes to their corresponding six-digit SOC code.[58] Then, I linked each SOC code to a three-digit Census code from the 2000 classification scheme using crosswalks provided by the Bureau of Labor Statistics. Finally, I use crosswalks from Autor and Dorn (2013) and Deming (2017) to link the 2000 Census codes to *occ1990dd*, a consistent occupation coding scheme for the Census across years developed by Autor and Dorn 2013. Thus, I have a crosswalk of O*NET-SOC code to *occ1990dd* code.

Each *occ1990dd* occupation's score in the O*NET measures is then the simple average of its linked O*NET-SOC codes. In most cases, there is no averaging to be done. 60% of *occ1990dd* codes are matched only with one O*NET-SOC code. A further 18% are matched to exactly two. 93% of the occupations are matched to four or fewer O*NET-SOC codes.

Using the crosswalks from Autor and Dorn (2013) and Deming 2017, I can assign O*NET measure values to occupation codes in the 1970, 1980, 1990, 2000, and 2010 Census occupation coding schemes.

A.2 Health Variables

I follow Blundell et al. (2021) to create a health index. I produce it in three steps. First, I extract the first principal component of three self-reported health variables in the HRS. Then, I regress this first component on a natural cubic spline in age, demographic indicators, and indicators for whether the individual has ever had each of the following conditions: high blood pressure, diabetes, cancer, lung disease, heart problems, strokes, and arthritis. The third

[57] The actual scheme changes depending on the Census year.

[58] This relationship is purely hierarchical: each O*NET-SOC corresponds to exactly one six-digit SOC code, and many six-digit SOC codes only have one corresponding O*NET-SOC code.

step produces the fitted values from the above regression, which become the health index. The procedure thus uses the objective health measures as instruments for the subjective health measures. Instrumenting deals with two potential sources of bias: measurement error and justification bias. The latter is a bias that comes from individuals *justifying* their current employment status (or lack thereof) by reporting poorer health in the subjective measures.

The three self-reported health variables used are self-reported health status, an indicator for whether health limits work, and an indicator for whether the person has mobility limitations. The self-reported health variable can take on five values: excellent, very good, good, fair, and poor. These responses are coded from 1 (for excellent) to 5 (for poor). The second subjective measure, whether health limits work, is a binary variable.

The final subjective measure, an indicator variable for whether the person has mobility limits, is constructed based on the response to a set of questions about mobility (Blundell et al. 2021). It takes on a value of 1 if an individual reported at least "some difficulty" when performing at least one of the following activities: walking several blocks, sitting for 2 hours, getting up from a chair, climbing several flights of stairs, climbing one flight of stairs, stooping/kneeling/crouching, carrying 10 lbs., picking up a dime, reaching/extending arms up, and pushing or pulling large objects. It takes on a value of 0 if the individual reported having less than "some difficulty" in performing all of the aforementioned activities.

B Trends in Occupation Characteristics

Appendix Figure 1 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 general population's occupations. By contrast, their occupations have slightly less decision-making and social tasks and less routine tasks.

Older men have also seen trends in occupational characteristics similar to those of the broader population. This can be seen in Appendix Figure 1 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 for this age group has been larger than the increase for men as a whole. For example, the 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, the 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. This group of men has similar trends in occupational characteristics to men ages 60 and older.

C Discussions of Additions of Controls and Robustness Checks

C.1 Figure 4

The additional set that produced the most movement in Figure 4(a) was the "Baseline Controls" set. In particular, it increased the (negative) coefficient on the routine characteristic. This result is expected given that more routine jobs likely had a higher incidence of defined pension benefits and retiree insurance. Not accounting for this relationship could bias downward the measured relationship between routine characteristics and older labor force participation because defined benefit pensions and retiree insurance generally reduce the returns from working longer. The relative stability of the coefficients to the inclusion of 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 I included in Figure 4 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 effects of the changing nature of work on old-age labor supply. Reassuringly, including education does not change much the estimated coefficients.

C.2 Table 4

Perhaps, as the United States population has aged, the changing mix of different ages has changed the relative supply and demand for older workers (Neumark and Yen 2020). 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 (Neumark and Yen 2020), but the point estimate for α barely changes.

In Columns 3, 4, and 5, I include controls similar to those I included in Figure 4. 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.[59] 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 dampens the estimate of α, but this is not enough to blunt its statistical significance. The evidence from estimates of Equation 4 indicates, therefore, that changing occupational characteristics have caused increased participation among older men.

D Model Appendix

D.1 Taxes

I use the tax schedule from French and Jones (2011). It is based on the federal income tax tables in 1998 and the state income taxes from Rhode Island in that same year. Rhode Island was chosen because it was "fairly representative" of state income taxation. The tax schedule also includes payroll taxes.

D.2 AIME Evolution

To model how additional labor earnings affect AIME, I follow French and Jones (2011). Recall that actual AIME is the average of an individual's best 35 earnings years. If an individual has worked fewer than 35 years, their total indexed earnings are still divided by 35 to produce AIME. Keeping track of the best 35 earning years is not possible in the model. Instead, AIME in the model evolves according to the formula

$$AIME_t+1 = (1+g\mathbb{1}\{age \leq 60\})AIME_t + \frac{1}{35}\max\{0, w_t n_t - \alpha_t(1+g\mathbb{1}\{age \leq 60\})AIME_t\}.$$

The first term captures how earnings are *indexed* to current average earnings. g is the average annual real growth rate of wages, set to 1.6% (French and Jones 2011). The indexing in AIME halts after age 60, as in the real-life computation of AIME. The second term captures the updating that happens when the current year's labor earnings, $w_t n_t$, are greater than that of the previous lowest-earnings year. α_t "approximates the ratio of the lowest earnings year to AIME," (French and Jones 2011). French and Jones (2011) estimated the α_t sequence using wage simulations of the model in French 2005. They estimated α_t until age 71, and I

[59] 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.

extend the sequence through ages 72 to 81 using linear extrapolation from the α_t values for ages 65 through 71.

E Social Security Reforms

E.1 Retirement Age Increase from 67 to 69

Under current policy, an individual is entitled to their full Principal Insurance Amount (calculated using Average Indexed Monthly Earnings) if they claim benefits at age 67. Claiming at any age before or after leads to an adjustment of the annual benefits to which they are entitled. Claiming benefits at age 62, for example, means that an individual's annual benefits will be set at 70% of their PIA. The corresponding numbers for claiming at subsequent ages are 75%, 80%, 86.6%, and 93.3%.[60] If an individual delays claiming benefits until they are past age 67, they receive an additional percentage boost in their Social Security benefits. The credit is an 8% increase in PIA for every age past the Full Retirement Age (currently 67) at which the individual claims Social Security benefits.

An increase in the Full Retirement Age changes the reference age on which all of these reductions and increases are based. After the increase in the Full Retirement Age to 69, a person who claims benefits at age 62 receives an annual Social Security benefit that is 61% of their PIA. The corresponding percentages for subsequent ages are 65.5%, 70%, 75%, 80%, 86.6%, and 93.3%. Further, there is now only one age at which individuals qualify for the Delayed Retirement Credit: age 70.

E.2 Progressive Change in AIME to Benefits Formula

With this policy change, I keep the Full Retirement Age at 67 and instead produce similar fiscal savings (SSA 2016) by changing the formula that converts AIME to PIA. Currently, there are two bend points in the AIME-to-PIA formula. Before the first bend point, every additional dollar of AIME corresponds to 90 additional cents of PIA. From the first bend point to the second bend point, this replacement rate is 32%. Finally, from the second bend point until the maximum taxable earnings, the replacement rate is 15%. The first bend point is currently at around 22% of the average wage index, and the second bend point is at around 133% of the average wage index.

The policy reform changes the bend points in the formula and the replacement rates. The first bend point increases to 25% of the average wage index. The second bend point decreases to 125% of the average wage index. The replacement rate for AIME's below the

[60] Note that, in reality, these adjustments occur at the monthly level; an additional amount is deducted from PIA for every month left until the person turns 67.

first bend point changes to 95%, while the other two replacement rates become 27.5% and 2%.

This reform is similar to one proposed by Rep. Sam Johnson in a package of Social Security reforms (SSA 2016). The long-term savings projected by the Office of the Chief Actuary of the Social Security Administration from his proposed change in the AIME-to-PIA formula were similar to the savings they projected from an increase in the Full Retirement Age from 67 to 69. His reform has some slight differences from the reform I implemented in the model. In particular, his reform added a bend point at 100% of the average wage index. The replacement rate between this bend point and the top bend point was 5%.

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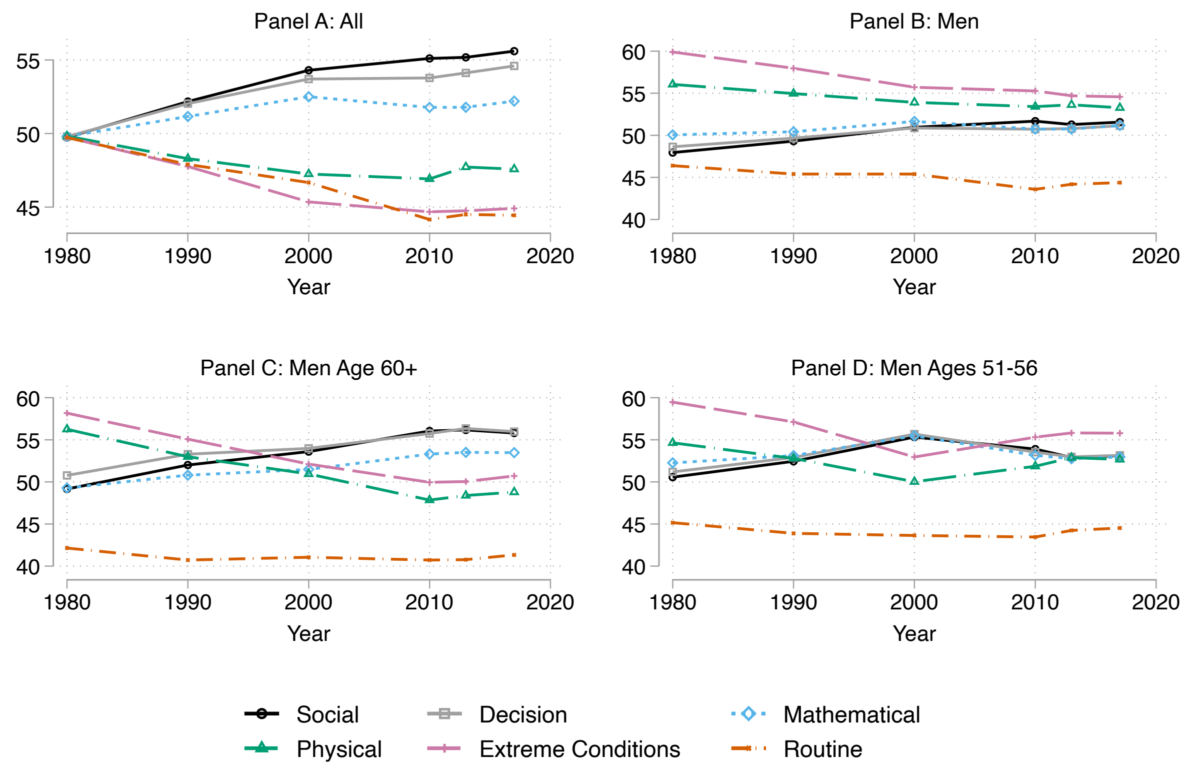
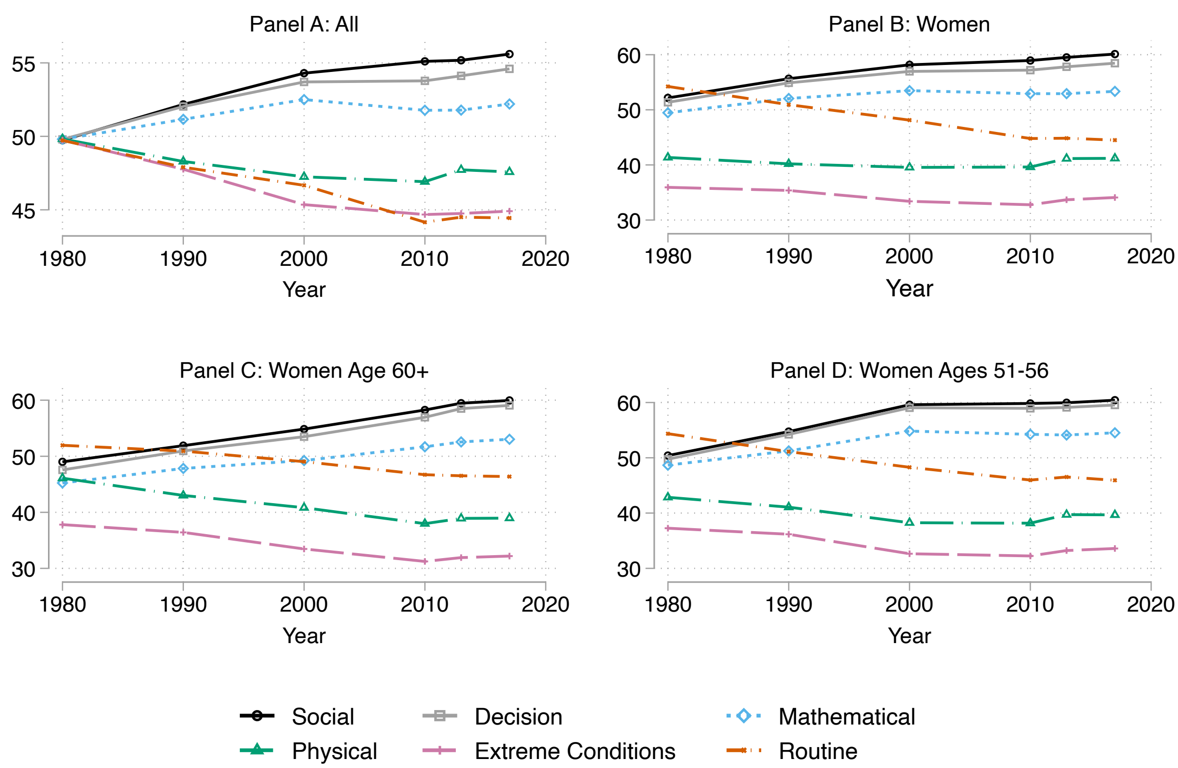
Appendix Figure 1: Trends in U.S. Employment Task Intensity: Men Subsets



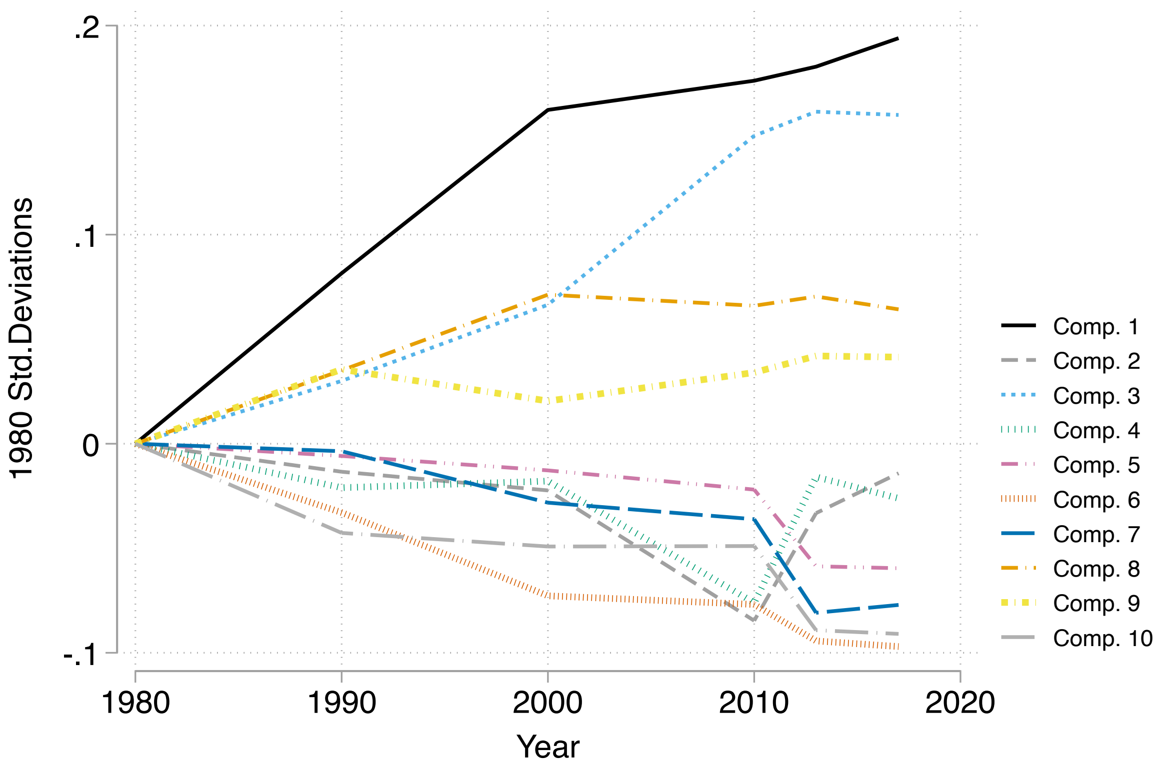
This figure shows the mean task intensity in the Census and ACS over time among different subsets of workers ages 20 and older. "All" refers to the full population, not just men. Data are from the 5% sample of the 1980, 1990, and 2000 Census as well as the 2008-2010, 2011-2013, and 2013-2017 multi-year samples of the American Community Survey. Tasks are constructed from O*NET scales (see Section 2.2). The measures are rescaled so that they are expressed in centiles of the 1980 task distribution.

Appendix Figure 2: Trends in U.S. Employment Task Intensity: Women Subsets



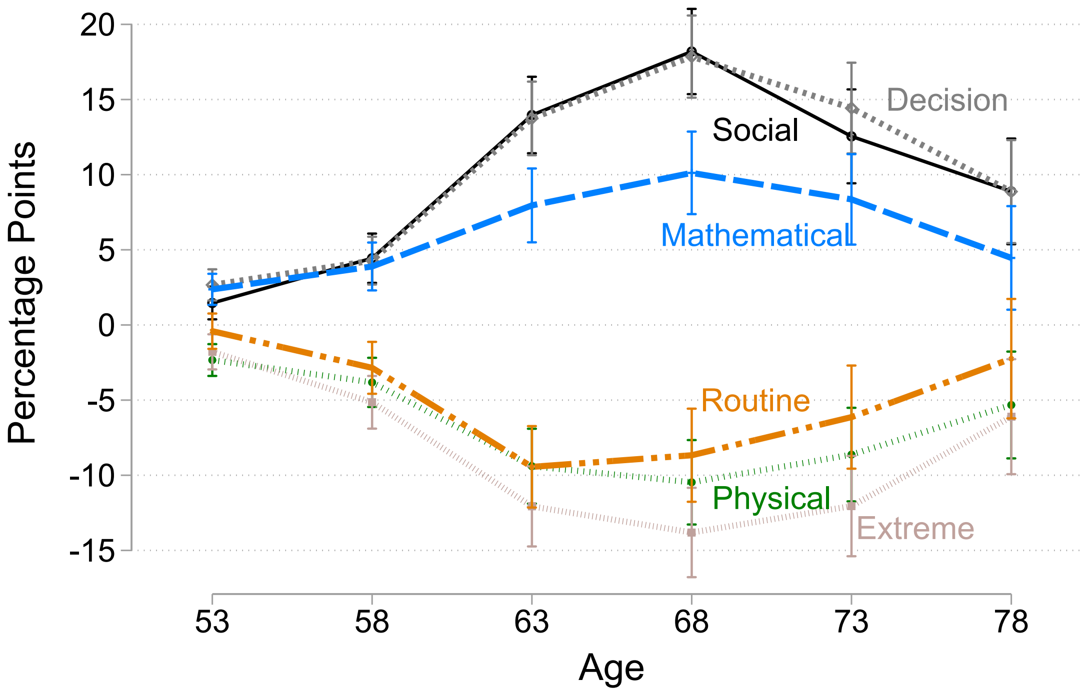
This figure shows the mean task intensity in the Census and ACS over time among different subsets of workers ages 20 and older. "All" refers to the full population, not just women. Data are from the 5% sample of the 1980, 1990, and 2000 Census as well as the 2008-2010, 2011-2013, and 2013-2017 multi-year samples of the American Community Survey. Tasks are constructed from O*NET scales (see Section 2.2). The measures are rescaled so that they are expressed in centiles of the 1980 task distribution.

Appendix Figure 3: Trends in U.S. Employment Task Intensity: PCA Variables



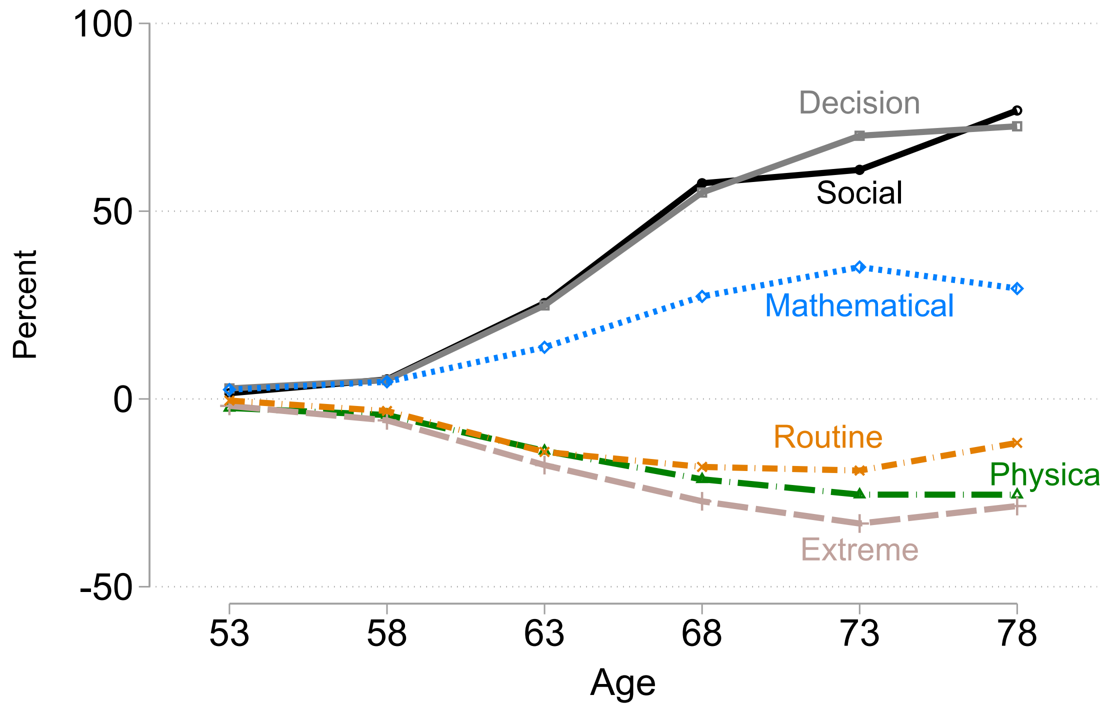
This figure shows the mean PCA occupation characteristic intensity in the Census and ACS over time. Data are from the 5% sample of the 1980, 1990, and 2000 Census as well as the 2008-2010, 2011-2013, and 2013-2017 multi-year samples of the American Community Survey. The PCA variables are constructed by taking a PCA of the O*NET measures of employed individuals in the 1980 Census. Afterwards, they are standardized.

Appendix Figure 4: Difference of Employment Rate Between Men in Top and Bottom Task Tercile



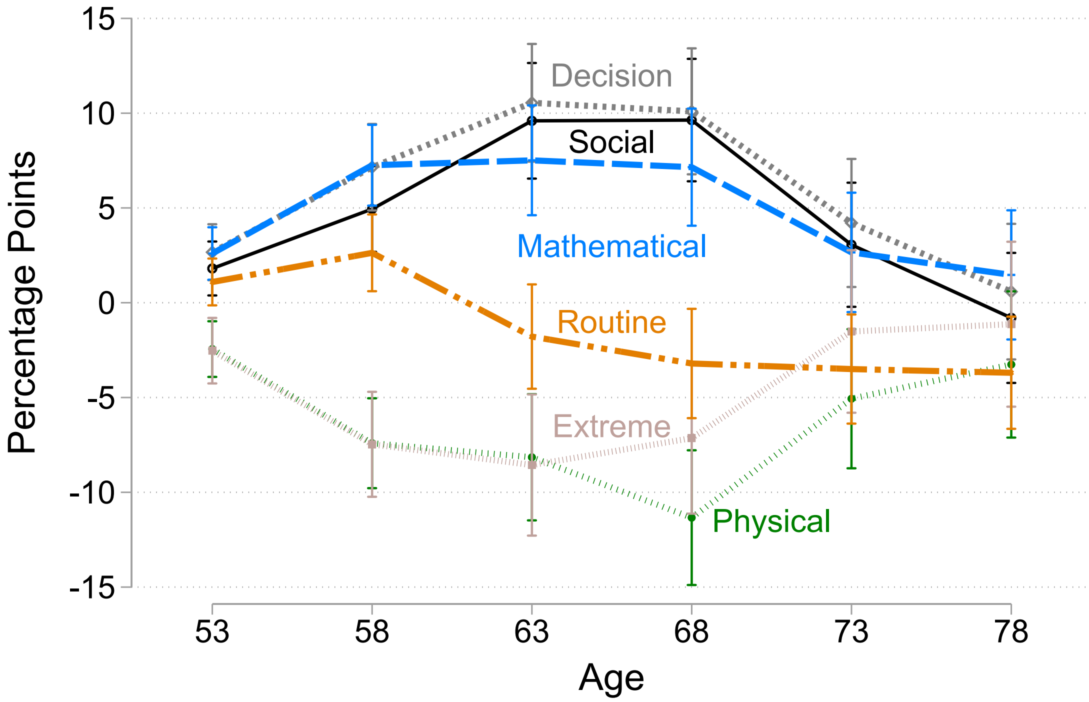
The figure plots the difference in the participation rate between individuals in the top tercile of a given task's intensity and the individuals in the bottom tercile of the same task's intensity. For a given task or characteristic, an individual falls in the "top" tercile if his initial occupation's 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 cohorts 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 5: Difference of Employment Rate Between Men in Top and Bottom Task Tercile Divided By Bottom Task Tercile Employment Rate



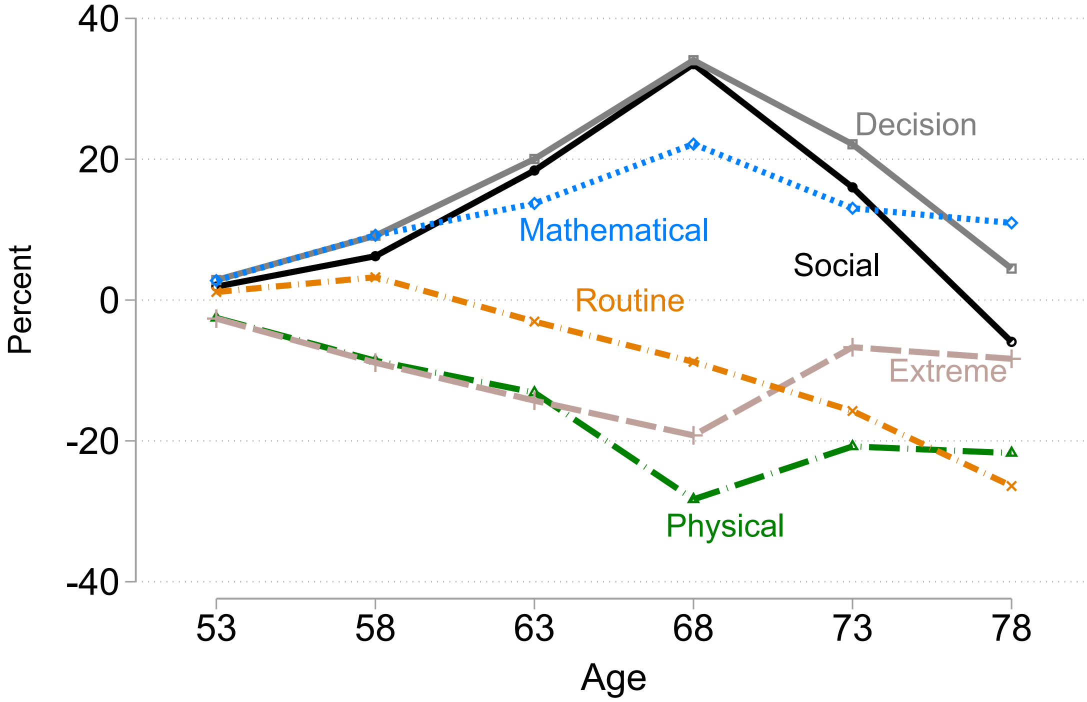
The figure plots the difference in the participation rate between individuals in the top tercile of a given task's intensity and the individuals in the bottom tercile of the same task's intensity. For a given task or characteristic, an individual falls in the "top" tercile if his initial occupation's value in that characteristic was larger than the 66.6th percentile of the 1980 distribution. Likewise, he falls in the "bottom" tercile if her 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 HRS cohorts 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. The point is plotted at the midpoint of the age bin.

Appendix Figure 6: Difference of Employment Rate Between Women in Top and Bottom Task Tercile



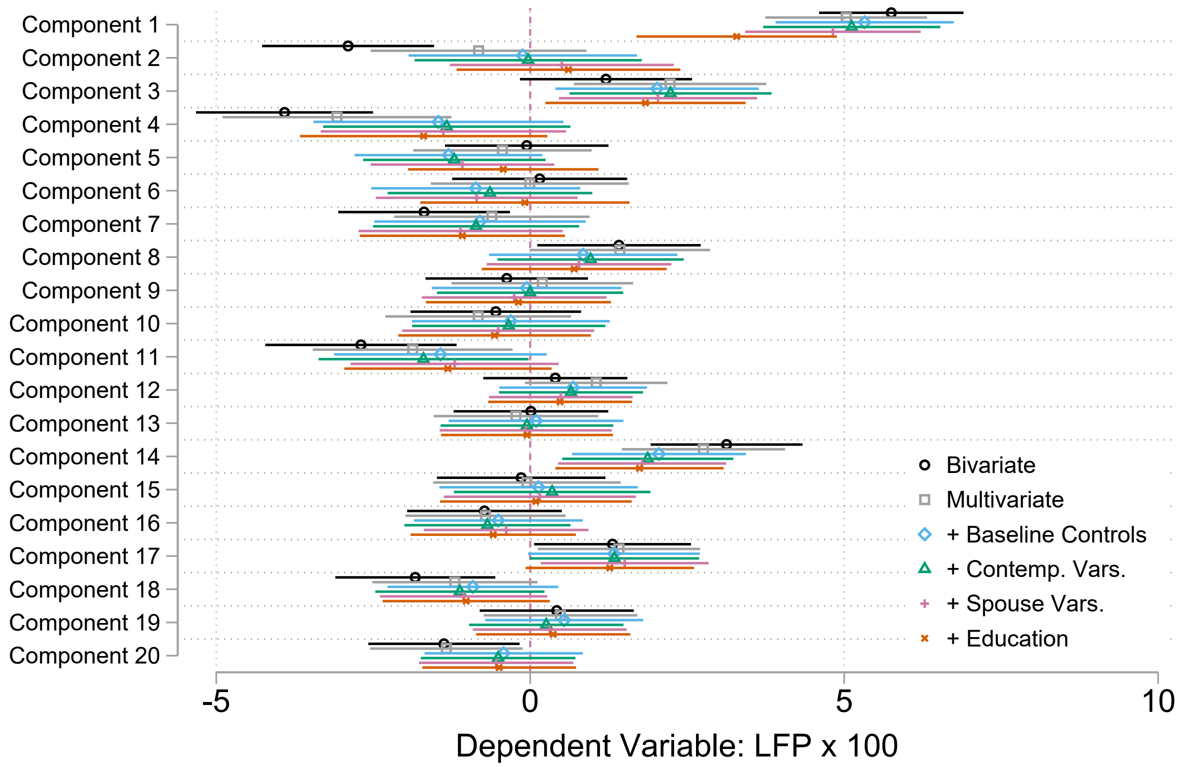
The figure plots the percent difference in the participation rate between individuals in the top tercile of a given task's intensity and the individuals in the bottom tercile of the same task's intensity. For a given task or characteristic, an individual falls in the "top" tercile if her initial occupation's value in that characteristic was larger than the 66.6th percentile of the 1980 distribution. Likewise, she falls in the "bottom" tercile if her initial occupation's value in that characteristic was lower than the 33.3rd percentile of the 1980 occupational distribution. The sample is women from the 1992, 1998, and 2004 HRS cohorts 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. The point is plotted at the midpoint of the age bin.

Appendix Figure 7: Difference of Employment Rate Between Women in Top and Bottom Task Tercile Divided By Bottom Task Tercile Employment Rate



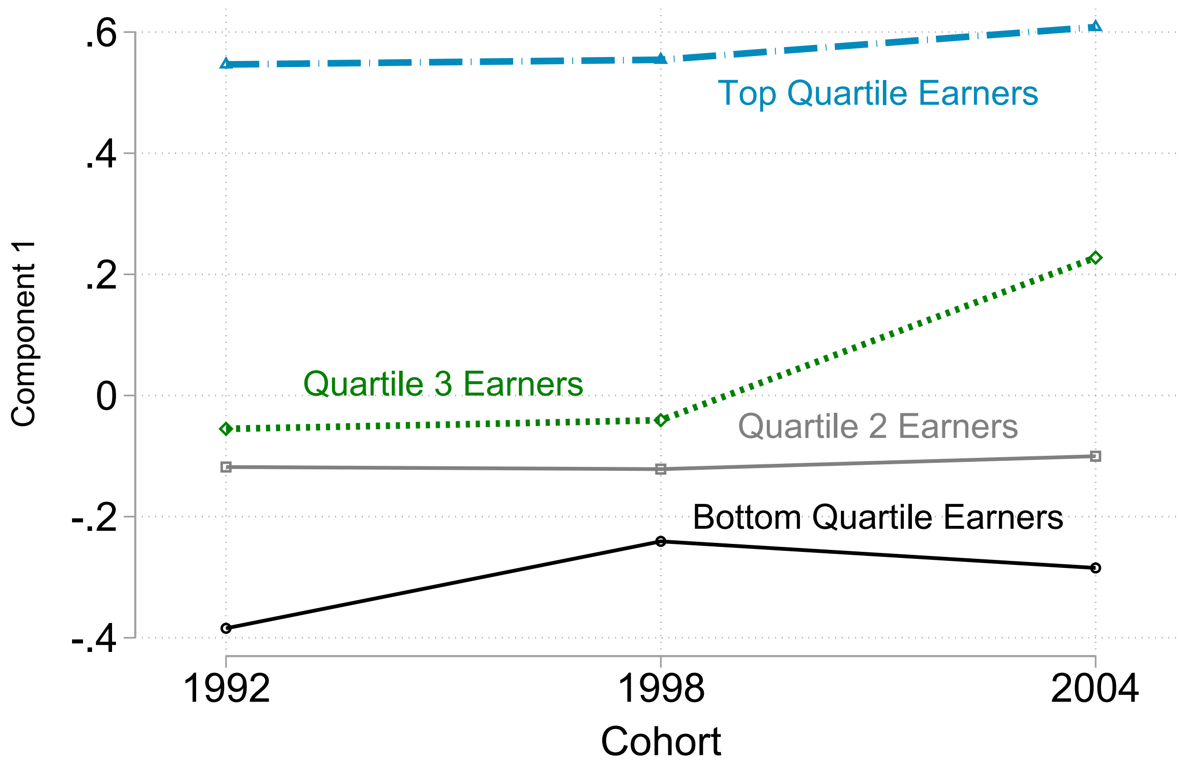
The figure plots the percent difference in the participation rate between individuals in the top tercile of a given task's intensity and the individuals in the bottom tercile of the same task's intensity. For a given task or characteristic, an individual falls in the "top" tercile if her initial occupation's value in that characteristic was larger than the 66.6th percentile of the 1980 distribution. Likewise, she falls in the "bottom" tercile if her initial occupation's value in that characteristic was lower than the 33.3rd percentile of the 1980 occupational distribution. The sample is women from the 1992, 1998, and 2004 HRS cohorts 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. The point is plotted at the midpoint of the age bin.

Appendix Figure 8: Male Labor Force Participation at Ages 60–69 and Initial PCA Task Input



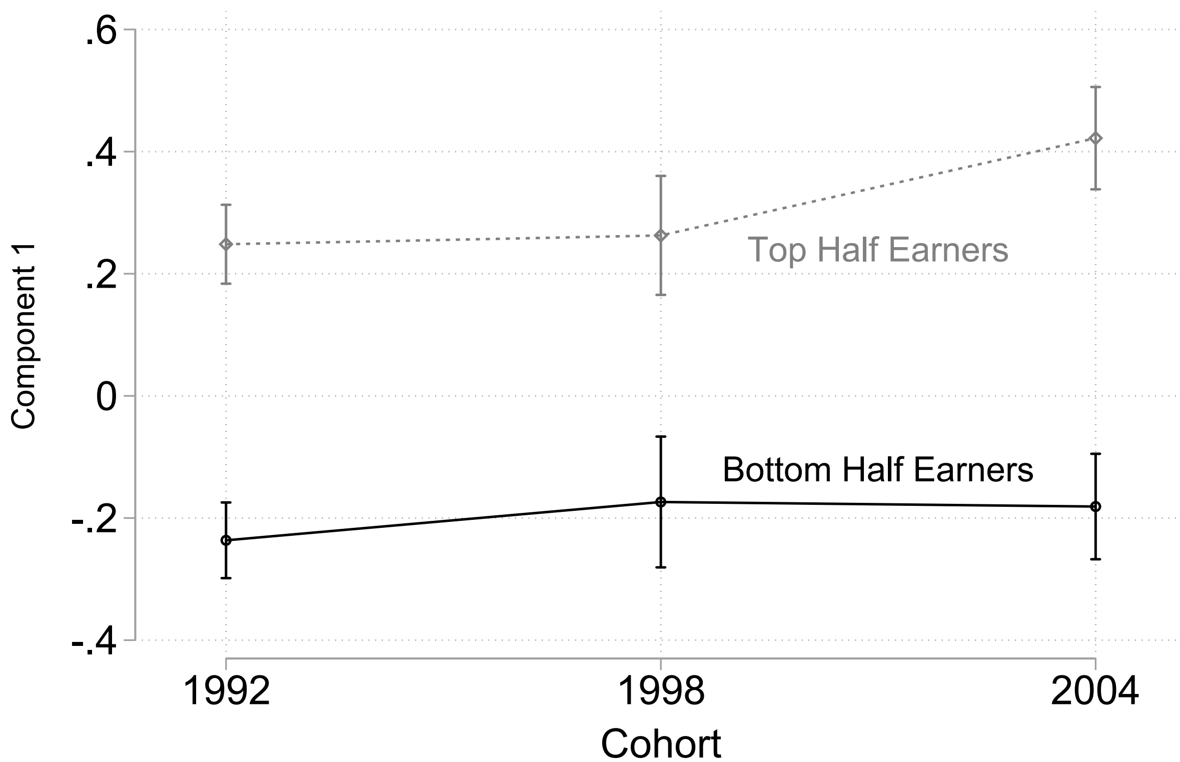
The figure displays the coefficients from a regression of an indicator for labor force participation (x 100) on initial occupation characteristics and additional control variables. The occupation characteristics measures are from the individual's first observed employment between ages 51 and 56. They are measured in standard deviations of the 1980 distribution of tasks. The sample includes all male 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 9: Mean of *Component 1* by Lifetime Income Quartile at Age 60 and Cohort, Men



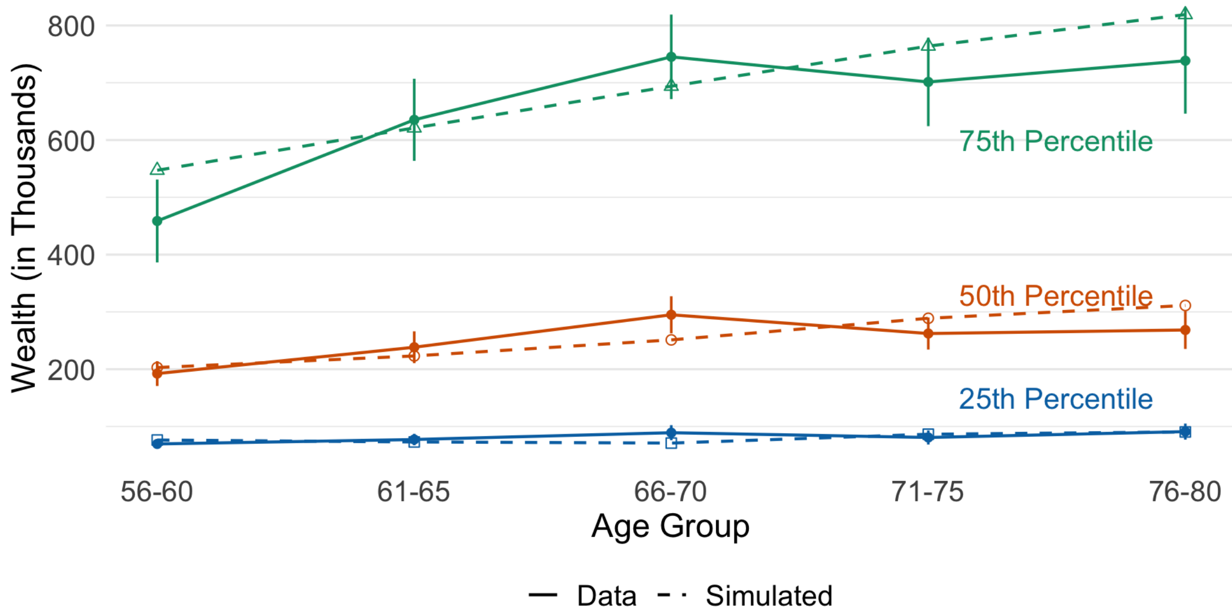
This figure displays the average value of *Component 1* by lifetime income quartile at age 60 and HRS cohort. Recall that occupation for individuals is defined as the first occupation in which they are observed at ages 51–56. Lifetime income is calculated by the HRS using tax records from the Detailed Earnings Record in Social Security administrative data. *Component 1* is described in more detail in Section 3.3.

Appendix Figure 10: Mean of *Component 1* by Lifetime Income at Age 60 and Cohort, Men



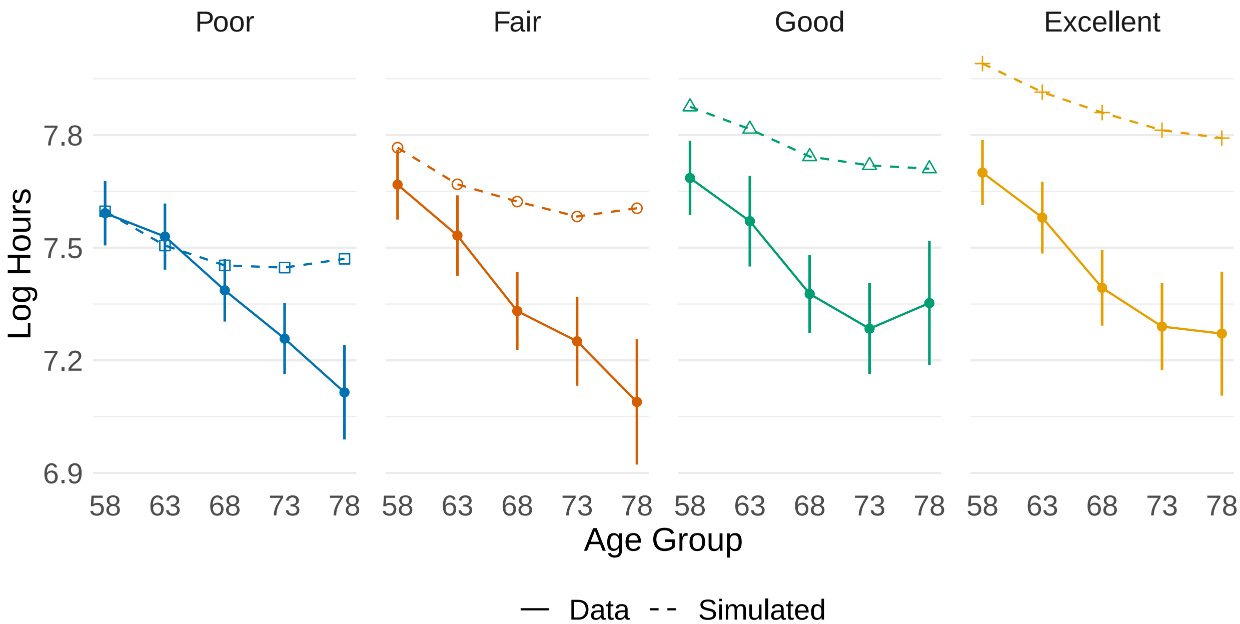
This figure displays the average value of *Component 1* by lifetime income quartile at age 60 and HRS cohort. Recall that occupation for individuals is defined as the first occupation in which they are observed at ages 51–56. Lifetime income is calculated by the HRS using tax records from the Detailed Earnings Record in Social Security administrative data. *Component 1* is described in more detail in Section 3.3.

Appendix Figure 11: Targeted Wealth Moments and Simulation Counterparts



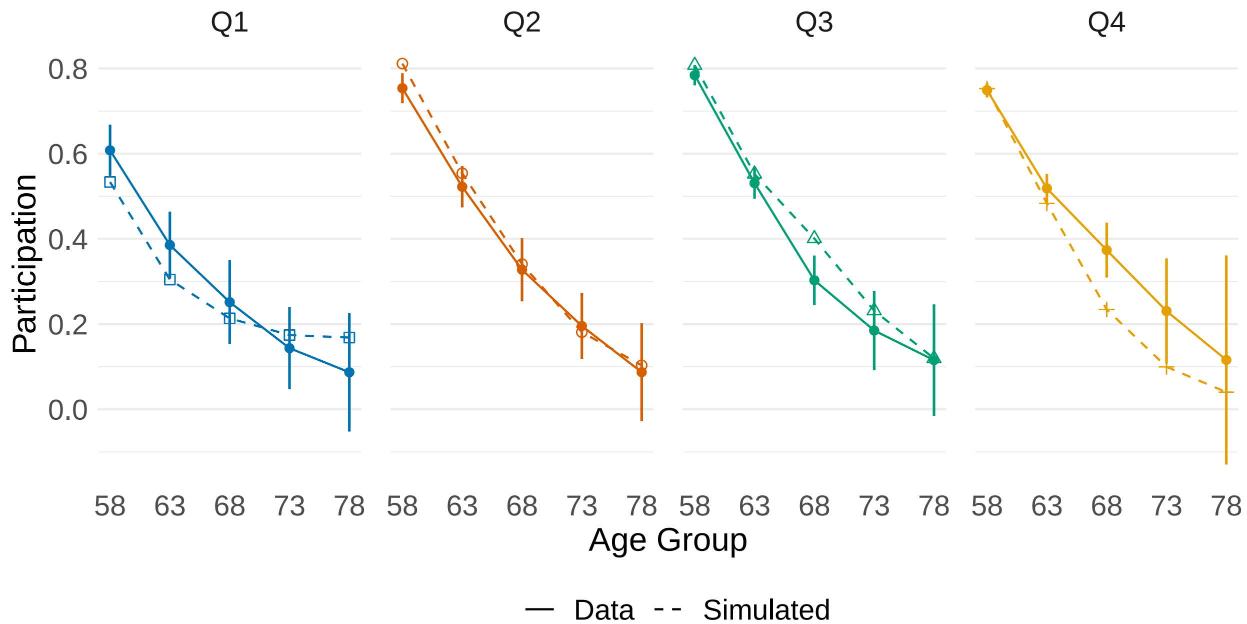
The figure plots the targeted wealth percentile moments in the data and the simulation counterparts.

Appendix Figure 12: Targeted Hours Moments and Simulation Counterparts



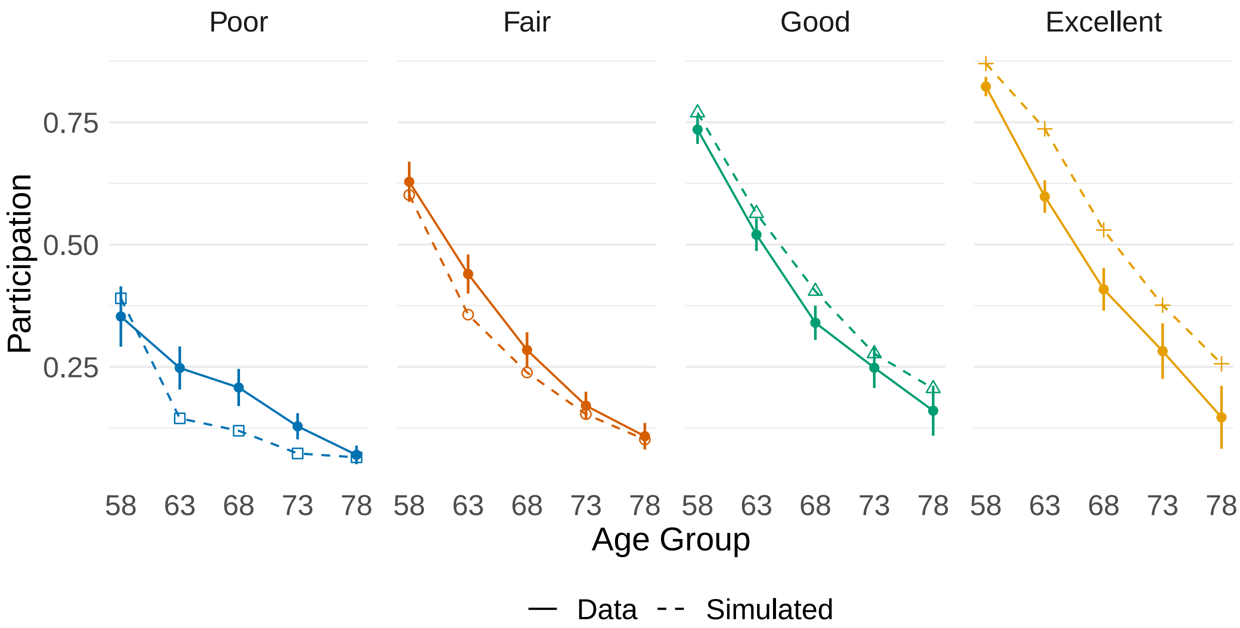
The figure plots the targeted log hours conditional on participation by health moments in the data and the simulation counterparts.

Appendix Figure 13: Targeted Wealth Quartile Participation Moments



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

Appendix Figure 14: Targeted Participation by Health Moments and Simulation Counterparts

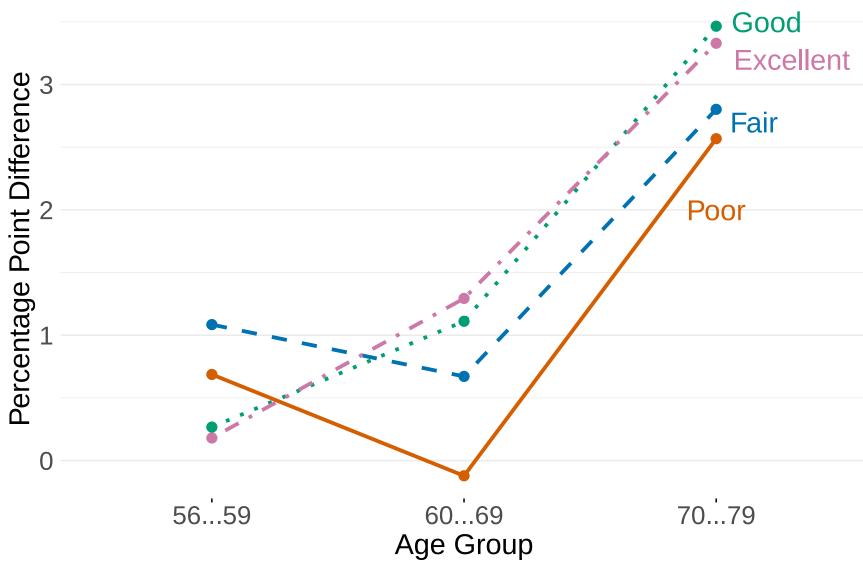


The figure plots the targeted participation by health moments in the data and the simulation counterparts.

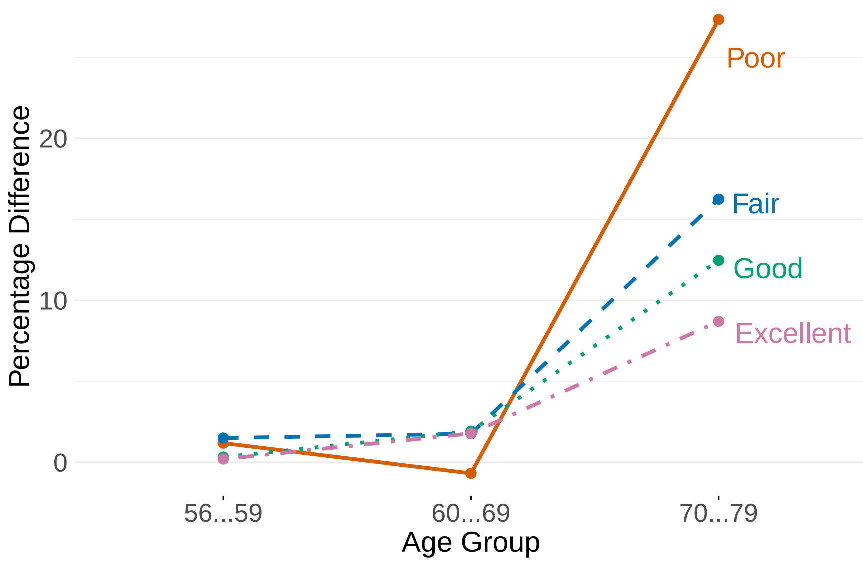
Appendix Figure 15: Participation Effects of Policy Changes Relative to Current Policy By Health

Policy 1: Increasing Retirement Age from 67 to 69

(a) Percentage Point Effect



(b) Percentage Effect



These figures display the difference in participation between the policy reform counterfactual and current policy by health level.

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

Panel A: Men

	(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	

Panel B: Women

	(1) Main Tasks	(2) All Tasks	(3) PCA Tasks
No Covariates	0.810	0.826	1.274
	(0.323)	(0.373)	(0.383)
Baseline Controls	0.731	0.876	1.208
	(0.365)	(0.416)	(0.421)
Add Contemp. Vars.	0.737	0.877	1.177
	(0.363)	(0.414)	(0.423)
Add Spouse Vars.	0.601	0.775	1.025
	(0.366)	(0.416)	(0.426)
Add Education	0.434	0.603	0.642
	(0.418)	(0.484)	(0.514)
LFP Change from 2000 to 2019		3.9	

The table displays the predicted change in the labor force participation (x100) from 2000 to 2019 of men and women ages 70 to 79. These are estimates of $LFP\Delta$ from Equation 3. The standard errors are based on the standard errors from Figure 4, 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 measurements of the change in mean occupational content in the Census, which is small. Column 2 repeats the exercise including seven 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 2.2 for more details on the PCA. See Figure 4 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). Regressions 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	0.939	0.210	0.0579	0.0539
	(0.0079)	(0.012)	(0.0060)	(0.0066)

Displayed are the estimates of the residual wage process described by Equations 11, 12, and 15. These are estimated using minimum distance methods, as in O'Dea (2018). Standard errors are shown in parentheses. They are computed using 500 bootstrap samples of the entire wage estimation procedure.

Appendix Table 4: Lifetime Benefits Reduction by Reform

Social Security Reform	Total	Type 1	Type 2	Type 3	Type 4	Type 5
Raise Retirement Age	-12.9%	-13.3%	-13.1%	-12.8%	-12.7%	-12.9%
Change AIME-to-Benefits Formula	-12.3%	-0.14%	-8.19%	-8.63%	-14.2%	-19.5%

This table presents the percent reduction in Social Security benefits paid out by the government under the two alternative Social Security reforms. The "Raise the Retirement" reform increases the Full Retirement Age from 67 to 69. The "Change AIME-to-Benefits Formula" reform keeps the FRA at 67 but reduces replacement rates for high AIME individuals. The column "Total" presents the total reduction in benefits paid out.

Appendix Table 5: Welfare Differences Across the Two Reforms

All Types	Types 2–5	Types 2–5 "Just Types"
1.15%	0.87%	0.84%

This table displays the welfare differences across the two Social Security reforms. It is expressed as the percentage increase in consumption needed to get welfare under the reform that increases the Full Retirement Age to equal welfare under the reform that changes the AIME-to-benefits formula. The "All Types" column refers to the result when aggregating welfare across all types. The "Types 2–5" column refers to the result when aggregating only across Types 2 through 5. The "Types 2–5 "Just Types"" refers to the result when types have been changed to be as in the "Just Types" counterfactual and when aggregating only across Types 2 through 5.