Research Dialogue | Issue no. 204
September 2023

Inequities in the golden years: How wealth shapes healthy and work–free life

Abstract

Recent work has established that the gradient of life expectancy with respect to wealth is large and widening. We make three contributions to build on that result, using two decades of individual data from the United States. First, the additional years are healthy, disability-free years, and reveal a substantial wealth gradient with gain accruing disproportionately to the wealthy. Second, the return to wealth in achieving these healthy years increased over two recent decades. Third, the additional years lived by the wealthy result in more years of paid work while also retaining more years work-free. These results inform the interactions of financial security in retirement with life expectancy, disability, and work; the progressivity of Social Security benefits; and the ability to manage longevity risk.

Hessam Bavafa
University of Wisconsin-Madison

Anita Mukherjee
University of Wisconsin-Madison

Tyler Q. Welch
University of Wisconsin-Madison

1. Introduction

Many individuals aspire to a set of "golden years" in later life with good health and reduced or no work obligations. Life expectancy gains over time have been accruing unequally, however, with gaps as large as 15 years for men in the top 1% versus the bottom 1% of the income distribution (Chetty et al., 2016). In parallel, there have been major gains in healthy (i.e., disability-free) life expectancy—this has increased on average by about two years, outpacing the overall growth in life expectancy (Chernew et al., 2017). Our goal in this paper is to "marry" these empirical findings and shed light on how wealth inequality contributes to healthy life expectancy both in a cross-section and across time. After documenting a clear wealth gradient in healthy life expectancy, we consider how wealth inequality may continue to widen due to differential propensities to continue working at older ages.

We begin with our motivation for studying disability. It is important to understand whether individuals with different levels of wealth entering retirement experience different disability (and mortality) patterns. Many policies that affect aging populations can be targeted to generate different benefits across wealth and income groups. For example, increases in the normal retirement age may affect the progressivity of Social Security and other program benefits as studied in Auerbach et al. (2017). Thus, in this paper, we try to answer two descriptive questions. We ask: (1) How different is the disability-free life expectancy at age 65 for the most versus least wealthy individuals? (2) How has that gradient changed over time?

We present our main findings both graphically and using regressions that allow us to quantify the expected disability-free life years conditional on wealth at age 65. Having established that there is a substantial gradient in which the wealthier live more disability-free life years and that this wealth gradient has widened over time, a natural question is to explore why these gradients exist and why they have changed. Ultimately, there are many potential mechanisms that could be at play and there are rich literatures exploring different facets of disparities in health and longevity outcomes across wealth at a point in time.[1] In this paper, we explore one of the potential pathways that could account for the shifts in disability-free life expectancy disparities by wealth over time. In particular, we examine whether the least wealthy are relatively sicker at age 65 in current cohorts than they were in the past. This could happen, for example, if earlier-life health shocks are having a bigger impact on wealth accumulation in recent cohorts than they did in the past.

For our first approach to analyzing that possibility, we redo our analysis using education as our differentiator. Here, education is another proxy for socioeconomic status because education cannot easily be "spent down" after a health shock. (We also show that the wealth gradient coincides with the education gradient.) We find very similar results, suggesting that the increased gradient in wealth likely might reflect something more fundamental about how differing economic prospects throughout life affect disability-free life years in older age. For our second approach, we more directly analyze measures of health at age 65. We find no evidence across a few different metrics that the difference in health at age 65 between higher and lower wealth quartiles has increased over time. These results suggest that the main reason the disability-free longevity wealth gradient has increased is not coming primarily from increasing differences across health status at age 65 for recent cohorts.

We then turn our attention to the wealth gradient for the propensity to engage in (paid) work at older ages. The reason this outcome is compelling is that disability itself affects the ability to work. Additionally, uneven participation in work may contribute to widening wealth inequalities—this would be true if the more wealthy are more likely to continue working at older ages, which we find. This analysis has a parallel structure to that of disability, in which we can partition life expectancy at age 65 into working life years and work-free life expectancy (similar to partitioning life expectancy at age 65 into disabled life years and disability-free life expectancy).

Our analysis combines the nationally representative Health and Retirement Study (HRS) data with life expectancy tables at older ages to compute disabled life years, disability-free life expectancy, working life years, work-free life expectancy, and related objects of interest. The analysis focuses on two cohorts of individuals turning 65 a decade apart, and wealth is measured in gender-specific quartiles at age 65.

We find that between two cohorts turning age 65 a decade apart, disability-free life expectancy gains accrued only to the wealthy. Specifically, we estimate disability-free life expectancy gains of 0.66 years for males and 0.24 years for females in the top wealth quartile. By contrast, for the bottom

1 Here, we note that prior work has identified how wealth correlates to healthcare access and private insurance (Dunlop et al., 2007), flexible work arrangements (Ameriks et al., 2020), and types of work (Breeze et al., 2001; Cambois et al., 2001), among others.

wealth quartile, we estimate disability-free life expectancy losses of 0.04 years for males and 0.13 years for females. We then examine whether the wealthy are using their longer, healthier lives to also work longer. Here, we estimate that work-free life expectancy decreased by 0.41 years for the top wealth quartile for males and 0.66 years for females. For the bottom quartile, the change is 0.09 years for males and -0.03 years for females. Note that even though the work-free life expectancy does not increase for the 2006 cohort compared to the 1996 cohort, there is a robust within-cohort gradient showing that the wealthy experience more work-free life expectancy.

The combined set of results shows that the most wealthy individuals use their longer, healthier lives to work for more years while still retaining more years work-free compared to the less wealthy. While it is difficult to take a stand on whether work at older ages is beneficial (it may be desired or undesired but necessary), understanding the patterns and how they respond to wealth over time helps inform retirement policy.

Our findings contribute to several strands of the existing literature, which we detail in the next section. After that, we describe our data in Section 3, detail our methodology in Section 4, and present and discuss our results in Section 5. Section 6 presents additional results related to the roles of the health-wealth channel and increased absolute wealth inequality; we then conclude in Section 7.

2. Background

There is an expansive literature on patterns in life expectancy, disability, and work capacity at older ages. Many of the studies on the U.S. population use data from the HRS, underscoring the relevance of the dataset we use. Our main contribution is to examine the role of wealth quartiles both within and between cohorts on these outcomes for the same sample. Below, we highlight some of the most related papers. We also include references to recent review papers for the interested reader to delve deeper into the related literatures.

2.1 Patterns in life expectancy

Our focus on disability-free life expectancy (DFLE) and work-free life expectancy (WFLE) in this paper takes as a critical ingredient the individual's vector of survival probabilities at each age, which reflect life expectancy. As our interest is in the gradient of wealth at age 65 with respect to these outcomes, two sets of papers that are strongly related document life expectancy gradients with respect to income and socioeconomic status. The first set includes Auerbach et al. (2017), which uses U.S. data and finds that the life expectancy gap between men in the highest income quintile and lowest income quintile grew from five years for a 1930 birth cohort to nearly 13 years for a 1960 birth cohort (for reference, we compare cohorts born in roughly 1931 and 1941). Auerbach et al. (2017) discusses how the income gradient in life expectancy over these cohorts generates a $150,000 (in 2018 U.S. dollars) gap in lifetime program benefits including Social Security, Medicare, and other programs between the upper and lower quintiles.

Another paper in this set, Chetty et al. (2016), uses U.S. data to document the gradient of life expectancy with respect to income using tax record data. The paper discovers life expectancy gaps as large as 15 years for men, comparing those in the top versus bottom 1% of the income distribution. This paper finds a 10-year gap for women across these extremes of the income distribution. A striking result from this paper is that life expectancy grew by three years for those in the top 1% of the income distribution, while those in the bottom 1% experienced no gain at all. We follow this paper closely in the construction of the survival probabilities, as detailed later in Section 4.1.

A second (and large) set of papers studies the effect of socioeconomic status on life expectancy. Perhaps the closest paper within this set, Hudomiet et al. (2021), uses U.S. data —HRS for cohorts born between 1934 and 1959—and Social Security wealth as the key metric of socioeconomic status. The paper presents analysis showing that life expectancy is likely to increase, though additional life years are likely to accrue to those with the most Social Security wealth. This paper's results help motivate ours, which asks about the breakdown in the changes in life expectancy into years containing disability or work.

Many of the papers that have looked at the effect of socioeconomic status on life expectancy have focused on education. Education is particularly interesting as a socioeconomic indicator because it is determined relatively early in life for most people, providing a measure of economic opportunity that is less affected by midlife decisions or shocks. Novosad et al. (2022) finds increased mortality among white, non-Hispanic men and women in the lowest 10th percentile of education using data from U.S. death records (1992–2018). A key contribution of this paper is to measure and address selection bias in educational achievement over time. The paper suggests that low educational achievement may encompass both past and present socioeconomic disadvantage, explaining its marked predictive power over mortality. Several other papers have also found a negative education-mortality gradient (Case and Deaton, 2021; Leive and Ruhm, 2021; Meara et al., 2008; Wu et al., 2018).

Still related to education, Sanzenbacher et al. (2021) discusses how, while the cross-sectional gradient of socioeconomic status with life expectancy is typically positive and robust, there are fewer clear findings about how these relationships change over time—a central focus of our study. That paper finds that mortality *inequality* is increasing across socioeconomic status as measured on U.S. data using predicted education quartile. Other recent work taking a more broad look at socioeconomic status has shown that there is substantial regional inequality in U.S. life expectancy that is underestimated due to interstate migration explained by the birth region's baseline mortality rate (Fletcher et al., 2023).

We note a relatively recent concern that life expectancy in the United States has stagnated in recent years, owing among other factors to flattening returns from cardiovascular disease treatment, the opioid overdose crisis, and the COVID-19 pandemic (reviewed in Harper et al., 2021). Crimmins and Zhang (2019) also provides a helpful review of the changes in life expectancy in the United States. A key takeaway from that review is that there is growing inequality by certain socioeconomic or spatial groupings, but diminishing inequality by race and gender.

2.2 Patterns in disability

There has been a long and continued interest in documenting disparities in health, including substantial attention to disability and its trends at older ages.[2] We borrow methodology from Chernew et al. (2017), which predicts disability and generates cohort differences in DFLE using health conditions as the key covariate of interest. That paper finds an increase in DFLE of 1.8 years between cohorts turning 65 between 1992 and 2008.

DFLE has increased over time due to medical advances, and prior work has quantified these effects. For example, Cutler et al. (2014) finds a DFLE increase of 1.6 years among 20 years of Medicare beneficiaries, with much of the sick states compressed to the late years. The paper also finds that while both white and non-white individuals gain DFLE over a recent period (1992–2004), non-white individuals experience a smaller DFLE. There is also large variation in DFLE by region in the United States, as shown in Farina et al. (2021). A related paper finds increases in DFLE but no increase in life expectancy among the disabled, leading the authors to conclude that there has been decreased incidence of disability over time, combined with improved recovery from disability (Crimmins et al., 2009).

A number of studies using data from other countries also provide useful background. For example, Bennett et al. (2021) uses data from England to show that DFLE gains among those with multiple long-term conditions accrued only among the most affluent, defined as the people in the highest tertile as measured by an area-level deprivation index. Smith et al. (2010) also uses data from England and finds that an income-based metric of regional socioeconomic status ("community deprivation") helps explain the DFLE gradient across the population. Related more closely to the present paper, Zaninotto et al. (2020) uses data from both England and the United States to show that there is a similarly strong and positive wealth-DFLE gradient in both countries.

Additionally, Sundberg et al. (2021) uses data from Sweden to show that DFLE gains for both men and women accrued mostly to those with the highest education. The trends appear true even across very different national settings; for example, Moreno et al. (2021) uses data from Chile and finds that those with higher socioeconomic status in Chile had both larger life expectancy and larger DFLE.

There are many more papers related to establishing patterns in DFLE around the world. For the United States, Crimmins et al. (2016) provides a useful overview of the trends in life expectancy, disabled life years, and DFLE over four decades of recent data. That paper documents that the increase in DFLE outweighs the increase in disabled life for both men and women; part of our contribution in the present paper is to examine the distribution of this mean effect across individual wealth.

2.3 Patterns in working at older ages

Labor force participation at older ages is prevalent; the summary statistics in our data will show that the near-majority of men engage in some paid work after age 65, and nearly one-third of women do the same after age 65. The willingness to work may be even higher, as many cannot work due to depreciated skills (Hudomiet & Willis, 2022). The main factor that prior scholars have studied to predict work at older ages is education. Coile et al.(2017), for example, finds that the highly educated showed the greatest improvements in self-assessed health, suggesting greater propensity to work at older ages compared to those with less education. The authors are careful to note that work at older ages may not be desirable, though it remains useful in assessing retirement disparity.

2 A key challenge is that disability is frequently measured from self-reported survey data, which might generate response bias—yet, Bago d'Uva et al. (2008) shows that such bias is likely to be limited.

Recent papers use data from Europe to examine working life expectancy (WLY). For example, Loichinger and Weber (2016) uses the European Union Labor Force Survey and finds that WLY at age 50 has increased more for men than women and that the correlation with education is very strong. The paper also finds that healthy life expectancy is more predictive of WLY than overall life expectancy. Parker et al. (2020b) uses data from England to show that many individuals have a WLY that contains unhealthy years to meet state pension eligibility. The authors also examine heterogeneity by various dimensions of socioeconomic status including gender, education, region, and markers of regional poverty, demonstrating that policymakers should be attuned to gradients along these variables in enforcing work requirements.

Using U.S. data (in fact, the HRS), Dudel and Myrskylä (2017) document substantial heterogeneity in working life expectancy by education, and by race, that has emerged since the Great Recession. The paper also documents that the work trends are somewhat volatile, suggesting greater need to understand the underlying factors determining work participation at older ages. Helping to explain this volatility, Mullen (2022) uses the HRS data to consider the nature of work at older ages, finding, for example, rising "gig work," which can generate larger variance in annual earnings.

Berkman and Truesdale (2023) provides a helpful review of work at older ages, focusing on how requiring this via a (further) delayed normal retirement age will be affected by disparities in who *is able to* work at older ages. In particular, the authors highlight how many older people may have problems working due to work conditions, caregiving expectations, poor health, and even age discrimination. Haider and Loughran (2010) also provides an in-depth empirical review of the factors associated with work at older ages, finding that healthier, more educated, and wealthier individuals (at least in a cross-section) are more likely to be working. The review finds that older workers are more likely to have a part-time contract, a finding also from Abraham et al. (2021).

Together, these papers provide a useful backdrop for the present work analysis by showing cross-sectional gradients of interest with respect to socioeconomic indicators including wealth. We note, however, that the literature on working life expectancy has important gaps, potentially stemming from the recency of attention to the topic. For example, Parker et al. (2020a) states: "The [meta-analysis] indicated that population indicators of health and work that could estimate the average number of years people are healthy and in work are rarely used, and that there are no current and reliable estimates." We hope that the present analysis helps push forward attention to the work patterns of older individuals.

3. Data

Our core data source is individual-level information from the 1996 through 2018 waves of the Health and Retirement Study (HRS). The HRS provides rich information on the lives of older individuals, and it is an ideal dataset for our research objectives due to the availability of panel data on wealth, health, and employment. We begin our analysis with the 1996 wave because it is the first wave in which respondents aged 64–66 are part of the primary sample, either due to initial interview or by entering as a primary respondent (i.e., not spouse or partner) in a previous wave. The cohorts we compare are those who turned 64–66 in 1996 versus 2006.

The HRS survey is conducted every two years; thus, we examine those aged 64–66 in the survey to capture the cohort turning age 65. We measure household wealth using the cross-wave imputations developed in Hurd et al. (2019); this is the net value of all wealth.[3] The continuous wealth variable is used to generate gender- and cohort-specific quartiles of wealth for each respondent.

The life expectancy metric is developed using the HRS interview status, as it collects whether the individual is alive (even if they did not respond to the survey) or was reported to have died in the survey wave.[4] HRS death records, at least through 2014, have been shown to be very accurate relative to death records. The disability metric is time-varying and binary, and captures whether the respondent reports any disability in activities of daily living (ADL)—these include

3 This is calculated by first summing the value of one's primary residence, bank accounts (checking, saving, and money market), and savings instruments (certificates of deposit, government savings bonds, and T-bills), with the net value of one's real estate (other than the primary residence and including a secondary residence, if applicable), vehicles, businesses, IRA and Keogh accounts, stocks, mutual funds, investment trusts, bonds, bond funds, and all other savings. Then, the measure nets out the value of all mortgages, home loans, and land contracts for the primary residence, plus all other debt. This variable contains some missing values. If we do not see a respondent precisely in the year they are 65, we substitute with wealth in the next survey. If that, too, is unavailable, we use wealth from the previous survey.

4 We estimate life expectancy using HRS observations through age 89. For ages 90 and above, we follow Chetty et al. (2016) and use National Center for Health Statistics (NCHS) and Social Security Administration (SSA) data to estimate life expectancy based on aggregated age-gender profiles. NCHS data are used between ages 90–99; beyond age 99, we use data from the SSA for tables that generate life expectancy for those individuals aged 100 or more (Bell and Miller, 2005).

bathing, dressing, eating, getting out of bed, or walking across a room. Measuring disability in this manner is consistent with prior research (e.g., Chernew et al., 2017), but we acknowledge that it leaves out substantial richness in reported health. The work metric is also time-varying and binary, and it is defined as whether the respondent reports working for pay at the time of the survey. We also examine hours worked in a separate analysis.

3.1 Summary statistics

Table 1 presents summary statistics for our sample. We begin with age, which is roughly 65 for both men and women in both cohorts, as expected (the lack of precision comes from using age 64–66). Next, we turn to wealth: in the 1996 cohort, the median for men is $238,000 and $202,000 for women. By 2006, this grew by 44% for men and by 16% for women. The differences in median wealth between men and women, along with differential growth over the cohorts studied, motivate our use of gender-specific wealth quartiles.[5]

We then turn our attention to the outcomes studied. We observe that the proportion of men ever experiencing a disability between ages 64–76 rises from 0.26 to 0.29 between 1996 and 2006; for women, the proportion declines slightly from 0.35 to 0.33. The proportion of individuals ever working (between ages 64 and 76) grew for both men and women across the cohorts. For men, the proportion ever working grew from 0.50 in 1996 to 0.57 in 2006, a 14% increase. For women, the proportion increased from 0.35 to 0.42, a 20% increase. These patterns suggest that work at older ages is prevalent among both genders, though the increase over time is higher for women relative to the 1996 baseline.

Table 1. Summary statistics

	1996 Cohort		2006 Cohort	
	(1) Men	(2) Women	(3) Men	(4) Women
Age	64.83	64.65	65.16	65.10
	(0.780)	(0.664)	(0.772)	(0.808)
Median Wealth	2.38	2.02	3.42	2.34
(age 65, $100,000)	(13.04)	(12.97)	(23.91)	(12.94)
Key Outcomes:				
Disabled (age 64–76)?	0.26	0.35	0.29	0.33
	(0.441)	(0.476)	(0.455)	(0.470)
Working (age 64–76)?	0.50	0.35	0.57	0.42
	(0.500)	(0.476)	(0.496)	(0.493)
Race:				
Black	0.12	0.19	0.13	0.17
	(0.329)	(0.390)	(0.341)	(0.376)
White	0.85	0.78	0.82	0.79
	(0.358)	(0.413)	(0.384)	(0.405)
Ethnicity				
Hispanic	0.08	0.08	0.10	0.10
	(0.265)	(0.264)	(0.301)	(0.296)
N	877	888	865	1159

Note: This table presents summary statistics of the cohorts turning age 64–66 in 1996 and 2006. Standard deviations are in parentheses. Wealth is in 2018 dollars. Source: HRS respondents aged 64–66 in 1996 and 2006.

5 Appendix Table B.1 shows both the wealth quartile cutoffs and the mean wealth within quartile for men and women in both cohorts. We observe meaningful differences in mean wealth by gender at each cohort-quartile.

The analysis that follows includes controls for race and ethnicity, hence those means are also presented in Table 1. The share reporting as being Black or White is similar across gender and cohorts. The share reporting Hispanic ethnicity increased from 8% to 10% for both genders between 1996 and 2006.

4. Methodology

Our goal is to compare how the wealth-outcome gradient has changed between the 1996 and 2006 cohorts. To achieve this goal, we first need to be able to calculate the outcomes of interest (DFLE, WFLE). We calculate DFLE using the methods in Chetty et al. (2016) and Chernew et al. (2017), and make a small modification to obtain WFLE.

In what follows, we describe the various elements of our calculation. First, we obtain the probability of being alive at each age, i.e., the survival probabilities. Then, we obtain the probabilities of disability and work (as observed, they are conditional on survival) at each age. Finally, we combine these ingredients as we describe below to obtain DFLE and WFLE.

4.1 Calculating survival probabilities

We calculate survival probabilities starting at age 65, conditional on reaching that age, for cohorts in 1996 and 2006. The survival probabilities vary by gender, age, and gender-specific wealth quartiles (we lose some variation at older ages, as discussed below). The estimation varies by age band as follows:

Ages 64–78: We use the HRS to observe deaths and generate survival probabilities by gender, age, and gender-specific wealth quartile.

Ages 79–89: We observe deaths in the HRS for this age band only for the 1996 cohort. Thus, using these deaths as an outcome, we estimate eight separate Gompertz models for each gender-specific wealth quartile. The Gompertz model is famously predictive of death using only age as an independent variable; it is a generalized linear model (GLM) with a binomial dependent variable and a log link function. The details of the Gompertz estimation are in Appendix A. We observe that consistent with its use in other settings, the Gompertz models fit the HRS data well ($R^2 \geq 0.96$ for all models).

Ages 90–99: We do not observe a sufficient number of individuals in the HRS to estimate the survival probabilities at these ages. Thus, we use life tables that contain gender and age variation from the NCHS spanning 1997–2013. The remaining variation in our model is thus coming from age and gender.

Ages 100+: The NCHS data are not available at these oldest ages, so we use the SSA life tables to generate survival probabilities that vary by age and gender. We calculate survival probabilities to age 105 for men and 110 for women.

Note that the study design does not allow for variation in mortality by wealth conditional on reaching age 90. This is a limitation also in Chetty et al. (2016), and likely attenuates the wealth gradients in our results. After obtaining the survival probabilities, we follow the standard way of calculating life expectancy at any age *a* (Cutler et al., 2014). For our purposes, we input $a = 65$ (in implementation, the age may be 64–66 depending on when the respondent is first observed):

$$\mathrm{LE}(a) = \sum_{s=1}^{S} \{\Pr[\text{Survive to } a+s \mid \text{Alive at } a] + 0.5 \times \Pr[\text{Die at } a+s \mid \text{Alive at } a]\}, \quad (1)$$

where $S = 40$ for men (to get to age 105) and $S = 45$ for women (to get to age 110). The equation captures the fact that life expectancy increases by a year for each additional year beyond age a that is survived. If an individual passes away within a year, they are assumed to have lived for half of that year.[6]

4.2 Calculating disability and work probabilities (within–cohort)

We estimate the following regression equation that generates the disability (and analogously for work) predictions for each cohort and gender-specific wealth quartile:

$$Disability_{i,t} = \alpha + \sum_{j=2}^{4} \beta_j \; WealthQ_i + \gamma \; Demographics_{i,t} + \epsilon_{i,t}. \tag{2}$$

The model is estimated via linear probability applying respondent-level survey weights. The dependent variable is whether individual i is disabled in wave t. The coefficient vector of interest is β as it captures the wealth gradient. The demographic controls follow Chernew et al. (2017); in particular, we include age-gender interactions and an indicator for whether the respondent died between this wave and the next wave (i.e., time-do-death of two years or less). This indicator helps account for unobserved factors—e.g., health condition, environment, lifestyle—and captures the fact that individuals are more likely to be disabled in their final years of life. This control necessitates using the final wave of data as an observation window only. We also include indicator variables for reporting as being Black, being White, and being Hispanic; these controls help capture some otherwise unobserved variation across individuals that improve prediction. The disability rate methodology varies by age band (similar to survival probabilities) as follows:

Ages 64–76: We use the HRS to observe disability; note that we cannot go to age 78 because the last wave is used for observation to fill in the "Died next wave?" variable. There is variation in disability rates by gender, age, gender-specific wealth quartile, and all listed covariates in equation (2).

Ages 76–89: We use the 1996 HRS cohort to generate predictions in disability using equation (2). Thus, as we move to these ages we lose the cohort variation but maintain gender, age, and gender-specific wealth quartile variation, along with variation coming from other model covariates.

Ages 90+: We use pooled HRS data (1996–2018) to predict disability using only gender-age interactions. Thus for these ages, we only have gender and age variation. We do not have any wealth variation for this age group.

We directly follow Chernew et al. (2017) to calculate DFLE using the necessary regression results. Following the notation in equation (1), DFLE is the sum of (probabilistic) disability-free years lived at age $a = 65$, for $S = 40$ (men) and $S = 45$ (women):

$$\begin{aligned} \mathrm{DFLE}(a) \quad = \quad & \sum_{s=1}^{S} \Big\{ \Pr[\text{Not Disabled at } a+s \mid \text{Alive at } a+s] \times \Pr[\text{Survive to } a+s] \\ & +0.5 \times \Pr[\text{Not Disabled at } a+s \mid \text{Die at } a+s] \times \Pr[\text{Die at } a+s] \Big\}. \end{aligned} \tag{3}$$

6 There is a small complexity given that we generate estimates at every age, but the HRS is conducted every two years. Following Chernew et al. (2017), we assume that if someone dies between one wave and the next, they would have lived for half of the time in between—we follow the same approach for disability and work. This assumption requires taking an average of the square root of survival probabilities in adjacent waves.

Using this framework, expected disability-free years at age 65 is a function of three terms: 1) probability of disability, given survival to age $a + s$, 2) probability of survival to age $a + s$, and 3) probability of disability, given death at age $a + s$. The WFLE analysis follows the same structure, including the varying methodology by age band, with a change in the dependent variable in equation (2). The outcome is replaced by an indicator for whether or not the respondent reported working for pay in the past two years (i.e., since the last survey wave).

4.3 Inequality estimation (between-cohort)

We then turn our attention to how the gradient of wealth has changed with respect to the outcomes across the 1996 and 2006 cohorts. We estimate the following regression for disability, and use an analogous equation for work:

$$\begin{aligned} Disability_{i,t} &= \alpha + \sum_{j=2}^{4} \theta_{j,1996}\, WealthQ_i + \delta\, Cohort2006_i \\ &+ \sum_{j=2}^{4} \theta_{j,2006}\, WealthQ_i \times Cohort2006_i + \boldsymbol{\gamma}\, Demographics_{i,t} + \epsilon_{i,t}, \quad (4) \end{aligned}$$

where i represents each individual and j represents gender-specific wealth quartile (Q1–Q4). The other controls are the same as described for equation (2). The coefficient vector of interest is θ, with the reference group being 1996–Q1. The regression estimates show the differential probability of being disabled as the wealth quartile changes both within a cohort and between cohorts. The *Cohort 2006* fixed effect will show how the outcome changed for the least wealthy in 2006 compared to the least wealthy in 1996. The sum of this *Cohort 2006* coefficient and the *Cohort 2006* wealth quartile interactions will show how the outcome changed for the other 2006 wealth quartiles compared to 1996.

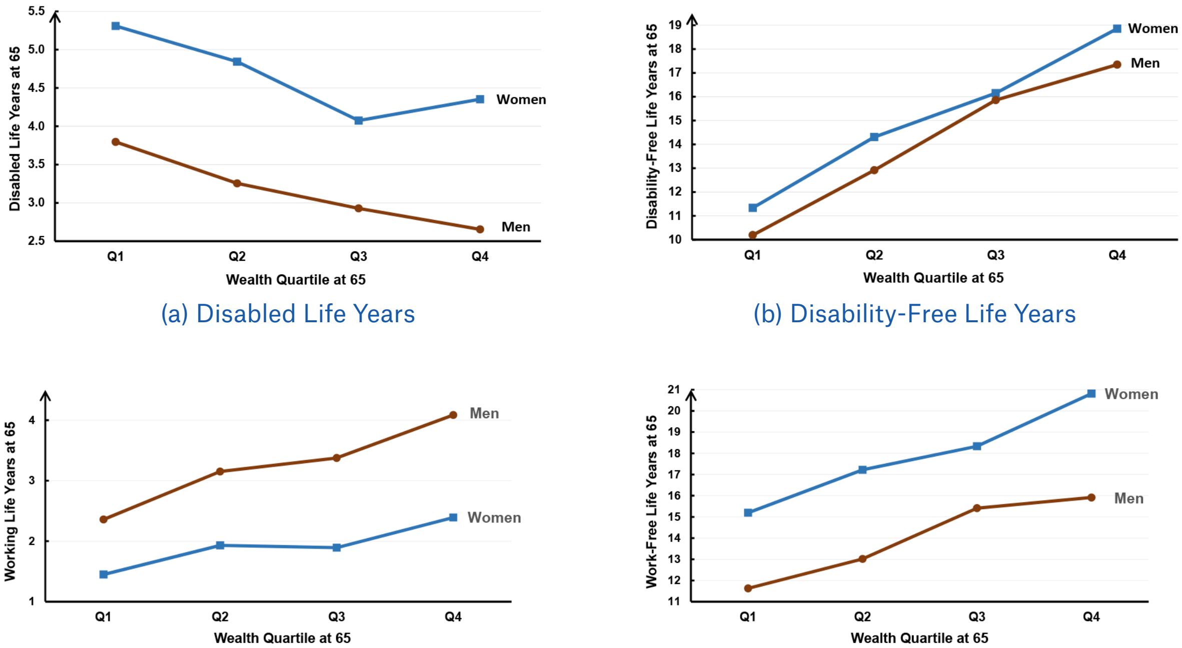
5. Results

We begin with establishing the within-cohort gradients in wealth to disability and work by presenting results for the 1996 cohort. We then examine the objects of interest—the *changes* in wealth gradients with respect to these outcomes for the 2006 cohort, compared to the 1996 cohort.

5.1 Within-cohort results for disability and work

Figure 1 shows the within-cohort (1996) results for four outcomes, all at age 65: disabled life years, disability-free life years, working life years, and work-free life years. Note that life expectancy at age 65 equals the sum of disabled life years and disability-free life years, so the numbers on the y-axis can be added across panels (a) and (b) to obtain life expectancy for the different quartiles. (In fact, the way we obtain disabled life years for example is to calculate life expectancy and subtract DFLE.) Similarly, life expectancy at age 65 can be partitioned into working life years in panel (c) and work-free life years in panel (d).

Figure 1. Within-cohort relationship of wealth to disability and work, 1996



(a) Disabled Life Years

(b) Disability-Free Life Years

(c) Working Life Years

(d) Work-Free Life Years

Note: Figure shows the outcomes labeled on the vertical axis for men and women. The horizontal axis in each plot is the gender-specific wealth quartile at age 65. Source: HRS respondents aged 64–66 in 1996 and 2006 (for disability and work prevalence, and life expectancy through age 89), plus SSA and NCHS for life expectancy after age 90.

We begin with panel (a), which presents the number of disabled life years expected at age 65 for men and women across the wealth quartiles. We observe that the least wealthy (Q1) men experience approximately 3.8 years of disability, compared to 5.3 years for women; the larger number for women is not surprising given their longer average life expectancy. We observe that the slope for men appears linear, with the most wealthy men (Q4) experiencing only 2.7 years of disability after age 65. For women, there appears to be some nonlinearity stemming from the wealthiest group who experience 4.4 years of disability after age 65; when we look at panel (b), which we discuss next, this appears to stem from longer life expectancies for this group.

Panel (b) shows the disability-free life years at age 65 for men and women. Here the patterns appear to be more linear with respect to wealth, where the least wealthy men can expect to live 10 years without disability compared to 17 years for the most wealthy. The range for women is similar: the least wealthy can expect to live 11 years without disability compared to nearly 19 for the most wealthy. Taken together, these results show that there is a strong gradient of wealth with disability within-cohort, in which wealth is negatively related to remaining life years with disability and thus positively related to remaining life years without disability.

Panels (c) and (d) of Figure 1 show the same wealth gradients but with respect to the number of working years at age 65. Interestingly, we observe that wealth is positively correlated with the propensity to work for both men and women. In panel (c), the least wealthy men work for 2.4 years after age 65 compared to 4 years for the most wealthy. For women, the most wealthy work nearly one more year than the least wealthy women (2.4 versus 1.5). Panel (d) shows the number of work-free life years after age 65 for both men and women. We find that the least wealthy men can expect to have 11.6 work-free life years at age 65 compared to about 15.9 years for the most wealthy. For women, the most wealthy experience 5.6 more work-free years compared to the least wealthy (20.8 versus 15.2). Taken together, the plots show a strong wealth-work gradient that highlights how resources accrue unevenly at older ages.

5.2 Between–cohort returns to wealth

Table 2 presents the between-cohort results, which reveal the extent to which the gradients have changed over the recent decade. In this subsection, we will discuss columns (1) and (2) as they relate to disability and work, respectively. Column (1) presents the results from estimating equation (4); the dependent variable is time-varying and captures whether the respondent reports a disability in the given survey wave. The reference category is the first wealth quartile in 1996.

Table 2. The effect of wealth quartiles on disability and work

	(1) Disabled?	(2) Working?
Wealth Quartile 2	-0.0631***	0.0277**
	(0.0119)	(0.0114)
Wealth Quartile 3	-0.106***	0.00640
	(0.0111)	(0.0110)
Wealth Quartile 4	-0.124***	0.0381***
	(0.0108)	(0.0110)
2006 Cohort	0.029**	0.0121
	(0.0121)	(0.0122)
Wealth Quartile 2, 2006	-0.0144	0.0420***
	(0.0156)	(0.0162)
Wealth Quartile 3, 2006	-0.0387***	0.0788***
	(0.0140)	(0.0157)
Wealth Quartile 4, 2006	-0.0420***	0.0820***
	(0.0137)	(0.0154)
Race/Ethnicity	✓	✓
Age/Gender Interactions	✓	✓
Died next wave?	✓	✓
Reference Group Mean	0.2430	0.2231
Observations	30426	30398
R^2	0.0666	0.188

Note: This table shows regression results with the dependent variable indicated by the column heading. Regressions use equation (4) and are estimated by linear probability applying individual HRS weights. The reference group is the first wealth quartile in 1996. Standard errors are in parentheses. Source: HRS respondents aged 64–66 in 1996 and 2006. Significance is given by: *p < 0.10, **p < 0.05, ***p < 0.01.

This estimation centers on three objects of interest. First, the three wealth quartile coefficients, *Wealth Quartile 2* through *Wealth Quartile 4*, serve to characterize the wealth-disability gradient. Second, the wealth quartile interaction terms, *Wealth Quartile 2, 2006* through *Wealth Quartile 4, 2006*, demonstrate the between-cohort changes in inequalities of most interest. Third, the change in disability in 2006 is estimated for the first quartile using the *2006 Cohort* coefficient, while for the remaining three quartiles, it is obtained by adding the quartile-specific interaction to the same coefficient.

We observe that the *Wealth Quartile 2* through *Wealth Quartile 4* coefficients are all statistically significant ($p < 0.01$) and progressively more negative, indicating that wealthier individuals have a lower likelihood of disability for the 1996 cohort. The *2006 Cohort* coefficient is positive ($p < 0.05$), indicating that the least wealthy quartile had a greater disability rate in 2006 versus 1996. For the other three wealth quartiles in 2006, we obtain their effect by adding the *2006 Cohort* coefficient to the quartile-specific coefficient. The *Wealth Quartile 2, 2006* coefficient is negative but not statistically significant, indicating that this group also had greater disability compared to the 1996 cohort based on the *2006 Cohor*t coefficient. The statistically significant ($p < 0.01$) negative coefficients for the third and fourth quartiles indicate an increase in inequality with regard to disability. Specifically, in 2006, the disparity in disability between the first quartile and the top two quartiles was wider than it was in 1996. Considering the overall impact, an analysis of the wealthiest group in 2006 shows a reduction of 0.013 percentage points ($0.029 - 0.0420 = -0.013$) in the likelihood of disability, which amounts to 5% of the average of the reference group (least wealthy in 1996).

Column (2) of Table 2 presents the analogous results for the time-varying dependent variable of whether a respondent reports having worked for pay in the given survey wave. The *Wealth Quartile 2* and *Wealth Quartile 4* coefficients are statistically significant and positive, indicating that these groups have a higher propensity to work compared to the least wealthy in 1996. The *2006 Cohort* coefficient is not statistically significant, indicating that the least wealthy in 2006 did not have a different propensity to work compared to the least wealthy in 1996. The *Wealth Quartile 2, 2006* through *Wealth Quartile 4, 2006* coefficients are all positive and statistically significant ($p < 0.01$), suggesting that these groups all had a greater propensity to work compared to their peer wealth quartile groups in 1996. These coefficients thus indicate a heightening of inequality between 1996 and 2006 with respect to the propensity to work. The steepness is also linear, with the most wealthy being the most likely to report working. The effect for the most wealthy in 2006 is $0.0121 + 0.0820 = 0.0941$, indicating that this group is 9.4 percentage points more likely to work than the least wealthy in 1996 (reference group)—a growth of 42%.[7]

We present staggered regression results for disability and work in Appendix Tables B.2 and B.3, respectively. In each of these tables, the baseline specification in column (1) includes age-gender interactions, column (2) adds the control for whether the respondent died in the next wave, and column (3) adds the race and ethnicity indicators. In Appendix Table B.2, we observe relative stability across the specifications, though the additional controls increase the R^2 by 1.6 percentage points from the baseline specification. The Hispanic and Black variables are statistically significant and positive, capturing a higher propensity to be disabled among these individuals. In Appendix Table B.3, we observe very little predictive gain by adding the controls; the R^2 increase from the baseline to the saturated specification is 0.3 percentage points. The Hispanic coefficient is again statistically significant. The coefficient is negative, capturing a lower propensity to work among those with this ethnicity.

5.3 Visualizing the between–cohort results

Armed with the regression results, we next plot the overall trends in DFLE and disabled life years (DLY) for both genders, between the 1996 and 2006 cohorts. Recall that life expectancy is also increasing in wealth and equals DFLE plus DLY, so these figures are showing trends in the breakdown of life expectancy. In panel (a) of Figure 2, we observe that men gained, in each ascending wealth quartile, -0.04, 0.71, 0.08, and 0.66 years of disability-free life expectancy between 1996 and 2006. For women, the analogs among the four ascending quartiles are -0.13, 0.05, 1.01, and 0.24. Thus, among both men and women, the least wealthy individuals experienced no positive returns to wealth in DFLE over time (in fact, they were even small negative returns) while wealthier individuals experienced clear, positive returns to wealth in DFLE. This

7 A technicality is that the work predictions become very negative using a linear probability model for older ages (not an issue with the disability outcome), so we use a logit model to obtain the predictions to feed into the WFLE and related calculations. The logit estimates are in Appendix Table B.4; the results are consistent with the binary outcome. In this table, we also show tobit estimates results related to hours worked, which has a mass at zero because many respondents do not work.

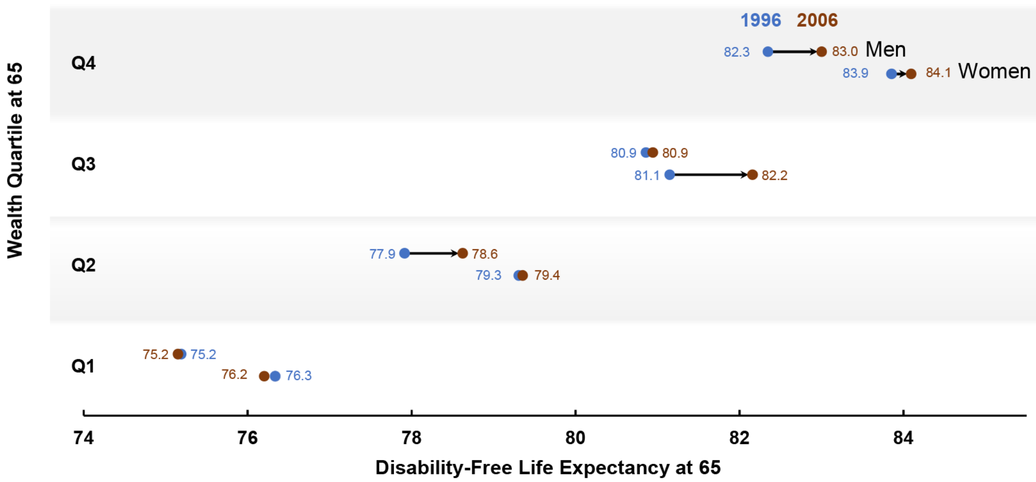
is indicative of worsening wealth-related inequality in DFLE over time for both men and women, with a concerning lack of improvement for the least wealthy.

Panel (b) of Figure 2 is an analog to panel (a) and shows the patterns in disabled life years. This figure provides an understanding of how long individuals live with a disability after age 65, and how that is changing over the cohorts. Here, the changes for each ascending wealth quartile, among men, from 1996 to 2006 are: 0.36, 0.37, -0.16, and 0.01. For women, the same changes are 0.27, 0.25, 0.20, and -0.13. Over time, for both men and women, there is an increase among the least wealthy in how much of their life is lived with a disability, while there is no change for the wealthiest individuals (and an improvement for the wealthiest women). Combined with panel (a), these figures highlight that the increased inequality in DFLE across the cohorts is stemming in large part from disparities in disabled life years (not just total life expectancy).

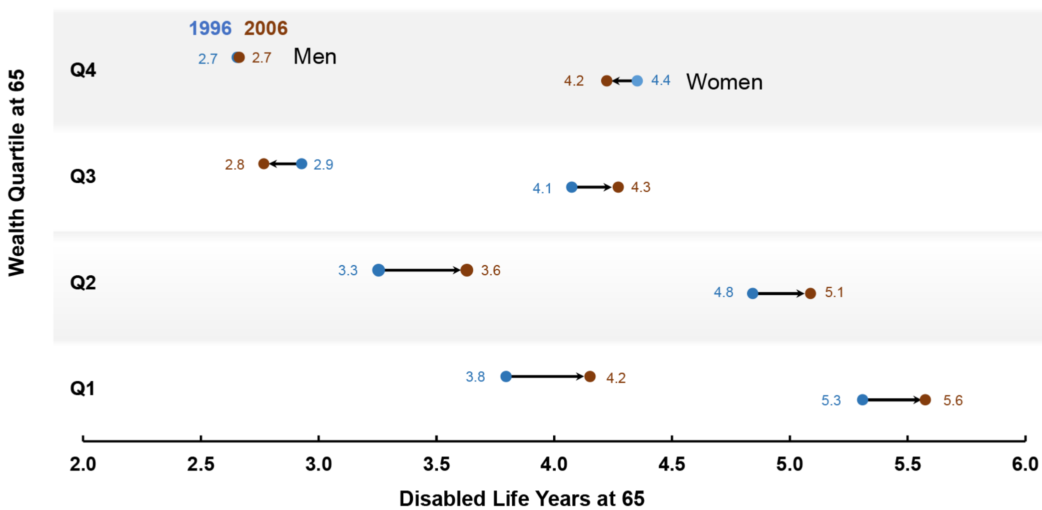
In Figure 3 we show the results for WFLE and working life years (WLY). In panel (a), we observe that WFLE changed by the following for the ascending wealth quartiles among men: 0.09, 0.37, -1.13, and -0.41. For women, the changes are -0.03, -0.12, 0.40, and -0.66. While these results do not exhibit the same monotonicity as the DFLE results, the wealthiest in 2006 have less WFLE than the wealthiest in 1996. This is explained by the patterns in panel (b), which plots the working life years at age 65. These changes for men from 1996 to 2006 are, for each ascending wealth quartile, 0.23, 0.71, 1.05, and 1.07. For women, the changes are: 0.16, 0.41, 0.81, and 0.76. Taken together, we observe that the wealthier half of respondents work more years both within- and between-cohorts. The coefficients for the work analysis exhibit more noise than the ones for disability, which is not surprising given that paid work in a given year at older ages is a noisier outcome.

The results from Figures 2 and 3 are robust to adding age-gender-wealth quartile interactions in the regression specifications for disability and work, which are then used to predict DFLE, DLY, WFLE, and WLY. These results are in Appendix Figures B.1 and B.2.

Figure 2. Between-cohort changes in DFLE and DLY, by gender



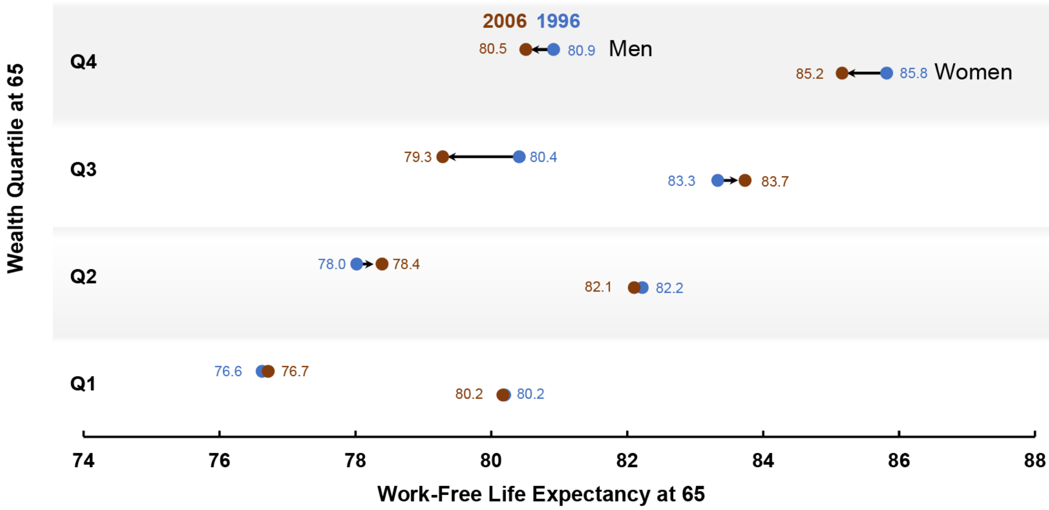
(a) Disability-Free Life Expectancy



(b) Disabled Life Years

Note: Figure shows changes in DFLE and DLY between 1996 and 2006; the outcome is indicated by the horizontal axis. In each panel, we show (gender-specific) wealth quartile on the vertical axis, and use arrows to depict the direction of changes from 1996 to 2006. Source: HRS respondents aged 64–66 in 1996 and 2006 (for disability prevalence and life expectancy through age 89) and all HRS respondents for disability after age 89, plus SSA and NCHS for life expectancy after age 89.

Figure 3. Between-cohort changes in WFLE and WLY, by gender



(a) Work-Free Life Expectancy

(b) Working Life Years

Note: Figure shows changes in WFLE and WLY between 1996 and 2006; the outcome is indicated by the horizontal axis. In each panel, we show (gender-specific) wealth quartile on the vertical axis, and use arrows to depict the direction of changes from 1996 to 2006. Source: HRS respondents aged 64–66 in 1996 and 2006 (for disability prevalence and life expectancy through age 89) and all HRS respondents for disability after age 89, plus SSA and NCHS for life expectancy after age 89.

6. Exploring mechanisms for the between–cohort wealth gradients

In this section, we provide additional analysis exploring two sets of mechanisms for our findings: changes in the relationship between health and wealth over time and the role of increasing wealth inequality in absolute terms.

6.1 Addressing changes in the health–wealth relationship

Here, we provide analyses on one potential mechanism that could be explaining the (widening) wealth-disability and wealth-work gradients. In particular, we examine whether the least wealthy are simply more likely in 2006 versus 1996 to enter age 65 in a sicker state, helping explain why they experience more disability and fewer years of work. This could happen if health affects wealth accumulation more in the 2006 versus 1996 cohort. To be clear, we acknowledge that health shocks can translate to wealth shocks: for example, García-Gómez et al. (2013) provides compelling evidence a hospitalization event produces a pronounced and lasting shock to income. The question is whether this path changed in 2006 versus 1996.

Our first approach to address such a possibility is to look at education instead of wealth as the key differentiator. We do this because, unlike other assets, education cannot be "spent down" in the face of a health shock as it is typically determined earlier in life. For this reason, education provides a proxy for socioeconomic status that is largely unaffected by health or other financial shocks approaching age 65.

Appendix Table B.5 shows the distribution of educational attainment by cohort and gender; note that the underlying data do not generate true quartiles because educational attainment is lumpy. We thus break education into four levels that mirror quartiles. The first quartile includes those with partial high school completion or a GED; the second quartile includes those with a high school diploma;[8] the third quartile includes those with some college; and the fourth quartile includes those with completed college degrees or more.

In Appendix Table B.6, we replace the individual's wealth quartile with their education "quartile" (pooled across genders, as the lumpiness in attainment is true for both men and women) and re-estimate equation (4). We observe in column (1) that the education-disability gradient is similar to the wealth-disability gradient, and that the gradient steepened in 2006 (i.e., all three 2006 cohort interactions are negative), just as for disability. Column (2) shows the results for the work outcome, which is also consistent with the main wealth results—the gradient of education-work steepened for the 2006 cohort (i.e., all three cohort 2006 interactions are positive).

The results are consistent with our findings in Table 2. Specifically, columns (1) and (2) show that there is an education gradient in disability and work that is similar to wealth—the more educated individuals in 1996 are less likely to be disabled and more likely to work. Moving to 2006, there is an increase in the propensity to be disabled for the least educated. By contrast, the most educated have a meaningful and statistically significant reduction in the propensity to be disabled. Column (2) shows the results related to working. Again, we observe that the more educated are more likely to work, and much more so in 2006 versus 1996.

Our second approach is to more directly analyze measures of health at age 65. In Appendix Table B.7, we estimate equation (4) but for outcome measures of health taken at age 65. The purpose of these regressions is to see if there is a change in the relationship of wealth to these measures of health for the 2006 cohort. The health measures are self-reported health (subjective, 1–5 where 5 is worst) and the numbers of doctor and hospital visits in the past two years (objective). In all three columns, we do not observe any statistically significant interactions for the 2006 cohort and wealth quartiles. Note that there is a statistically significant *2006 Cohort* fixed effect in column (1) for self-reported health, which is consistent with prior research showing an overall decline in this outcome (Dwyer-Lindgren et al., 2017).

Taken together, these results using education and health suggest that *differences* in the allocation of health status to wealth quartiles at age 65 do not explain the widening wealth-health gradient.

6.2 The role of increased absolute wealth inequality

A striking feature of Appendix Table B.1 is that wealth at age 65 changed substantially between 1996 and 2006. The average wealth increased overall and for the top three quartiles but decreased for the least wealthy quartile. There is also a substantial difference by gender. Moving from 1996 to 2006, for example, the first quartile cutoff for men increased from \$90,066 to \$110,706 while the third quartile cutoff increased from \$603,106 to \$822,204. For women, the first quartile

8 The results are consistent if we were to include individuals with a GED in the second education quartile.

cutoff decreased from $66,131 to $54,856 while the third quartile cutoff increased from $438,660 to $640,100.

To the extent that absolute wealth matters more than relative wealth (within a cohort), in this section, we provide an analysis that "fixes" wealth inequality by applying the 1996 gender-specific wealth quartile cutoffs for the 2006 cohort. The results are in Appendix Table B.8. The results show the familiar wealth gradient, but there is some loss in statistical significance due to the reassignment of wealth quartiles based on the 1996 wealth distribution. We interpret this finding to be that there remains a broad wealth gradient with respect to disability and work, but rank (i.e., within-cohort quartile) plays a predictive role on top of absolute wealth. This analysis also indicates that the escalation in wealth inequality over time may account for a portion of the augmented disparities in both disability and work propensity observed between the two cohorts.

7. Discussion

The increasing wealth inequality in the United States, especially in contrast to other developed nations, is a source of policy concern (Poterba & Venti, 2017).

Health spending, particularly in Medicare, is also affected by these changes in the amount and composition of health expectancy. Cai (2013) uses data from the Medicare Beneficiary Survey to find that the cost of adding a disability-free life year is about 40% less expensive than adding a life year with disability. Thus while total spending increases with life expectancy, the delayed onset of disability can erode some of the health costs of aging. Echoing these results, Chetty et al. (2016) finds that life expectancy is negatively correlated with per-capita Medicare spending and positively correlated with spending on preventative care. There are of course individual and societal benefits to longer lives, which Goldman et al. (2013) estimate to be very high using quality-adjusted life-years metrics. That paper suggests that policy shift to fiscally accommodate delayed aging by considering changes such as raising the eligibility ages for Medicare and Social Security.

This paper documents a new set of stylized facts using data from 1996 to 2018 that contribute to the policy challenge of how to best care for older individuals. We find that the least wealthy do not experience gains in the number of healthy (disability-free) years lived. We find that the gains in healthy life expectancy accrue to the most wealthy, enabling these individuals to both remain healthier and to work more years. These findings help shed light on the composition of aggregate gains in life expectancy and health.

References

Abraham, K.G., Hershbein, B., & Houseman, S.N. (2021). Contract work at older ages. *Journal of Pension Economics & Finance, 20*(3), 426–447.

Ameriks, J., Briggs, J., Caplin, A., Lee, M., Shapiro, M.D., & Tonetti, C. (2020). Older Americans would work longer if jobs were flexible. *American Economic Journal: Macroeconomics, 12*(1), 174–209.

Auerbach, A.J., Charles, K.K., Coile, C.C., Gale, W., Goldman, D., Lee, R., Lucas, C.M., Orszag, P.R., Sheiner, L.M., Tysinger, B., Weil, D.N., Wolfers, J., & Wong, R. (2017). How the growing gap in life expectancy may affect retirement benefits and reforms. *Geneva Papers on Risk and Insurance: Issues and Practice, 42*, 475–499. https://doi.org/10.1057/s41288-017-0057-0

Bago d'Uva, T., Van Doorslaer, E., Lindeboom, M., & O'Donnell, O. (2008). Does reporting heterogeneity bias the measurement of health disparities? *Health Economics, 17*(3), 35–375.

Bell, F.C., & Miller, M.L. (2005). *Life tables for the United States Social Security area, 1900–2100.* Actuarial Study No. 120. Social Security Administration. https://www.ssa.gov/oact/NOTES/pdf_studies/study120.pdf

Bennett, H.Q., Kingston, A., Lourida, I., Robinson, L., Corner, L., Brayne, C.E., Matthews, F.E., & Jagger, C. (2021). The contribution of multiple long-term conditions to widening inequalities in disability-free life expectancy over two decades: Longitudinal analysis of two cohorts using the Cognitive Function and Ageing Studies. *EClinicalMedicin*e, *39*, 101041.

Berkman, L.F. & Truesdale, B.C. (2023). Working longer and population aging in the U.S.: Why delayed retirement isn't a practical solution for many. *The Journal of the Economics of Ageing, 24,* 100438.

Breeze, E., Fletcher, A.E., Leon, D.A., Marmot, M.G., Clarke, R.J., & Shipley, M.J. (2001). Do socioeconomic disadvantages persist into old age? Self-reported morbidity in a 29-year follow-up of the Whitehall Study. *American Journal of Public Health, 91*(2), 277–283.

Cai, L. (2013). The cost of an additional disability-free life year for older Americans: 1992–2005. *Health Services Research, 48*(1), 218–235.

Cambois, E., Robine, J.-M., & Hayward, M.D. (2001). Social inequalities in disability-free life expectancy in the French male population, 1980–1991. *Demography*, *38*(4), 513–524.

Case, A. & Deaton, A. (2021). Life expectancy in adulthood is falling for those without a BA degree, but as educational gaps have widened, racial gaps have narrowed. *Proceedings of the National Academy of Sciences, 118*(11).

Catherine, S., Miller, M., & Sarin, N. (2022). *Social Security and trends in wealth inequality.* Jacobs Levy Equity Management Center for Quantitative Financial Research Paper. http://dx.doi.org/10.2139/ssrn.3546668

Chernew, M., Cutler, D.M., Ghosh, K., & Landrum, M.B. (2017). Understanding the improvement in disability free life expectancy in the U.S. elderly population. In *Insights in the Economics of Aging* (pp. 161–201). University of Chicago Press.

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A., & Cutler, D. (2016). The association between income and life expectancy in the United States, 2001–2014. *Journal of the American Medical Association, 315*(16), 1750–1766. https://doi.org/10.1001/jama.2016.4226

Coile, C., Milligan, K., & Wise, D.A. (2017). Health capacity to work at older ages: Evidence from the United States. In *Social Security programs and retirement around the world: The capacity to work at older* ages (pp. 359–394). University of Chicago Press.

Crimmins, E.M., Hayward, M.D., Hagedorn, A., Saito, Y., & Brouard, N. (2009). Change in disability-free life expectancy for Americans 70 years old and older. *Demography, 46*(3), 627–646.

Crimmins, E.M., Zhang, Y., & Saito, Y. (2016). Trends over 4 decades in disability-free life expectancy in the United States. *American Journal of Public Health, 106*(7),1287–1293. https://doi.org/10.2105/AJPH.2016.303120

Crimmins, E.M. & Zhang, Y.S. (2019). Aging populations, mortality, and life expectancy. *Annual Review of Sociology, 45*, 69–89.

Cutler, D.M., Ghosh, K., & Landrum, M.B. (2014). Evidence for significant compression of morbidity in the elderly U.S. population. In *Discoveries in the economics of aging* (pp. 2151). University of Chicago Press.

Dudel, C. & Myrskylä, M. (2017). Working life expectancy at age 50 in the United States and the impact of the great recession. *Demography, 54*, 2101–2123.

Dunlop, D.D., Song, J., Manheim, L.M., Daviglus, M.L., & Chang, R.W. (2007). Racial/ethnic differences in the development of disability among older adults. *American Journal of Public Health, 97*(12), 2209–2215.

Dwyer-Lindgren, L., Mackenbach, J.P., Van Lenthe, F.J., & Mokdad, A.H. (2017). Self-reported general health, physical distress, mental distress, and activity limitation by US county, 1995–2012. *Population Health Metrics, 15*(16), 1–12.

Farina, M.P., Zajacova, A., Montez, J.K., & Hayward, M.D. (2021). US state disparities in life expectancy, disability-free life expectancy, and disabled life expectancy among adults aged 25 to 89 years. *American Journal of Public Health, 111*(4), 708–717.

Fletcher, J.M., Schwarz, H., Engelman, M., Johnson, N.J., Hakes, J., & Palloni, A. (2023). Understanding geographic disparities in mortality. *Demography, 60*(2), 351–377.

García-Gómez, P., Van Kippersluis, H., O'Donnell, O., & Van Doorslaer, E. (2013). Long-term and spillover effects of health shocks on employment and income. *Journal of Human Resources, 48*(4), 873–909.

Goldman, D.P., Cutler, D., Rowe, J.W., Michaud, P.-C., Sullivan, J., Peneva, J., & Olshansky, S.J. (2013). Substantial health and economic returns from delayed aging may warrant a new focus for medical research. *Health Affairs, 32*(10), 1698–1705.

Haider, S.J. & Loughran, D.S. (2010). Elderly labor supply: Work or play? In *Workplace flexibility: Realigning 20th-century jobs to 21st-century workers* (pp. 110–127). Cornell University Press.

Harper, S., Riddell, C.A., & King, N.B. (2021). Declining life expectancy in the United States: Missing the trees for the forest. *Annual Review of Public Health, 42*, 381–403.

Hudomiet, P., Hurd, M.D., & Rohwedder, S. (2021). Forecasting mortality inequalities in the U.S. based on trends in midlife health. *Journal of Health Economics, 80*, 102540.

Hudomiet, P. & Willis, R.J. (2022). Computerization, obsolescence and the length of working life. *Labour Economics, 77*, 102005.

Hurd, M.D., Meijer, E., Moldoff, M., & Rohwedder, S. (2019). Reducing cross-wave variability in survey measures of household wealth. *Journal of Economic and Social Measurement 44*(2–3), 117–139. https://doi.org/10.3233/JEM-190465

Leive, A.A. & Ruhm, C.J. (2021). Has mortality risen disproportionately for the least educated? *Journal of Health Economics, 79*, 102494.

Loichinger, E. & Weber, D. (2016). Trends in working life expectancy in Europe. *Journal of Aging and Health, 28*(7), 1194–1213.

Meara, E., Richards, S., & Cutler, D. (2008). The gap gets bigger: changes in mortality and life expectancy by education, 1981–2000. *Health Affairs, 27*(2), 350–360.

Moreno, X., Lera, L., Moreno, F., & Albala, C. (2021). Socioeconomic inequalities in life expectancy and disability-free life expectancy among Chilean older adults: Evidence from a longitudinal study. *BMC Geriatrics, 21*(176), 1–7.

Mullen, K.J. (2022). Using the Health and Retirement Study for research on the impact of the working conditions on the individual life course. *Forum for Health Economics & Policy, 25*(1–2), 85–104. https://doi.org/10.1515/fhep-2021-0059

Novosad, P., Rafkin, C., & Asher, S. (2022). Mortality change among less educated Americans. *American Economic Journal: Applied Economics, 14*(4), 1–34.

Parker, M., Bucknall, M., Jagger, C., & Wilkie, R. (2020a). Extending working lives: a systematic review of healthy working life expectancy at age 50. *Social Indicators Research, 150*, 337–350.

Parker, M., Bucknall, M., Jagger, C., & Wilkie, R. (2020b). Population-based estimates of healthy working life expectancy in England at age 50 years: Analysis of data from the English Longitudinal Study of Ageing. *Lancet Public Health, 5*(7), e395–e403.

Poterba, J.M. & Venti, S.F. (2017). *Financial well-being in late life: Understanding the impact of adverse health shocks and spousal deaths* (Working Paper RRC NB17-03). National Bureau of Economic Research.. https://www.nber.org/programs-projects/projects-and-centers/retirement-and-disability-research-center/center-papers/rrc-nb17-03

Sanzenbacher, G.T., Webb, A., Cosgrove, C.M., & Orlova, N. (2021). Rising inequality in life expectancy by socioeconomic status. *North American Actuarial Journal, 25*(sup1), S566–S581.

Smith, M.P., Olatunde, O., & White, C. (2010). Inequalities in disability-free life expectancy by area deprivation: England, 2001–04 and 2005–08. *Health Statistics Quarterly, 48*, 36–57.

Sundberg, L., Agahi, N., Wastesson, J.W., Fritzell, J., & Fors, S. (2021). Increasing inequalities in disability-free life expectancy among older adults in Sweden, 2002–2014. *Scandinavian Journal of Public Health*, 1–8.

Wu, S., Wang, X., Wu, Q., & Harris, K.M. (2018). Household financial assets inequity and health disparities among young adults: Evidence from the National Longitudinal Study of Adolescent to Adult Health. *Journal of Health Disparities Research and Practice, 11*(1), 122–135.

Zaninotto, P., Batty, G.D., Stenholm, S., Kawachi, I., Hyde, M., Goldberg, M., Westerlund, H., Vahtera, J., & Head, J. (2020). Socioeconomic inequalities in disability-free life expectancy in older people from England and the United States: A cross-national population-based study. *Journals of Gerontology—Series A: Biological Sciences and Medical Sciences, 75*(5), 906–913.

Appendices

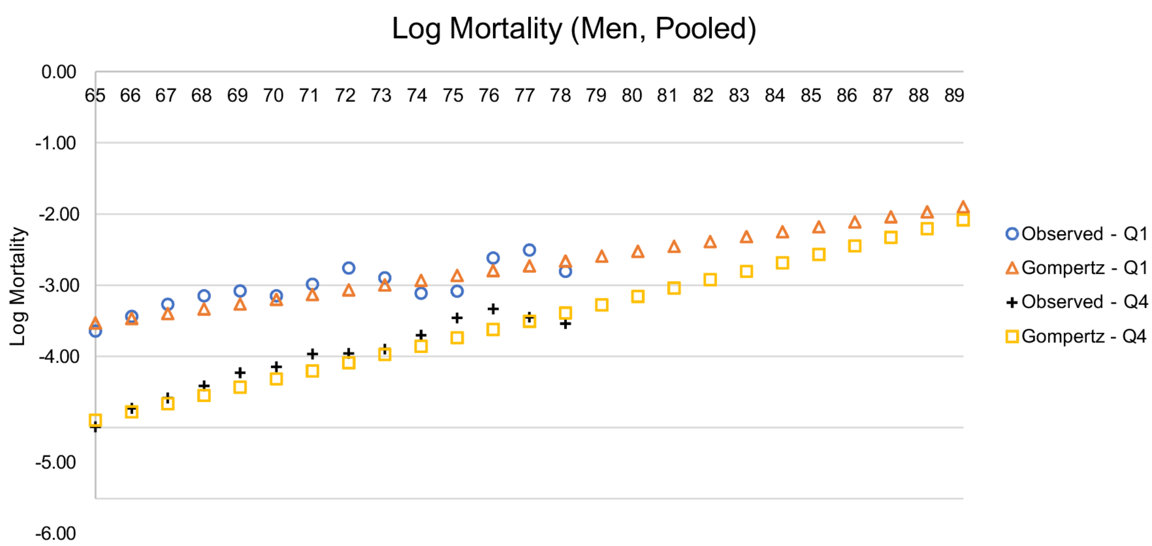
A. Gompertz approximation and fit for survival probabilities

We follow Chetty et al. (2016) to estimate Gompertz models for survival probability estimation for ages 78–89. We specify a generalized linear model (GLM) in which a respondent's death is the dependent variable and the model has just one independent variable, the respondent's age. We apply individual-level HRS weights in all estimations. To assess the fit of the Gompertz curve, we use the observed death data for ages 64–78 for the pooled 1996-2018 HRS sample. We regress the experienced log mortality variable on the log of predicted mortality from the Gompertz model; this exercise yields an R^2 value greater than 0.96 in separate estimations for all men aged 64–78 and all women aged 64–78. Elements in Figures A.1 and A.2 show the fit of the Gompertz estimation to the observed HRS data. Panel (a) of Figure A.1 plots log mortality by age for the pooled set of men. This plot highlights the strong model fit, and shows the results from using the pooled Gompertz estimation from age 79–89.

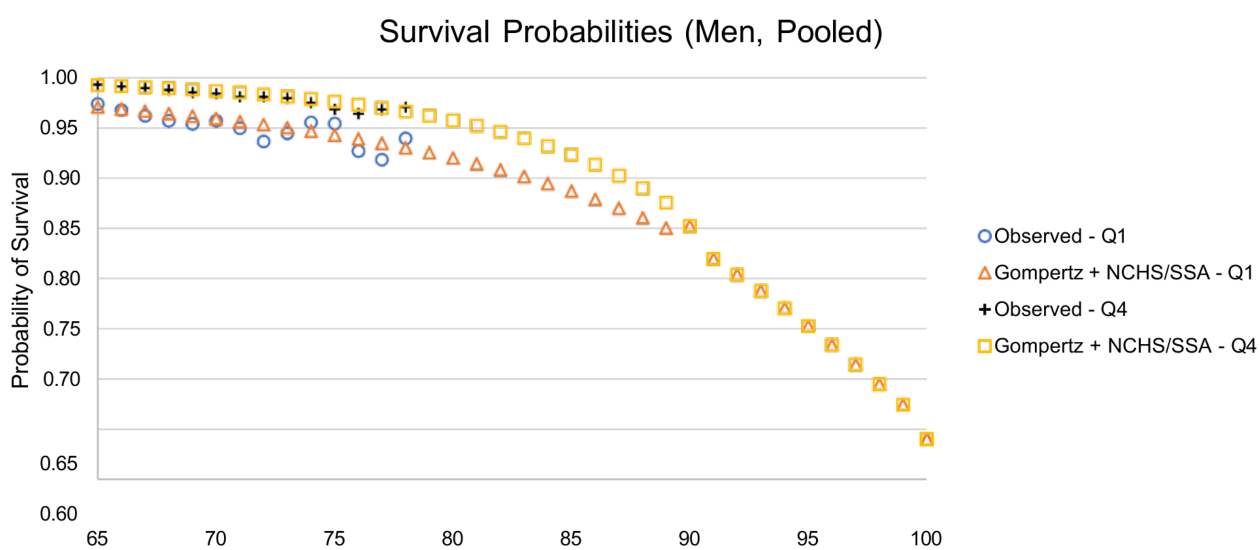
Panel (b) of Figure A.1 plots survival probabilities for men at different ages. Again, through age 78, we see observed and Gompertz predictions for different wealth quartiles, and then after age 79, we observed Gompertz predictions using pooled data through age 89. At age 90, our use of NCHS life tables becomes apparent. At 100, and for all years after 100 (not plotted), we use SSA life tables. Thus, after age 89, we don't assess heterogeneity in survival by wealth levels. We provide the analogous panels for women in Figure A.2.

Figure A.3 that follows shows the life expectancy estimates that result from the combined methods as described in Section 4.1. The plot shows life expectancy for cohorts turning age 65 in 1996 and 2006, for men in panel (a) and for women in panel (b).

Figure A.1: Gompertz results for men



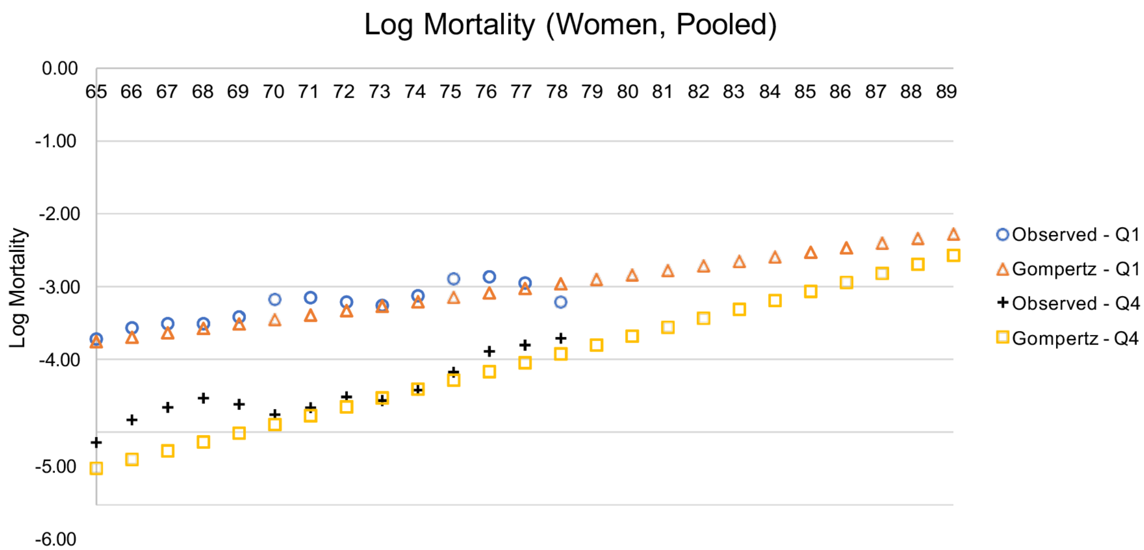
(a) Log Mortality



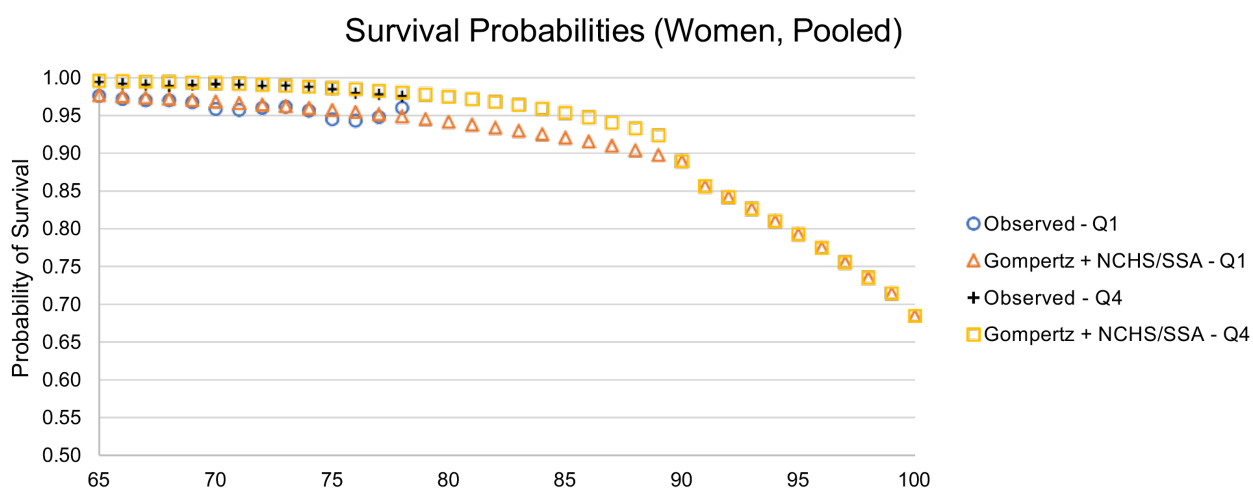
(b) Survival Probabilities

Note: Figure shows log mortality and the survival curve for men in our sample. In panel (a), we show the natural log of the mortality rate, on the vertical axis, at each age on the horizontal axis. We show this value for the first and fourth gender-specific wealth quartiles with observed and Gompertz estimates, based on the key, through age 78. At age 79, we lack enough data, so we turn to Gompertz approximation. In panel (b), we estimate the probability of survival, on the vertical axis, by age on the horizontal axis. This panel highlights the use of observed data through age 78, Gompertz approximation with our data through age 89, and then SSA/NCHS data after 90. Both panels use a blue circle marker for "1st Quartile—Observed," an orange triangle marker for "1st Quartile—Gompertz," a black plus-sign marker for "4th Quartile—Observed," and a yellow square marker for "4th Quartile—Gompertz." Source: HRS data 1996–2018 (for life expectancy through age 89), plus NCHS data for ages 90–99 and SSA data for ages 100+.

Figure A.2: Gompertz results for women



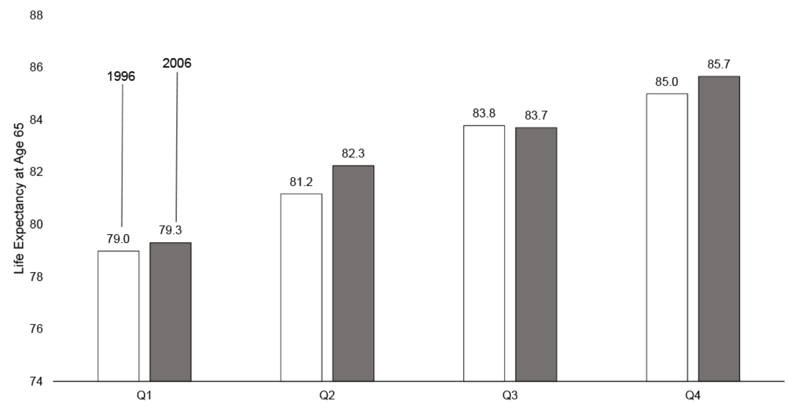
(a) Log Mortality



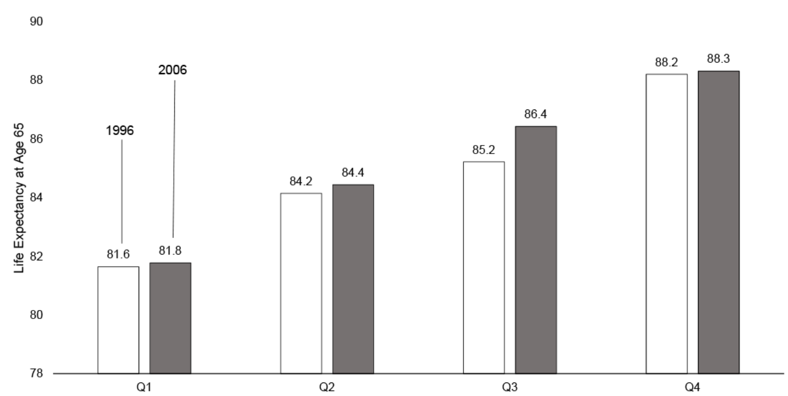
(b) Survival Probabilities

Note: Figure shows log mortality and the survival curve for women in our sample. In panel (a), we show the natural log of the mortality rate, on the vertical axis, at each age on the horizontal axis. We show this value for the first and fourth gender-specific wealth quartiles with observed and Gompertz estimates, based on the key, through age 78. At age 79, we lack enough data, so we turn to Gompertz approximation. In panel (b), we estimate the probability of survival, on the vertical axis, by age on the horizontal axis. This panel highlights the use of observed data through age 78, Gompertz approximation with our data through age 89, and then NCHS/SSA data after 90. Both panels use a blue circle marker for "1st Quartile—Observed," an orange triangle marker for "1st Quartile—Gompertz," a black plus-sign marker for "4th Quartile—Observed," and a yellow square marker for "4th Quartil—Gompertz." Source: HRS data 1996–2018 (for life expectancy through age 89), plus NCHS data for ages 90–99 and SSA data for ages 100+.

Figure A.3: Life expectancy at age 65 by wealth quartile and gender



(a) Men

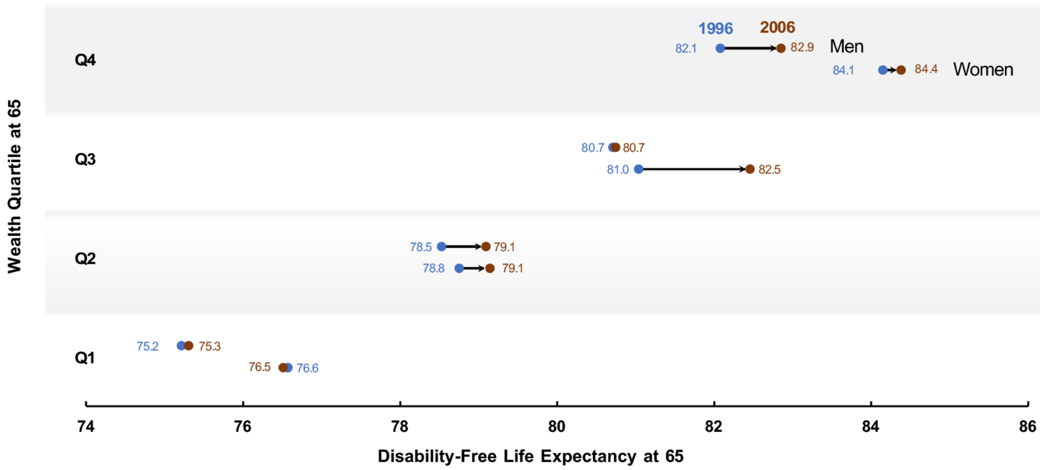


(b) Women

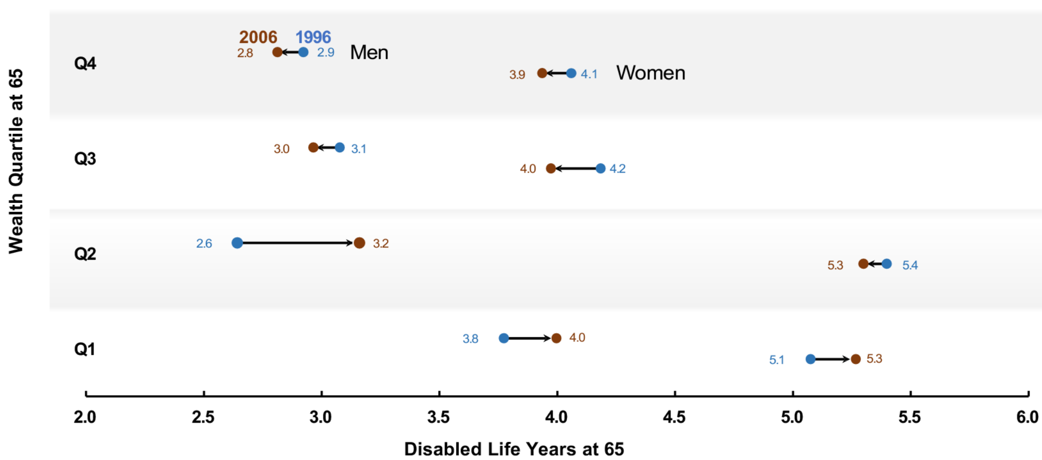
Note: Figure shows life expectancy estimates at age 65 (vertical axis) for men and women of each gender- specific wealth quartile (horizontal axis) in 1996 (left bar) and 2006 (right bar). Life expectancy estimates were derived as described in the text. Source: HRS data 1996-2018 (for life expectancy through age 89) where we pool between cohorts after age 78, plus NCHS data for ages 90–99 and SSA data for ages 100+.

B. Additional exhibits

Figure B.1: Between-cohort changes in DFLE and DLY, by gender (with wealth-gender-age interactions)



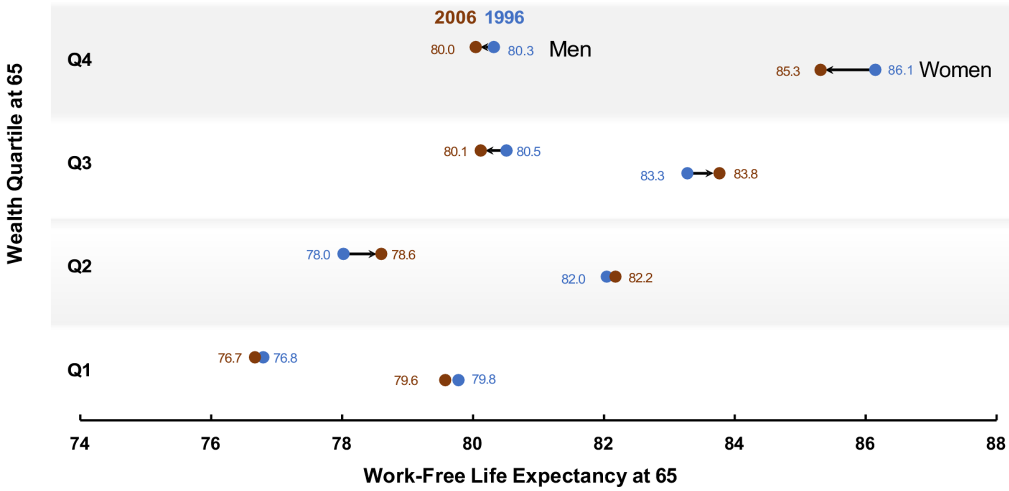
(a) Disability-Free Life Expectancy



(b) Disabled Life Years

Note: Figure shows changes in DFLE and DLY between 1996 and 2006; the outcome is indicated by the horizontal axis. In each panel, we show (gender-specific) wealth quartile on the vertical axis, and use arrows to depict the direction of changes from 1996 to 2006. The underlying regression uses equation (4) and adds wealth-gender-age interactions. Source: HRS respondents aged 64-66 in 1996 and 2006 (for disability prevalence and life expectancy through age 89) and all HRS respondents for disability after age 89, plus SSA and NCHS for life expectancy after age 89.

Figure B.2: Between-cohort changes in WFLE and WLY, by gender (with wealth-gender-age interactions)



(a) Work-Free Life Expectancy

(b) Working Life Years

Note: Figure shows changes in WFLE and WLY between 1996 and 2006; the outcome is indicated by the horizontal axis. In each panel, we show (gender-specific) wealth quartile on the vertical axis, and use arrows to depict the direction of changes from 1996 to 2006. The underlying regression uses equation (4) and adds wealth-gender-age interactions. Source: HRS respondents aged 64-66 in 1996 and 2006 (for disability prevalence and life expectancy through age 89) and all HRS respondents for disability after age 89, plus SSA and NCHS for life expectancy after age 89.

Table B.1: Wealth distribution across cohort and gender

	1996	2006	1996—Men	1996—Women	2006—Men	2006—Women
Quartile Cutoffs						
Q1	77,588	73,439	90,066	66,131	110,706	54,856
Q2	218,198	277,641	238,363	201,249	342,067	233,850
Q3	503,921	716,690	603,106	438,660	822,204	640,100
Quartile Means						
Q1	22,758	19,040	32,433	14,657	32,329	12,867
Q2	144,407	166,495	165,361	125,298	216,682	134,284
Q3	344,181	471,477	392,941	307,712	559,531	409,452
Q4	1,640,678	2,249,908	1,793,999	1,462,571	2,688,256	1,915,640
Overall Mean	529,542	735,639	632,738	506,750	895,093	627,903

Note: This table presents distributional values for respondent wealth at age 65 for each cohort. Wealth is in 2018 USD.
Source: HRS respondents aged 64–66 in 1996 and 2006, within a wealth quartile in the given year.

Table B.2: Staggered between-cohort regression: disability

	Disabled?		
	(1)	(2)	(3)
Wealth Quartile 2	-0.0762***	-0.0707***	-0.0631***
	(0.0121)	(0.0119)	(0.0119)
Wealth Quartile 3	-0.125***	-0.116***	-0.106***
	(0.0111)	(0.0109)	(0.0111)
Wealth Quartile 4	-0.145***	-0.135***	-0.124***
	(0.0107)	(0.0105)	(0.0108)
2006 Cohort	0.0261**	0.0298**	0.0298**
	(0.0123)	(0.0121)	(0.0121)
Wealth Quartile 2, 2006	-0.0105	-0.0124	-0.0144
	(0.0158)	(0.0156)	(0.0156)
Wealth Quartile 3, 2006	-0.0333**	-0.0367***	-0.0387***
	(0.0142)	(0.0140)	(0.0140)
Wealth Quartile 4, 2006	-0.0374***	-0.0408***	-0.0420***
	(0.0138)	(0.0137)	(0.0137)
Black			0.0350**
			(0.0140)
Hispanic			0.0475***
			(0.00933)
White			0.0139
			(0.0120)
Age-Gender Interactions	✓	✓	✓
Died next wave?		✓	✓
Race/Ethnicity			✓
Reference Group Mean	0.2430	0.2430	0.2430
Observations	30435	30435	30426
R^2	0.0508	0.0652	0.0666

Note: This table shows regression results for whether disabled in a given wave. Regressions use equation (4) and are estimated by linear probability applying individual HRS weights. The reference group is the first wealth quartile in 1996. Standard errors are in parentheses. Source: HRS respondents aged 64–66 in 1996 and 2006. Significance is given by: *p < 0.10, **p < 0.05, ***p < 0.01.

Table B.3: Staggered between-cohort regression: work

	Working?		
	(1)	(2)	(3)
Wealth Quartile 2	0.0331***	0.0300***	0.0277**
	(0.0112)	(0.0112)	(0.0114)
Wealth Quartile 3	0.0138	0.00906	0.00640
	(0.0107)	(0.0107)	(0.0110)
Wealth Quartile 4	0.0469***	0.0412***	0.0381***
	(0.0105)	(0.0105)	(0.0110)
2006 Cohort	0.0134	0.0114	0.0121
	(0.0122)	(0.0122)	(0.0122)
Wealth Quartile 2, 2006	0.0409**	0.0420***	0.0420***
	(0.0162)	(0.0161)	(0.0162)
Wealth Quartile 3, 2006	0.0768***	0.0788***	0.0788***
	(0.0157)	(0.0156)	(0.0157)
Wealth Quartile 4, 2006	0.0802***	0.0821***	0.0820***
	(0.0155)	(0.0154)	(0.0154)
Black			0.0152
			(0.0182)
Hispanic			-0.0252**
			(0.0110)
White			0.0111
			(0.0163)
Age-Gender Interactions	✓	✓	✓
Died next wave?		✓	✓
Race/Ethnicity			✓
Reference Group Mean	0.2231	0.2231	0.2231
Observations	30407	30407	30398
R^2	0.185	0.187	0.188

Note: This table shows regression results for whether working in a given wave. Regressions use equation (4) and are estimated by linear probability applying individual HRS weights. The reference group is the first wealth quartile in 1996. Standard errors are in parentheses. Source: HRS respondents aged 64–66 in 1996 and 2006. Significance is given by: *p < 0.10, **p < 0.05, ***p < 0.01.

Table B.4: Nonlinear estimation models related to work

	Logit (1) Working?	Tobit (2) Hours Worked
Wealth Quartile 2	0.191**	3.089*
	(0.0783)	(1.687)
Wealth Quartile 3	0.0449	0.162
	(0.0785)	(1.698)
Wealth Quartile 4	0.264***	3.233**
	(0.0753)	(1.631)
2006 Cohort	0.125*	3.173**
	(0.0737)	(1.578)
Wealth Quartile 2, 2006	0.145	2.896
	(0.0964)	(2.029)
Wealth Quartile 3, 2006	0.363***	6.470***
	(0.0953)	(2.006)
Wealth Quartile 4, 2006	0.309***	7.110***
	(0.0918)	(1.934)
Race/Ethnicity	✓	✓
Age-Gender Interactions	✓	✓
Died next wave?	✓	✓
Reference Group Mean	0.2231	7.6883
Observations	30398	30074

Note: This table presents regression results with different dependent variables and specifications, as indicated by each column heading. Standard errors are in parentheses. Individual HRS weights are used. For the logit regression, the model follows the same design as equation (4) and the second column of Table 2. For the tobit regression, the lower limit is set to zero, and we set hours worked to zero if a respondent was alive but not working. Reference group mean refers to the weighted mean of the outcome among individuals in the first wealth quartile in 1996. Source: HRS respondents aged 64-66 in 1996 and 2006. Significance is given by: *p < 0.10, **p < 0.05, ***p < 0.01.

Table B.5: Summary statistics for education "quartiles"

	(1) 1996—Q1	(2) 1996—Q2	(3) 1996— Q3	(4) 1996— Q4	(5) 2006— Q1	(6) 2006—Q2	(7) 2006— Q3	(8) 2006— Q4
Median Wealth	0.93	2.50	3.29	4.89	0.74	2.87	3.73	7.17
(age 65, $100,000)	(5.246)	(13.48)	(15.90)	(17.51)	(7.846)	(8.705)	(17.36)	(32.05)
Male	0.50	0.42	0.48	0.56	0.45	0.39	0.43	0.55
	(0.500)	(0.493)	(0.500)	(0.497)	(0.498)	(0.489)	(0.496)	(0.498)
Black	0.24	0.11	0.12	0.10	0.24	0.15	0.16	0.10
	(0.427)	(0.310)	(0.325)	(0.300)	(0.426)	(0.354)	(0.366)	(0.304)
White	0.70	0.87	0.85	0.88	0.68	0.83	0.80	0.85
	(0.457)	(0.334)	(0.356)	(0.330)	(0.466)	(0.373)	(0.398)	(0.354)
Hispanic	0.14	0.04	0.06	0.02	0.22	0.05	0.08	0.04
	(0.352)	(0.203)	(0.240)	(0.130)	(0.414)	(0.224)	(0.266)	(0.187)
N	854	744	425	410	762	866	615	554

Note: This table presents summary statistics within respondent education "quartiles" for each cohort. The groups are not true quartiles because educational attainment is lumpy, so observed cutoffs do not divide the data evenly. Education "quartiles" are defined as: Q1 = limited high school or GED, Q2 = high school graduate, Q3 = some college, and Q4 = college and above. Wealth is in 2018 dollars. Standard deviations are in parentheses. Source: HRS respondents aged 64–66 in 1996 and 2006.

Table B.6: Regression results with education "quartiles"

	(1) Disabled?	(2) Working?
Education Quartile 2	-0.0617***	0.0574***
	(0.00882)	(0.00814)
Education Quartile 3	-0.0922***	0.0800***
	(0.00952)	(0.00979)
Education Quartile 4	-0.0752***	0.103***
	(0.00981)	(0.00992)
2006 Cohort	0.0395***	-0.0178*
	(0.0102)	(0.00968)
Education Quartile 2, 2006	-0.0343***	0.0676***
	(0.0123)	(0.0127)
Education Quartile 3, 2006	-0.0140	0.0755***
	(0.0131)	(0.0145)
Education Quartile 4, 2006	-0.0655***	0.127***
	(0.0128)	(0.0145)
Race/Ethnicity	✓	✓
Age-Gender Interactions	✓	✓
Died next wave?	✓	✓
Reference Group Mean	0.2240	0.1833
Observations	34821	34791
R^2	0.0573	0.207

Note: This table shows regression results with different dependent variables, as indicated by each column heading, portraying equation (4) for disability and work, applying individual HRS weights. Education "quartiles" are defined as: 1) limited high school or GED, 2) high school graduate, 3) some college, and 4) college and above. Standard errors are in parentheses. Reference group mean refers to the weighted mean of the outcome among individuals in the first education "quartile" in 1996. Significance is given by: *p < 0.10, **p < 0.05, ***p < 0.01.

Table B.7: Health composition across cohorts at age 65

	(1) Self-Reported Health	(2) Doctor Visits	(3) Hospital Visits
Wealth Quartile 2	-0.291***	-0.134	-0.336***
	(0.0924)	(1.563)	(0.118)
Wealth Quartile 3	-0.564***	-2.568***	-0.377***
	(0.0927)	(0.879)	(0.118)
Wealth Quartile 4	-0.804***	-2.355**	-0.457***
	(0.0906)	(1.069)	(0.113)
2006 Cohort	0.165*	2.057	-0.0764
	(0.0908)	(1.371)	(0.165)
Wealth Quartile 2, 2006	0.0312	0.273	0.179
	(0.126)	(2.170)	(0.183)
Wealth Quartile 3, 2006	-0.111	0.0597	0.0419
	(0.122)	(1.551)	(0.175)
Wealth Quartile 4, 2006	-0.0632	0.143	0.0845
	(0.116)	(1.673)	(0.171)
Race/Ethnicity	✓	✓	✓
Age-Gender Interactions	✓	✓	✓
Died next wave?	✓	✓	✓
Reference Group Mean	3.1148	9.7456	0.6951
Observations	3348	3245	3339
R^2	0.141	0.0508	0.0480

Note: This table shows regression results with the dependent variable indicated by the column heading. Self-reported health is on a 1-5 scale where 1 is best. The number of doctor and hospital visits is provided over the last two years. Regressions use equation (4) and are estimated by linear probability applying individual HRS weights. The reference group is the first wealth quartile in 1996. Standard errors are in parentheses. Source: HRS respondents aged 64–66 in 1996 and 2006. Significance is given by: *p < 0.10, **p < 0.05, ***p < 0.01.

Table B.8: Regression results using 1996 wealth quartile cutoffs

	(1) Disabled?	(2) Working?
Wealth Quartile 2	-0.0777***	0.0192*
	(0.0109)	(0.0103)
Wealth Quartile 3	-0.107***	0.00651
	(0.0127)	(0.0147)
Wealth Quartile 4	-0.123***	0.0377***
	(0.0108)	(0.0110)
2006 Cohort	0.0228*	0.0199
	(0.0121)	(0.0122)
Wealth Quartile 2, 2006	-0.00184	0.0264*
	(0.0144)	(0.0149)
Wealth Quartile 3, 2006	-0.00437	0.105***
	(0.0162)	(0.0207)
Wealth Quartile 4, 2006	-0.0341**	0.0636***
	(0.0135)	(0.0150)
Race/Ethnicity	✓	✓
Age-Gender Interactions	✓	✓
Died next wave?	✓	✓
Reference Group Mean	0.2430	0.2231
Observations	30426	30398
R^2	0.0637	0.187

Note: This table shows regression results with the dependent variable indicated by the column heading. Here, (gender-specific) wealth quartiles are set, in both cohorts, using the 1996 wealth distribution. Regressions use equation (4) and are estimated by linear probability applying individual HRS weights. The reference group is the first wealth quartile in 1996. Standard errors are in parentheses. Source: HRS respondents aged 64–66 in 1996 and 2006. Significance is given by: *p < 0.10, **p < 0.05, ***p < 0.01.

About the authors

Professor Bavafa is an Associate Professor of Operations and Information Management at the Wisconsin School of Business. His research focuses on innovative technologies and service delivery models, people-centric and behavioral factors that affect performance, healthcare resource management, and quality management. He is an affiliate faculty of the Department of Family Medicine and Community Health at the University of Wisconsin School of Medicine and Public Health. He is also affiliated with the Center for Demography of Health and Aging. Professor Bavafa received his Ph.D. and master's degrees in Operations Management from The Wharton School, University of Pennsylvania. Professor Bavafa also holds a master's degree in Operations Research from the Sauder School of Business, University of British Columbia, and a bachelor's degree in Industrial Engineering from the Sharif University of Technology.

Professor Mukherjee is an Associate Professor of Risk and Insurance at UW-Madison's Wisconsin School of Business. A key stream of her research is on household finance, retirement, and financial literacy, and she is currently an editor at The Journal of Pension Economics and Finance. She is a fellow of the TIAA Institute, a consultant at the Federal Reserve Bank of Chicago (Insurance Initiative), and a member of the G53 Financial Literacy and Personal Finance Research Network. She is also an affiliated faculty at the University of Wisconsin Law School, and a member of the Risk Theory Society. Professor Mukherjee earned her Ph.D. in Applied Economics at The Wharton School, University of Pennsylvania and holds an M.S. in Management Science and Engineering, a B.S. in Mathematics, and a B.A. in Economics, all from Stanford University.

Mr. Welch is a Ph.D. Candidate in the Risk and Insurance department at the University of Wisconsin-Madison's Wisconsin School of Business. His research focuses on how individuals and insurance markets interact, specifically with individual decision-making, social insurance systems, public policy, aging, and health. He is a Graduate Research Fellow at the Institute for Research on Poverty and an Associate Member at the National Academy of Social Insurance. He holds a BBA in Risk Management and Insurance from Temple University's Fox School of Business and is a Certified Employee Benefits Specialist.

About the TIAA Institute

The TIAA Institute helps advance the ways individuals and institutions plan for financial security and organizational effectiveness. The Institute conducts in-depth research, provides access to a network of thought leaders, and enables those it serves to anticipate trends, plan future strategies, and maximize opportunities for success.

To learn more, visit tiaainstitute.org.

Join the conversation online:
@TIAAInstitute

All authors are based at the Wisconsin School of Business, University of Wisconsin-Madison. Bavafa: hessam.bavafa@wisc.edu; Mukherjee: anita.mukherjee@wisc.edu; Welch: tyler.welch@wisc.edu. We are grateful for helpful comments from Raj Chetty, David Cutler, Shanthi Ramnath, Dan Sacks, Justin Sydnor, and seminar participants at the 2022 ARIA Annual Conference; the 2021 ARC Centre of Excellence in Population Ageing Research Conference at UNSW Business School; the 2019 AEA Annual Meeting; the 2019 Michigan Retirement and Disability Research Center, especially our discussant Nicole Maestas; the 2019 University of Wisconsin-Madison Health Economics Working Group; and the 2018 NBER Determinants of Life Expectancy Conference. Junhao Liu provided excellent research assistance. This research was sup-ported by funding from the Social Security Administration and the TIAA Institute. The content, findings, and conclusions are the responsibility of the author(s) and do not necessarily represent the views of Social Security Administration, TIAA, or the TIAA Institute.

TIAA Institute

(09/23)