Inequities in the Golden Years: How Wealth Shapes Healthy and Work-Free Life*

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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 recent decades of data from the United States. First, the additional years are in healthy, disability-free years, indicating substantial gains for the wealthy. Second, the return to wealth in achieving these healthy years is increasing over two recent decades for all but the poorest quartile. Third, the additional years lived by the wealthy result in more years of work (and the most work-free years), exacerbating wealth inequality. The subjective expectations of individuals appear misaligned with the empirical findings, with the least wealthy reporting excessive optimism about life expectancy gains. 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.

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1 Introduction

Many individuals in developed nations anticipate a set of "golden years" in later life with good health and no work obligations. Yet, life expectancy gains over time have been accruing unequally, 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). That same analysis finds temporal gains, between 2001-2014, of three years in life expectancy for the wealthiest, with zero gain for the poorest. Recent work has also identified that, between 1992 and 2008, disability-free life expectancy (DFLE) has grown by 1.8 years, which outpaced the growth in life expectancy overall (Chernew et al., 2017). These two pieces of evidence highlight not only the growing wealth gap in life expectancy, but *healthy* life expectancy.

Wealth-related inequality in life expectancy is important for understanding how redistributive systems are working in accordance with their intended design. Specifically, the Social Security program in the US is designed to re-distribute earnings from high earners to low earners in the form of a higher replacement percentage of pre-retirement income. Recent work has considered this: with life expectancy gains being distributed to higher earners, the average lifetime gap in Social Security program benefits for men widens, between the highest and lowest income quintile, by $130,000 between 1930 and 1960 birth cohorts (Auerbach et al., 2017). This move is in accordance with a life expectancy gap growing by 8 years between these birth cohorts. With the wealth gap in life expectancy, social insurance programs, and other redistribute mechanisms, stand to have their impact dampened when the wealthiest live far longer and far healthier than the poorest.

We study DFLE and work-free life expectancy (WFLE) to ascertain how the growing inequality in life expectancy is materializing in ways more directly tied to retirement savings and longevity risk management. Critically, we expand the consideration of DFLE to include wealth heterogeneity to better understand differentials in healthy life expectancy between the most and least wealthy individuals in the US. Our newly developed term, WFLE measures the length of life, after 65, spent free of paid work. This measure allows us to consider how older, wealthier Americans are spending their longer, healthier lives.

Our analysis focuses on two cohorts of individuals turning 65 a decade apart. Analyzing individuals at this age is particularly important for our motivation in analyzing late-in-life wealth inequality, retirement savings, and longevity risk management. Our primary measure of wealth is measured at age 65, which reflects not just wealth but likely also prior health (e.g., someone who was disabled earlier in life may have used their savings). The estimation strategy fixes the poorest quartile in the first cohort as the reference category, and examines how other wealth quartiles interacted by cohort compare with respect to the outcomes of interest (e.g., disability). Note that we treat wealth as static at age 65, though we acknowledge important trends in life expectancy by wealth when examining income mobility as studied in Kreiner et al. (2018).

Our estimation strategy of comparing wealth quartiles by cohorts directly deals with an important source of reverse causality. Wealth is endogenous to health, as someone with a health shock may have used their savings to pay for health expenditures or related shocks earlier in life. Thus, they would arrive at age 65 with less wealth, and they may experience disability or reduced life expectancy because of their prior health problems. As long as this type of path appears for individuals turning 65 in both cohorts a decade apart, taking the difference in coefficients mitigates the presence of health-wealth reverse causality affecting our results.

To compute our measures of DFLE and WFLE, we use publicly-available and nationally-representative Health and Retirement Study (HRS) data, combined with data from other sources related to life expectancy at extreme older ages. We first estimate life expectancy and then join disability and work estimates with the mortality estimates. We follow Chetty et al. (2016) closely in setting up the life expectancy estimates - first by empirically estimating life expectancy by wealth-at-65 and then using a Gompertz Approximation method at older ages, all before turning to life tables for age 90 and beyond. We also follow Chernew et al. (2017)'s design in computing DFLE, which we expand to also compute WFLE. This methodology uses static and temporal regression estimations to predict the probability of being disabled (and working) for years after age 65. These regression estimates are then used, in conjunction with the life expectancy estimates, to compute DFLE and WFLE.

We find that, over time, gains in disability-free life expectancy accrued only to the wealthiest individuals. Specifically, we estimate DFLE gains of 0.9 (2.4) years for men (women) in the fourth quartile of wealth-at-65, while the analogs for the first wealth quartile are changes of 0 (-0.3) years for men (women). These findings coincide with our life expectancy results, and allow us to understand that the wealth gap in life expectancy is not only in the length of life, but also in the quality of life.

Our final contribution is to consider how wealthier individuals are using these longer, healthier lives. In that vein, we estimate that WFLE, without the same monotonicity as DFLE, increased for the wealthiest quartile by 0.2 (2.4) years for men (women) from 1992 to 2002. For men (women), the poorest quartile experienced WFLE contractions, over the same period, of 0.5 (0.8) years. These results highlight an important feature of our WFLE analysis: the wealthiest individuals are able to use their longer, healthier lives to both 1) work longer and 2) retain more of their life as work-free.

We also use response data from the HRS to estimate subjective life expectancy and subjective morbidity expectations, using the same methodology as for DFLE and WFLE. Our subjective findings indicate that there is some recognition of the wealth gradient in life expectancy, but that, temporally, the poorest individuals perceive gains in their mortality that are not empirically found. With subjective morbidity, the wealthiest individuals recognize some of their lowered morbidity risk, but the poorest individuals perceive no change in their morbidity risk. Overall, although the subjective results are not the cornerstone of this analysis, they present some insights into the mismatch between empirical observations and subjective beliefs, which may have ramifications for how individuals manage their longevity.

Taken together, our results indicate that wealth inequality is exacerbating important measures beyond just life expectancy; namely, DFLE and WFLE gaps are growing and, most concerning, the poorest individuals are experiencing no gain temporally (and even experiencing small contractions). With wealth inequality growing over time and the poor becoming poorer quartile-wise, we re-estimate our models fixing wealth inequality at the 1992 level. When we do this, we determine that the absolute level of wealth contributes to the trends in DFLE and WFLE, but that the trends by wealth quartile remain the same.

This work contributes to several strands of the existing literature, which we detail in the next section. Broadly, we contribute to the literature on life expectancy, showing that the life expectancy gains for the wealthy, as seen in prior studies, are primarily in healthy, disability-free years. To the best of our knowledge, this insight has not yet been established in the literature. Second, building directly from Chernew et al. (2017), we provide the first dynamic estimates of growing wealth inequality in DFLE, along with the extension of this framework to a new measure, WFLE. Understanding growing inequality in these measures helps us extend the discussion related to the redistributive concerns of social insurance programs in (Auerbach et al., 2017).

After the literature review, Section 3 describes the data; Section 4 the methodology; and Section 5 the results. In Section 6, we discuss the implications of our findings.

2 Literature Review

Here, we review the literature on patterns pertinent to our main estimates of DFLE and WFLE. Specifically, we detail research findings on patterns in life expectancy, disability, and work capacity at older ages.

2.1 Patterns in life expectancy

Life expectancy, including its movements over time, heterogeneity amongst sub-populations, and its role in forming policy, is a critical subject of research. Recent research has shown that, during the time of our study and beyond, specifically from 1970-2010, life expectancy has increased worldwide (Wang et al., 2012). Beyond the broad-stroke movements in life expectancy, though, are important findings of life expectancy other than the well-understood sources of differences such as sex, age, and health. Much of our inspiration comes from recent work, with particularly stark results, on the life expectancy gap and how it is tied to wealth. Two recent studies, in particular, have a salient impact on our work. The first is work that finds the life expectancy gap, between men in the highest income quintile and lowest income quintile, grows from 5 years for a 1930 birth cohort to nearly 13 years for a 1960 birth cohort (Auerbach et al., 2017). Auerbach et al. (2017) also provides a thorough review of related findings.

The second recent paper we note here is an analysis that found life expectancy gaps as large as 15 years for men, between those in the top 1% of the income distribution and the bottom 1% (Chetty et al., 2016). This paper finds a smaller gap for women, though it was still a 10-year difference. Particularly stark in this work are the temporal gains in life expectancy for those in the top 1% of the income distribution, gaining 3 years of life expectancy between the study period of 2001-2014. However, those in the bottom 1% experienced no gain at all. To highlight these differences directly from Chetty et al. (2016), the authors state that life expectancy for men (from the US) in the bottom 1% of the income distribution (at age 40) ranks similar to Sudan and Pakistan; however, men (from the US) in the top 1% have "higher life expectancies than the mean life expectancy for men in all countries at age 40 years."

Other important work has also identified heterogeneity in life expectancy. Some researchers have identified heterogeneity by education (Meara et al., 2008; Leive and Ruhm, 2021). Similarly, Sanzenbacher et al. (2021) finds that while life expectancy gains have accrued across the board, mortality inequality is increasing across socioeconomic statuses. This paper uses a unique approach, to avoid changes in the education distribution temporally, by looking at educational heterogeneity by assigning people to education quartiles based on things correlated with education levels (i.e., wage). In addition, others have discussed both morbidity and mortality risk. Specifically, recent work has shown that gaps between individuals in higher income quintiles and individuals in lower income quintiles are large for both mortality and morbidity risk, with larger gaps for morbidity risk (Makaroun et al., 2017).

With respect to heterogeneity in life expectancy, new work has also focused on understanding how to decompose these differences in the US and Denmark, specifically with respect to survivability (i.e., the ability for the poorest to live a point of life expectancy gains) and mortality trends (Dahl et al., 2021).

2.2 Patterns in disability

With respect to morbidity risk, and directly in the line of our paper, we also recognize important work in the development of understanding around DFLE. In fact, many papers have found that DFLE has been increasing over time. Markedly, there were increases in DFLE during the 1980s (Crimmins et al., 1997). Two other recent studies have showed similar results. Namely, the first is a study which found increases in DFLE of 1.6 years between 1992 and 2005 (similar to the period we study), along with increases in disease-free survival (Cutler et al., 2014). The second study measures increases in active life expectancy and analyzes sensitivity to various definitions of disability levels (Cai and Lubitz 2007). Similarly, other work has found increases in DFLE but no increase in disabled life expectancy - which allows the authors to note decreased incidence of disability over time, combined with better recovery (Crimmins et al. 2009).

With regard to DFLE, we rely on Chernew et al. (2017). Specifically, between 1992 and 2008, Chernew et al. (2017) found increases in DFLE of 1.8 years or so, which outpaced the growth in life expectancy overall. The Chernew et al. (2017) analysis not only argues for compression of morbidity in later life years (which much of the prior literature has argued, too), but it also analyzes the medical conditions which have contributed the most to increases in DFLE temporally. While we do not analyze medical conditions, we do rely on the structure of this analysis, specifically in developing a linear probability model for the chance of being disabled (where we replace the medical condition heterogeneity with a focus on wealth quartiles).

In addition to analyzing DFLE in the US, there has been investigation into this measure internationally. Some work has warned of the difficulty in comparing the results between countries due to differences in disability insurance programs and medical care (Crimmins et al. 1989). Nonetheless, we find it useful to discuss some results more broadly. As such, some research has focused on the relationship between living in an established market economy and spending a smaller percentage of one's life with a disability (Murray and Lopez, 1997). These authors also present weighted disability measures, with a careful discussion of disability burdens.

2.3 Patterns in work capacity at older ages

Our research also forwards the literature regarding work behavior at older ages, including after retirement. We note, though, that it is critical to understand that working during retirement is not an uncommon phenomenon. In fact, seminal work has addressed this idea of unretirement (Maestas, 2010). In this analysis, it is clear that the process of unretirement is generally expected before retirement and that those individuals who have unmet expectations are likely experiencing that because of either positive news on wealth or negative news on health. The intricate details behind the demand, supply, and future work at older ages is carefully discussed in Maestas and Zissimopoulos (2010).

There is also a stream of literature regarding changes in working life expectancy (WLE). In particular, there are findings of general temporal increases in Europe (Loichinger and Weber, 2016) and decreases in the US, especially during the Great Recession (Dudel and Myrskylä, 2017). This latter work also analyzes HRS data and finds that WLE, though quite volatile over the study period, was equal to, for example, 14.5 years at age 50 for men between 1993-1997. For women, that value was about three years less. Recent work from England has highlighted healthy working life expectancy (being healthy and working) to be roughly 9.5 years at age 50 for men (slightly less for women) (Parker et al., 2020). In this work, overall WLE (adding in unhealthy working years) amounts to roughly 13 years for men and 10 years for women (from age 50). In each of these analyses, there is no conclusion surrounding heterogeneity based on wealth, though there are other focuses in these papers (education, race, etc.).

3 Data

Our core data source is individual-level information from the 1992 through 2012 waves of the Health and Retirement Study (HRS). These data are well-suited to our research goal of examining the changing gradient to wealth of life expectancy, disability, work, along with certain subjective expectations of these outcomes. To generate the needed life expectancy calculations for those aged 90 and above (not observed in the HRS), we use age-sex life tables from the National Center for Health Statistics (NCHS) and the Social Security Administration (SSA).

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 excluding an individual's second home, which 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), vehicles, businesses, IRA and Keogh accounts, stocks, mutual funds, investment trusts, bonds, 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.[1] We use the continuous wealth variable to generate within-cohort quartiles of wealth for each respondent in our analyses.

The life expectancy metric is developed using the HRS interview status, namely whether the individual is alive (even if they did not respond to the survey) or reported to have died in the past two years.[2] The HRS verifies all death reports with the National Death Index and is

[1] This variable contains some missing values. If we do not see a respondent precisely in the year which they are 65, we substitute with wealth in the next survey. If that, too, is unavailable, we use wealth from the previous survey (i.e., roughly age 64). We employ a similar strategy with respect to the HRS weights, where missing weights are replaced by the most recent available weight.

[2] We estimate life expectancy using HRS observations through age 89. For ages 90 and above, we follow Chetty et al. (2016) and use NCHS and SSA data to estimate the life expectancy based on aggregated age-sex profiles. NCHS data is 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).

able to correctly identify and classify deaths where the data resemble most life tables.[3] The disability metric is time-varying and binary, and captures whether the respondent reports any Disability in Activities of Daily Living (ADL) – these include bathing, dressing, eating, getting out of the bed, or walking across a room. Measuring disability in this manner is consistent with prior research (e.g., Chernew et al. 2017), but leaves out substantial richness in reported health. The work metric is also time-varying and binary, and is defined as whether the respondent reports working for pay at the time of survey. We also examine hours worked in separate analyses.

The HRS also asks respondents about their self-assessed probabilities of life expectancy and work-limiting disability. These questions are asked to a subset of the full survey respondents, however, so we expand the sample to those aged 60-65 to increase the statistical power of our analyses. We use the following two questions from the survey:

1. "What is the percent chance that you will live to be 75 or more?"

2. "What about the chances that your health will limit your work activity during the next 10 years?"

Each respondent offers a value, from 0-100 (out of 100), in response to each question. We convert this variable to a probability $p \in [0, 1]$ and use that as the dependent variable in our analyses.

3.1 Summary Statistics

Table 1 presents summary statistics for our sample. In the table, birth year provides an important check and vindication of our analysis' samples. The fact that it is not precisely equal to the observation year minus 65 years is because we use those aged 64-66 in a given wave. The difference in the number of male and female observations between 1992 and 2002 comes from HRS sampling design.[4]

[3]The validity of HRS mortality data is highlighted in a recent report (Weir, 2016).

[4]For the first HRS wave, our 1992 cohort, they aimed to sample individuals born between 1931-1941, thus making our respondents aged 64-66 spouses of those interviewed, where the higher prevalence of men in 1992 comes from the nuance of age in marriage structure.

Table 1: Summary Statistics

	1992 Cohort		2002 Cohort	
	(1) Men	(2) Women	(3) Men	(4) Women
Birth Year	1927.22	1927.43	1937.00	1937.02
	(0.797)	(0.585)	(0.823)	(0.816)
Wealth-at-65 (100,000)	4.26	3.59	5.28	4.86
	(7.403)	(5.743)	(9.573)	(14.70)
Ever Disabled?	0.28	0.31	0.29	0.33
	(0.450)	(0.462)	(0.455)	(0.472)
Ever Working?	0.41	0.17	0.53	0.40
	(0.492)	(0.380)	(0.499)	(0.491)
N	387	190	1,032	1,205

Notes: This table depicts summary statistics for our data. Columns 1 & 2 provide information for the 1992 cohort, while columns 3 & 4 do the same for the 2002 cohort. Men and women are shown in columns 1 & 2, and 3 & 4, respectively. Standard deviations are in parentheses. We define wealth-at-65 as total household assets at age 65 (at age 64 or 66 if not interviewed at 65) in hundreds of thousands. "Ever Disabled?" measures the percentage of respondents who report a disability between ages 64-76. "Ever Working?" measures the percentage of respondents who report working for pay between ages 64-76. Wealth is in 2012 USD. Source: HRS data from 1992-2012, specifically: in columns 1 & 2 - HRS respondents aged 64-66 in 1992, and in columns 3 & 4 - HRS respondents aged 64-66 in 2002.

We see that wealth-at-65 is different between cohorts. In the 1992 cohort, the average for men is \$426,000 and \$359,000 for women. In 2002, those grow to \$528,000 and \$486,000 for men and women, respectively. This highlights a nearly 24% increase in the average wage for men between cohorts and a 35% temporal increase for women, an indication of expanding wealth inequality. We see that the proportion of individuals ever being disabled between ages 64-76 is more or less the same between cohorts and across sex: 0.28, 0.31, 0.29, and 0.33 for men and women in 1992 and 2002, respectively. In the proportion ever working between ages 64-76, we see that, between cohorts, the difference between men and women is similar, where women are less likely to ever work at these ages compared to men. However, for both men and women in 1992, with proportions ever working for pay between ages 64-76 equal to 0.41 and 0.17, working seems to become more popular over time, where in 2002 those values are 0.53 and 0.40 for men and women, respectively.

4 Methodology

We contribute stylized facts along with difference-in-differences-type estimation similar to that in Chernew et al. (2017), which also studies DFLE, to analyze the temporal patterns in DFLE and WFLE. The first part of our methodology relates to calculating DFLE, which requires two "ingredients": life expectancy and disability prevalence. We require these estimates by age, sex, and, importantly, wealth quartile groups. We port the methodology for the WFLE estimation by replacing the binary disability outcome with a binary working outcome.

4.1 Calculating Life Expectancy

We calculate life expectancy at age 65 (thus, conditional on reaching age 65) for those cohorts entering age 64-66 in 1992 and 2002, by gender and age. We estimate life expectancy using the HRS data itself (and reported deaths) through age 76. After age 76, we follow prior literature in estimating life expectancy. In particular, we use a Gompertz model to estimate life expectancy for those aged 77-89, as we no longer observe individuals above age 76 in our constructed cohorts. Similar to recent work in this manner, we fit a generalized linear model (GLM) of a binomial dependent variable and log-link function (Chetty et al., 2016) to estimate life expectancy for each wealth quartile and by sex. We observe that the Gompertz model fits well, as evidenced by a high R^2 value (0.9841). The details of the Gompertz model design, and the relevant discussion, are provided in Appendix A.

For ages 90 and above, we turn to well-developed life tables to estimate life expectancy. NCHS life expectancy data is gathered, by sex, for those aged 90-99 from NCHS life tables spanning 1997-2013.[5] For ages 100 and above, we use the SSA life expectancy data. Given the waved nature of the HRS data, we only have individual data every two years, not every year. Thus, to get a probability of surviving to age t+1, we average the square root of survival rates at age t and at age t+1. Similar to Chernew et al. (2017), when we observe someone has died in a given wave, we assume they lived half of the wave. With our later

[5] These are taken from each of the associated National Vital Statistics Reports.

disability and work analysis, we assume they would have been disabled or worked for half of the wave (one year).

In summary, life expectancy is a summation of the average years lived at each age, conditional on surviving to that age.[6]

4.2 Constructing and Analyzing DFLE

We use the pooled HRS data to obtain the prevalence of disability.[7] Note here that the pooled data assumes the same disability prevalence for a given person of a certain age and sex, which means that we have not yet allowed disability estimates to be impacted by wealth quartile. Given our aim in this work, we estimate the following prediction equation that adjusts disability estimates for each wealth quartile (this is the within-cohort analysis):

$$Disability_{i,t} = \beta\ WealthQuartile_{i,t} + \gamma\ Demographics_{i,t} + \epsilon_{i,t}. \tag{1}$$

The coefficient vector β is of key interest for this work given our interest in disability-wealth relationships. This vector contains seven coefficients (reference category is the 1992-Q1): 1992-Q2, 1992-Q3, 1992-Q4, 2002-Q1, 2002-Q2, 2002-Q3, and 2002-Q4. The inclusion of demographics follows prior work (Chernew et al. (2017)); in particular, we include age-sex dummies (e.g., male 70-74 years) to capture differential disability probabilities and a time-to-death dummy for 2 years prior to death (given the waved nature of our data). The latter dummy accounts for the observation that individuals are more likely to be disabled in their final years of life. We do not observe individuals with one or three year(s)-to-death because the HRS survey is every two years, so they are excluded to avoid collinearity.

Here, we note a methodological concern that wealth and health are reversely correlated, and we recognize prior literature has helped establish the direction of causality using im-

[6]For example, at age 70, the average number of years lived is the product of two elements: 1) probability of surviving to 70 (products of survival probabilities at each age, 65-69) and 2) the chance of surviving to 71 plus one half the chance of death. This second element is telling us how much of the year, at age 70, people are living - based on how many live to 71 and then assuming those that die between 70-71 as having lived half of a year. This is then multiplied by the first element, which is the probability of living to age 70.

[7]The disability variable is not available in Wave 1 (1992).

proved identification techniques (e.g., stock market fluctuations as in Schwandt (2018); Supplemental Security Income benefits as in Herd et al. (2008)). In addition, previous work has found that, after controlling for initial health levels, wealth is an important determining factor of eventual mortality and future health outcomes (Attanasio and Emmerson, 2003). Nonetheless, it is not hard to imagine a story where this presents itself. Someone with a health shock may have used their savings to pay for health expenditures or related shocks earlier in life. Thus, they would arrive at age 65 with less wealth, and they may experience disability or reduced life expectancy because of their prior health problems. For this analysis, as long as this type of path appears for individuals turning 65 in both cohorts a decade apart, taking the difference in coefficients mitigates the presence of health-wealth reverse causality affecting our results.

To calculate DFLE using our regression results, we again follow a similar design to that in Chernew et al. (2017) and to the one described above for life expectancy results. Here, DFLE is, in short, the sum of average disability-free years lived from age 65 onward.[8] Note that we are able to determine DFLE by wealth-at-65 cohort and sex for both the 1992 and 2002 cohorts.

We then turn to the dynamic portion of the analysis, in which we examine whether the DFLE-wealth gap has been widening or narrowing as we move from the 1992 cohort to the 2002 cohort. If the results with respect to DFLE mirror the results recently documented in life expectancy, there should be increasing returns to wealth over time. We estimate the following regression (this is the between-cohort analysis):

$$Disability_{i,t} = \theta \; WealthQuartile_{i,t} \times Cohort_i + \gamma \; Demographics_{i,t} + \epsilon_{i,t}. \qquad (2)$$

[8]Using the framework from above, average disability-free years at each age are a function of three products: 1) probability of survival, 2) chances of disability and living, and 3) chances of disability and dying. The actual value, at age 70 for example, would be the product of 1) probability of surviving to this age (products of survival probabilities at each age, 65-69) and 2) disability weighting of the 70th year. This second term includes both the chance that someone survives to 71 with no disability and the chance that someone dies between 70-71 without a disability.

Here, we have designed the estimation so that the dependent variable is the probability that an individual belonging to cohort i is disabled in year t. The coefficient vector θ is of key interest, and the variables are defined as before. Of importance here is that, when we reference a year, we are referencing a given HRS wave. Thus, the dependent variable could also be interpreted as us asking the key question: what is the probability that individual i is disabled in this wave of the HRS?

We compare cohorts turning 65 in two years (1992 and 2002) in the HRS; then, θ is a vector with 7 elements (where we consider the first quartile of wealth in 1992 to be the reference category) that inform the DFLE inequalities within and across years. Put another way, this empirical design will tell us the differential probability of being disabled as the wealth quartile changes within a cohort (i.e., we move from the first income quartile of those aged 64-66 in 1992 to the second income quartile of those aged 64-66 in 1992) and between cohorts (i.e., moving from the first income quartile of those aged 64-66 in 1992 to the first income quartile of those aged 64-66 in 2002).

4.3 Constructing and Analyzing WFLE

Our WFLE analysis follows closely with the development of DFLE discussed above. Yet, here we replace the dependent variable from Equation 1 with an indicator for whether or not an individual reports to having been working for wages in a given wave. This presents the same static analysis but for work.

In this estimation, we use the same covariates as we did in the disability rate estimation. Our calculation of WFLE is similar, too, and follows the DFLE inspiration from Chernew et al. (2017) to expand to work. Here, we develop the probability of non-working survival by separately summing two probabilities: (1) surviving to next year without working (the product of the probability surviving to next year multiplied by the probability you are not working before the next wave, given you survive) and (2) dying by next year without working (the product of the probability of dying by next wave with the probability you are not working, given you die by the next wave). This second probability is weighted by one half, as our design specifies that those dying within a year are assumed to live and work half of a year. After adding these two pieces together, resulting in the probability of being work-free next year, we multiply it by the chance that one survived to this year in the first place (the product of all previous survival rates). Summing across all years, as we did for life expectancy, yields a WFLE solution. Note that we are able to develop WFLE values by gender, wealth-at-65 quartile, and HRS wave (1992 or 2002).

Just as we did with DFLE, we are also keenly interested in the temporal nature of WFLE and its dynamic results. Thus, we modify Equation 2 to include the same work dependent variable as described above.

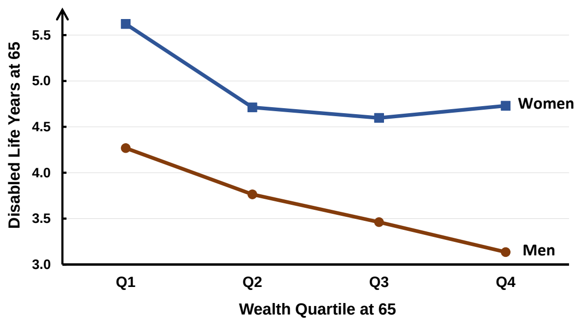
5 Results

Here, we present the results of our three sets of analyses. The first set relates to the within-cohort (static) relationship between wealth and DFLE, and wealth and WFLE, for the 1992 and 2002 cohorts of individuals aged 65. The second set relates to the between-cohort (temporal) patterns in these relationships – the regression results here are suggestive of widening inequality in DFLE and WFLE as a function of wealth. Finally, the third set involves analogous regression results for the subjective measures of life expectancy and disability, illustrating a wedge between the observed patterns and individual expectations – especially among those least wealthy.

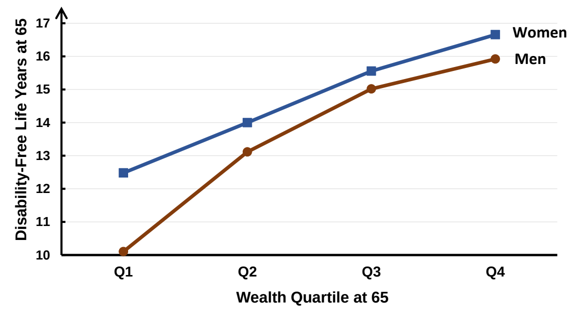
5.1 Within-Cohort Results for Disability and Work

Figure 1 plots the static, within-cohort results on DFLE and WFLE for the cohort of respondents aged 65 in 2002. Panel (a) presents the relationship of wealth to the number of disabled life years at age 65. Here, we observe that the least wealthy (Q1) men experience approximately 4.5 years of disability, compared to 5.6 years for women. The larger number for women is at least partially due to their longer average life expectancy. We observe that the slope for men is quite linear, with the most wealthy men (Q4) experiencing only 3.1 years of disability after age 65. For women, however, the slot is more flat between Q2-Q4 and even the most wealthy women experience 4.8 years of disability at age 65. In panel (b),

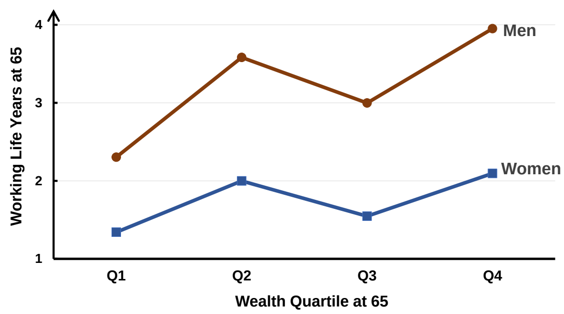
Figure 1: Within-Cohort Relationship of Wealth to DFLE and WFLE, 1992



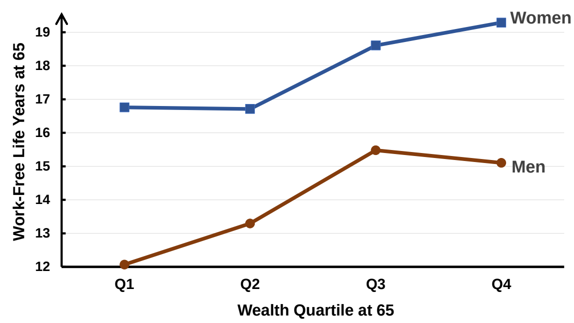
(a) Disabled Life Years



(b) Disability-Free Life Years



(c) Working Life Years



(d) Work-Free Life Years

Notes: Figure shows how men and women relate to various measures, as indicated by the vertical axis in each panel. In each panel, we graph wealth quartile on the horizontal axis. Regressions for disability and work prevalence are the same as Equation 1, where we also include dummy variables for time-to-death and age-sex groups. In those regressions, we omit HRS waves 10 and 11 (2010 and 2012) and weight values based on HRS weights provided. Life expectancy estimates were derived as described in the text. Source: HRS respondents aged 64-66 in 1992 and 2002 (for disability and work prevalence, and life expectancy through age 89), plus SSA and NCHS for life expectancy after age 90.

we take into account life expectancy and present DFLE by gender and wealth quartile for this cohort. Here, the patterns appear to be more linear with respect to wealth – the least wealthy men can expect to live 10 years without disability at age 65 compared to 16 years for the most wealthy. The range for women is more compressed: the least wealthy can expect to live 12.5 years without disability at age 65 compared to 16.8 for the most wealthy. Taken together, these results show that there is a strong wealth-DFLE gradient within-cohort. The most important takeaway is that wealthier individuals don't just live longer, but they live more disability-free years as well.

Panel (c) of Figure 1 presents the relationship of wealth to the number of working life years at age 65. As a reminder, this metric simply counts the number of years reported as having worked for pay since age 65 – here, we observe that both men and women work more as a function of wealth. Specifically, the least wealthy men work for 2.2 years after age 65 compared to 4 years for the most wealthy. For women, the least wealthy work 1.3 years after age 65 compared to 2.1 years for the most wealthy. Just as we did with DFLE in panel (b), in panel (d) we incorporate the life expectancy results to generate WFLE by wealth for men and women. We find that the least wealthy men can expect to have 12 years of WFLE at age 65 compared to about 15 years for the most wealthy (there is some slight nonlinearity in the upper quartiles). For women, the least wealthy can expect to live 16.8 years of WFLE at age 65 compared to 19.1 years for the most wealthy. We recognize that these raw correlations are the product of many economic forces – yet, the strong patterns of increased work as a function of wealth, yet also more years *without* work as a function of wealth, are compelling in the context of economic inequality.

5.2 Between-Cohort Returns to Wealth

Table 2 presents the comprehensive set of between-cohort results. In this subsection, we will discuss columns 1 and 2 as they relate to the understanding of DFLE and WFLE.

In Table 2, we first focus on column 1 to understand the regression results developed related to disability, based on the methodological specification in Equation 2. With the first wealth quartile in 1992 serving as our reference category, we are able to analyze the changing prevalence of disability by wealth quartile. As is clear, each wealth quartile above the first experiences a statistically significant, negative difference in the probability of being disabled. Thus, our static results from above are apparent here. Note that we have also included age-sex and time-to-death dummy variables in all of our specifications, along with providing the mean of each dependent variable for the reference group. Dynamically now, we take note that the first wealth quartile in 2002 has a probability of being disabled that is not statistically different from the first wealth quartile in 1992. This is a particularly important result, given that F-tests testing the equality of each wealth quartile over time (i.e., equality of the second wealth quartile's coefficient in both 1992 and 2002) show that all three of the higher quartiles experienced reductions in the probability of being disabled where the changes for the second and fourth quartile were statistically significant at the 10% level. Thus, increasing returns to wealth, over time, in disability are present in a significant fashion.

This discussion of the increasing returns to wealth in disability over time lends itself to increasing returns to wealth in DFLE given that life expectancy is also increasing in wealth. Panel (a) of Figure 2 identifies this pattern for both men and women. Temporally here, we note that men gained, in each ascending wealth quartile, -0.04, 0.74, 0.57, and 0.91 disability-free life years between 1992 and 2002. For women, the analog among the four quartiles was: -0.32, 1.6, 0.90, and 2.42. Thus, among men and women, the poorest 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.

Returning now to the second column of Table 2, we turn our attention to the results related to the probability of working as given by the specification in Equation 2.[9] Again, as we are using the probability of working given one is in the first wealth quartile in 1992 as the baseline, we see that both the second and fourth wealth quartiles have greater probabilities, in a statistically significant manner, of working than the poorest quartile in 1992. This is represented by the static results presented earlier. However, when we turn to the regression results over time, we see that, again, the first wealth quartile experienced no significant change in the probability of working over time. However, and again using F-tests to analyze the within wealth quartile change in the coefficient over time, all three of the higher quartiles experienced statistically significant (at the 5% level) increases in the probability of working.

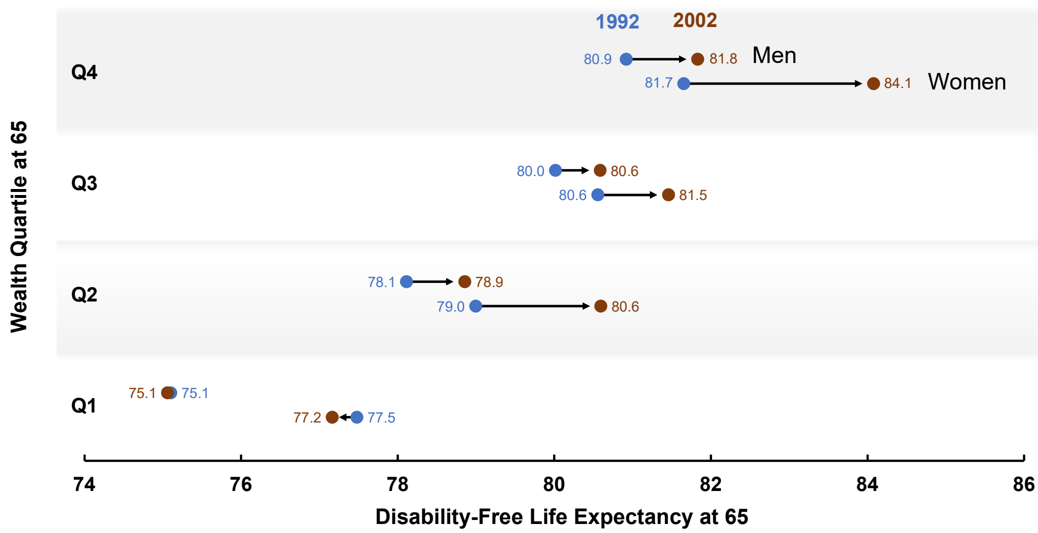
[9] In Table B.1 of Appendix B, we have provided supplementary material that shows both 1) logit results for work, which we used to avoid the probabilities of working becoming negative at extreme older ages, that are not materially different from the linear probability model we show in Table 2, and 2) tobit results for a regression of hours worked on wealth quartile using our same design.

Table 2: The Effect of Wealth Quartiles on DFLE, WFLE, and Subjective Metrics

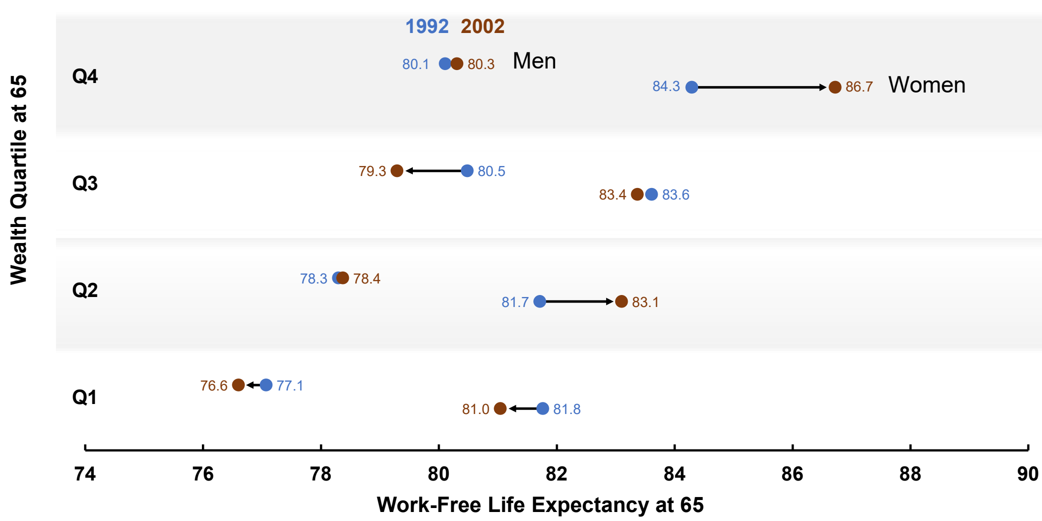
	Objective		Subjective	
	(1) Disabled?	(2) Working?	(3) Pr(Live to 75)	(4) Pr(Work Lim. Health Cond. in Next 10yrs)
Wealth quartile:				
1–1992 (most poor)	reference group		reference group	
2–1992	-0.0792***	0.0652**	0.0962***	-0.0230
	(0.0291)	(0.0265)	(0.0242)	(0.0260)
3–1992	-0.127***	-0.0102	0.115***	-0.00372
	(0.0276)	(0.0236)	(0.0226)	(0.0251)
4–1992 (most rich)	-0.151***	0.0559**	0.154***	-0.0279
	(0.0256)	(0.0243)	(0.0219)	(0.0257)
1–2002 (most poor)	-0.00460	0.0118	0.0393**	-0.0188
	(0.0254)	(0.0240)	(0.0196)	(0.0230)
2–2002	-0.117***	0.118***	0.0730***	-0.0390*
	(0.0249)	(0.0239)	(0.0192)	(0.0223)
3–2002	-0.153***	0.145***	0.119***	-0.0840***
	(0.0246)	(0.0238)	(0.0190)	(0.0220)
4–2002 (most rich)	-0.182***	0.107***	0.165***	-0.103***
	(0.0245)	(0.0237)	(0.0187)	(0.0219)
Age-Sex Dummies	✓	✓	✓	✓
Time-to-Death Dummy	✓	✓	✓	✓
Reference Group Mean	0.2984	0.1212	0.5436	0.4610
Observations	18265	18258	8925	5908
R^2	0.0631	0.155	0.0382	0.0308

Notes: This table depicts regression results with different dependent variables, as indicated by each column heading, portraying Equation 2 for disability and work (grouped as objective), plus the same model for the subjective questions in columns 3 & 4. Standard errors are in parentheses. In each regression, we include dummy variables for time-to-death and age-sex groups. In these regressions, we omit HRS waves 10 and 11 (2010 and 2012) and weight values based on HRS weights provided. In each instance, the reference group is the first wealth quartile in 1992. Subjective answers were originally given on a 0-100 scale, and so we scale those down by 100 to provide values between 0 and 1. Source: HRS respondents aged 64-66 in 1992 and 2002 for disability and work prevalence, and those aged 60-65 in 1992 and 2002 for the subjective questions. Significance is given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2: Between-Cohort (Dynamic) Changes in DFLE and WFLE, by Gender



(a) Disability-Free Life Expectancy



(b) Work-Free Life Expectancy

Notes: Figure shows how men and women experience changes in disability-free life expectancy (DFLE) and work-free life expectancy (WFLE) over time, as indicated by the vertical axis in each panel. These points can be read as changes in DFLE (Panel (a)) and in WFLE (Panel (b)), and so, for example, in Panel (a), the first wealth quartile of men experiences no gain in DFLE between 1992 and 2002. For women, the analog was a decrease of 0.3 years. These values are read as the DFLE and WFLE at age 65 (where, if complemented with disabled or working life expectancy, would total overall life expectancy). In each panel, we graph wealth quartile on the vertical axis, and use arrows to depict the direction of changes from 1992 to 2002. Regressions for disability and work prevalence are the same as Equation 2 where we also include dummy variables for time-to-death and age-sex groups. In those regressions, we omit HRS waves 10 and 11 (2010 and 2012) and weight values based on HRS weights provided. Life expectancy estimates were derived as described in the text. Source: HRS respondents aged 64-66 in 1992 and 2002 (for disability and work prevalence, and life expectancy through age 89), plus SSA and NCHS for life expectancy after age 90.

Taken together, we see that the poorest individuals are not experiencing, over time, an increase in their chances of working at age 65 while each of the higher wealth quartiles is able to do so in a statistically significant way.

Again, circling back now to Panel (b) of Figure 2, we can see the temporal changes in WFLE over time, combining the regression results for working with overall life expectancy. Here, we see changes (from 1992 to 2002) in WFLE for each of the ascending four quartiles with changes of -0.47, 0.08, -1.19, and 0.20 respectively for men. For women, the changes are: -0.72, 1.39, -0.24, and 2.43. While these results do not have the same monotonicity as our DFLE results, they still present an area of contribution and, hopefully, future discussion. Specifically, we see that, for both men and women (though to varying degrees), the wealthiest quartile is able to maintain a higher WFLE and grow that difference over time, implying increasing returns to wealth in WFLE between the first and fourth quartiles. We note that the third wealth quartile shows a decrease as well, which is also shown in the regression results with a sign change in the coefficient on the third wealth quartile between 1992 and 2002. Taken together, we know that the individuals in the fourth wealth quartile are able to both 1) work more and 2) live more of their life work-free than those in the first wealth quartile, and that these differences are growing over time - again, likely pointing to exacerbated wealth inequality at older ages coupled with the aforementioned inequality in life expectancy and healthy life years.

5.3 The Role of Increased Absolute Wealth Inequality

Naturally, one may ask about the dynamics of inequality and, specifically, potential exacerbated wealth inequality over time. New work has shown, over a 200 year period from 1820-2020, that wealth inequality was growing (Chancel and Piketty, 2021). This same global analysis finds that within-country inequality was declining between 1910-1980 (within the birth and working years of our cohorts) but growing between 1980-2020 (near the end of the working life of our cohorts). Other new work has shown a similar type of change in the 1980s with respect to inequality (Garbinti et al., 2021). In that spirit, we display the wealth distribution information used for the baseline analysis in Appendix Table B.2. The means of wealth-at-65 in the 1992 and 2002 cohorts are \$404,305 and \$505,210, respectively. Beyond this difference, it is also true that the quartiles have changed substantially. Moving from 1992 to 2002, the first quartile marker has moved from \$89,042 to \$59,058 while the third quartile marker has moved from \$463,611 to \$530,555. This movement, whereby the level of wealth in the first quartile has shrunk while the level of wealth in the fourth quartile has jumped, is indicative of exacerbated wealth inequality temporally.

To supplement the analyses above, we now consider the effect that levels of absolute wealth have on our outcomes. To do so, we fix inequality at the 1992 level via our distributional cutoffs for wealth quartiles. In effect, what we do is set wealth quartiles for both the 1992 and 2002 cohorts using wealth quartiles generated for the 1992 cohort, as seen in column 1 of Appendix Table B.2. We then perform the same regression analysis from Table 2 using those 1992 distributional cutoffs in Appendix Table B.3.

The results show that there was not much of a change in the magnitude of any of the coefficients, with the exception of the first wealth quartile in 2002. In essence, this coefficient is measuring the between-cohort variation in the propensity to be disabled (column 1) or working (column 2) when we fix inequality at the 1992 level. Or, to put it another way, when we compare that result to the result from the corresponding columns of Table 2, we are going to have now assumed that wealth inequality is fixed and not exacerbated over time. With this in mind, we find that the coefficient on the first wealth quartile in 2002 for disability, while still statistically insignificant, has increased from -0.00460 in the baseline results (Table 2) to -0.0238 in these fixed inequality results (Appendix Table B.3). This second value is more than four times higher than the first, though each individually is not distinguishable from 0. This implies that, potentially, without exacerbated inequality, the gains in disability prevalence for the poorest could have been larger. The same idea holds for the work results, as well.

The intuition here is that when we fix inequality at the 1992 levels, we are shifting individuals around in the placement of quartiles. Thus, some of the 2002 cohort will now look (from a quartile perspective) poorer (i.e., someone with wealth at age 65 of $75,000 is now a part of the first quartile, not the second), while some look wealthier (i.e., someone with wealth at age 65 of $500,000 is now a part of the fourth quartile, not the third). Thus, the coefficient on the first quartle in 2002 is likely to grow because wealthier people are a larger part of it than we had seen in our baseline results.

The results there highlight that, holding distributional inequality constant at the 1992 level, individuals in the poorest quartile still experience an insignificant temporal gain in disability and work, but the point estimate indicates a much larger potential temporal gain for the poorest than baseline results, pointing to the idea that distributional inequality being exacerbated disturbs the ability for the poor to make gains. In essence, the poor get poorer with exacerbated inequality. When we fix inequality at the level in 1992, we see that the poorest people would have potentially had larger gains in their ability to work and manage their morbidity risk. Taken together with our baseline results, these additional analyses continue to paint the picture of exacerbated wealth inequality over time, and that the worsening inequality is, at least in part, to blame for the poorest being unable to gain temporally.

5.4 Subjective Expectations of Life Expectancy and Disability

The third and fourth columns of Table 2 identify regressions modeling the design of Equation 2, but for subjective life expectancy and subjective disability, respectively. Specifically, using Equation 2, we replace disability and work with subjective responses to the questions about survival and morbidity, as described in Section 3.

For the subjective life expectancy question, we see in column 3, with regard to the poorest quartile, each wealthier quartile feels they have a (statistically) significantly greater chance of living to age 75. These are the static-type results for 1992. Thus, there is some evidence that people recognize the wealth gradient in life expectancy. Over time, though, the first wealth quartile, interestingly, believes it has seen a gain in subjective life expectancy from

1992 to 2002. We know, empirically, that there was no gain for the first wealth quartile in the probability of living to age 75 from 1992 to 2002 (neither for men nor women). Another interesting piece here is that the three wealthier quartiles see statistically insignificant changes in coefficients from 1992 to 2002 (via an F-test), though those groups all experienced increased probabilities of living to age 75 empirically.

With regard to the subjective morbidity question, we see, in column 4, that there is no meaningfully recognized difference in the chances of having a work-limiting health condition in the next 10 years among the wealth quartiles, though each of the wealthier quartiles is lower than the first wealth quartile. Over time, we see only statistically significant (at the 0.1% level) decreases for the third and fourth wealth quartiles, with none that are recognizable for the first and second wealth quartiles. Therefore, we provide some evidence that the wealthiest individuals perceive increases in the chances of being disabled over time.

6 Discussion and Implications

Our analysis identifies wealth inequality in healthy and work-free years that affect social insurance progressivity beyond differences in length of life. In addition, we find that the subjective beliefs are not well aligned with the empirical trends. We are also interested in formulating a discussion about what the wealth impact on DFLE and WFLE imply for policy. Our results imply that the literature's understanding of Social Security progressivity must also account for 1) disability prevalence's impact on quality of life, 2) heterogeneity in the ability to work, and 3) individual ability to understand risks of health and mortality.

There has been significant concern in the literature for the progressivity of the Social Security program as life expectancy has produced gains for those with higher incomes. Auerbach et al. (2017) describes a particularly important perspective: with life expectancy gains being distributed to higher earners, the average lifetime gap in Social Security program benefits for men widens, between the highest and lowest income quintile, by $130,000 between 1930 and 1960 birth cohorts. The authors clarify that these gaps are driven by Social Security and Medicare benefits. Other work has also documented the challenge with progressivity –

if that is indeed a goal – when higher income groups are more likely to live longer (Goda et al., 2011).

In addition to there being public policy interest in the scope of lifetime benefits as a function of years lived, there are concerns related to the ability of healthier workers, i.e., those with the longest life expectancies and largest proportions of life lived without disabilities, to work longer and delay claiming. Not only do workers who work longer have potentially higher benefits based on the Social Security benefit formula being a function of one's highest 35 years of earnings, but workers who are more healthy later in life may be more physically capable of delaying retirement. Delaying retirement comes with more-than-actuarially-fair increases to lifetime benefits or, to put it another way, delayed retirement credits were designed, in current form, for workers with shorter life expectancies (Munnell and Chen, 2019). As pointed out in recent research, the decision to delay retirement is important (Manoli and Weber 2016) and has the strongest incentive for those who will live longest (Duggan et al., 2019).

Other recent work has established that additional work capacity does currently exist at older ages, compared with workers of the same makeup nearly 50 years ago (Coile et al., 2017). This analysis by Coile et al. (2017) asks two important questions, in the face of whether social insurance programs should presume workers can work longer now than decades ago. Both questions can be summarized as asking if current workers could work longer than workers in the past, conditional on the same value of some important attribute (mortality rate or health). Their results will then suggest how much additional work capacity we should have today, and the results are stark: workers today should be able to work between 31-42 percentage points more between ages 65-69. Given these findings from Coile et al. (2017), and our findings with respect to different propensities to work by wealth quartile, wealth-related inequality in the ability to work at older ages could be an important feature of future policy debate if policymakers decide to change retirement ages solely based on additional work capacity.

One concern that arises from the gap we document in objective and subjective mortality expectations is that the least wealthy individuals may be more likely to face late-in-life financial insecurity, especially as they over-estimate the chance they will live 10 years into the future (after age 65). Even over these 10 years, household wealth is important in navigating health shocks, especially when the opportunity to work (or even return to work) is less than that of their wealthier counterparts. These results are important in the context of evidence of both an income gradient in the ability to manage consumption discontinuities at retirement (Bernheim et al., 2001), and an income gradient in savings (Dynan et al., 2004). Taken together, we hope that our results help forward the literature on how wealth inequality shapes retirement-age health and longevity.

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Appendices

A Calculating Life Expectancy and Gompertz Approximation: Details and Discussion

In our use of the Gompertz approximation method for suvival rates after age 76, we follow Chetty et al. (2016) quite closely and so we make no innovation in this methodological work. We make use of the same Stata setup, whereby we specify a generalized linear model (GLM) in which a respondent's death, the dependent variable, has just one independent variable, the respondent's age. This GLM is estimated for each cohort (those aged 64-66 in 1992, those aged 64-66 in 2002, and then pooled) and by wealth quartile, too. We do apply weighting, in accordance with those provided with HRS data.

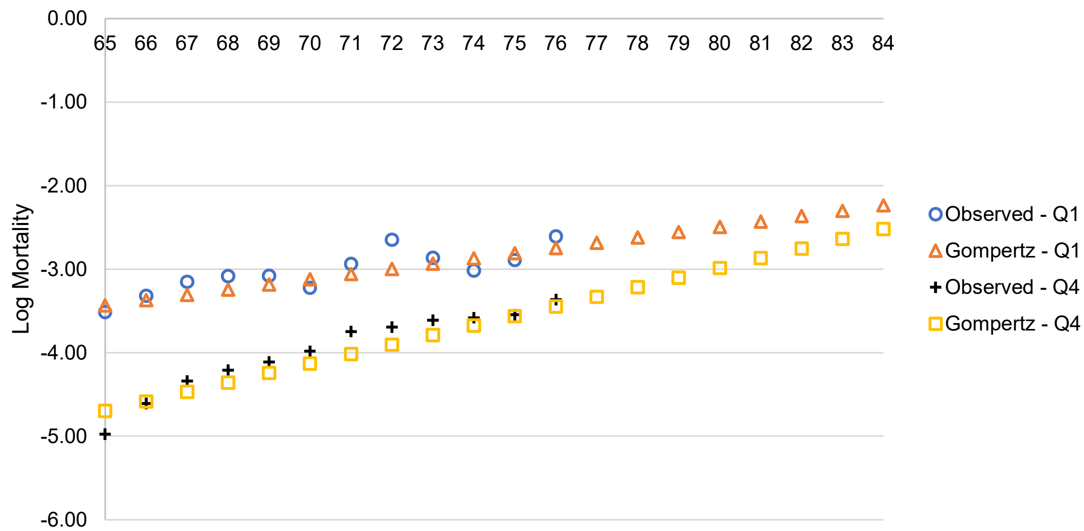
Then, to check the fit of the Gompertz curve, we find the survival rates (since previous waves) using our HRS data to develop a probability of dying from our actual data. We regress our experienced log mortality variable on the log of predicted mortality from the Gompertz model. This exercise yields an R^2 value greater than 0.98. In Figure A.1 below, which is two-paneled, we show what we have just described: the remarkable fit of the Gompertz estimation to our HRS data estimates and the survival probabilities for each age. This production follows Chetty et al. (2016) closely. In Panel (a), we graph log mortality by age for the pooled set of men (meaning, we analyze all HRS waves we have data for). This graph highlights the high model fit of regressing log observed mortality on log mortality from our Gompertz model. As we see, at age 76, our observed mortality ends and we proceed with our pooled Gompertz estimation.

In panel (b), we graph survival probabilities for men at certain ages. Again, through age 76, we see observed and Gompertz data for different income quartiles, and then after age 76, we see Gompertz pooling data together through age 85. After that point, Gompertz is unable to assess income heterogeneity due to our lack of data for those turning age 65 in 1992. At age 90, our use of NCHS life tables becomes apparent. At 100, and for all years after 100 which we don't show here, we use SSA life tables. Thus, after age 85, we don't assess heterogeneity in survival by income levels. We provide the same two panels for women in Figure A.2 below, using the same design.

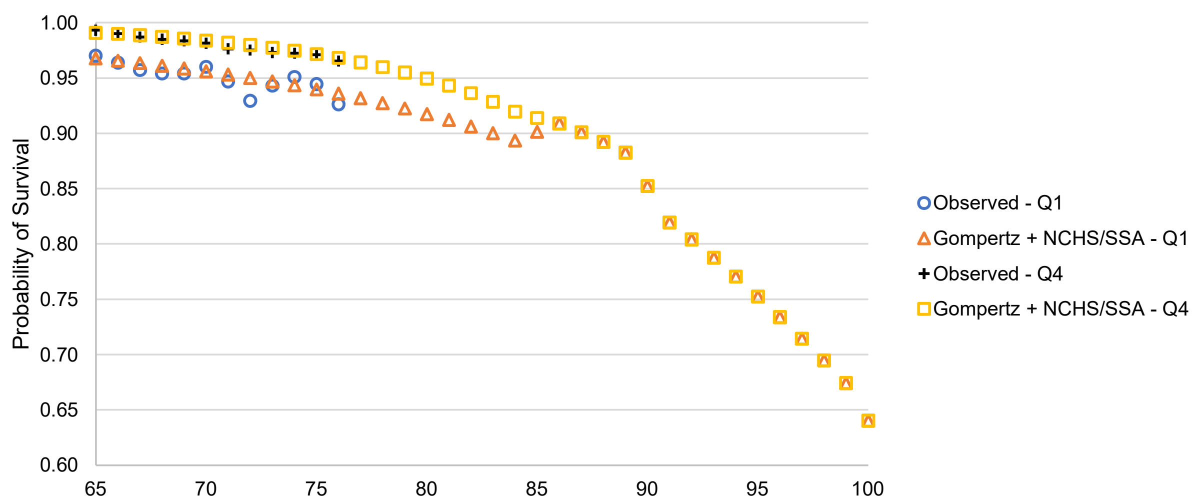
Though life expectancy results are not the main result of this paper, we find it useful to highlight exactly what our life expectancy results look like after having described the methodology of their design. Figure A.3 below shows a two-paneled design for life expectancy, by wealth quartile, at age 65. Note that these graphs are composed of both disabled and disability-free years, but also note that our life expectancy estimates are in-line with those in Chetty et al. (2016). The results here indicate substantial returns to wealth in life expectancy.

In Panel (a), we see that men have significant differences in life expectancy at age 65 by wealth quartile - notably, the difference between the first quartile and the second quartile was 4.7 years in 1992 and expanded to 5.6 years in 2002. Similar results, though a bit more striking, are presented for women in Panel (b). There, we notice the gap is 3.3 years in 1992 and 6.7 years in 2002.

Figure A.1: Gompertz Results for Men



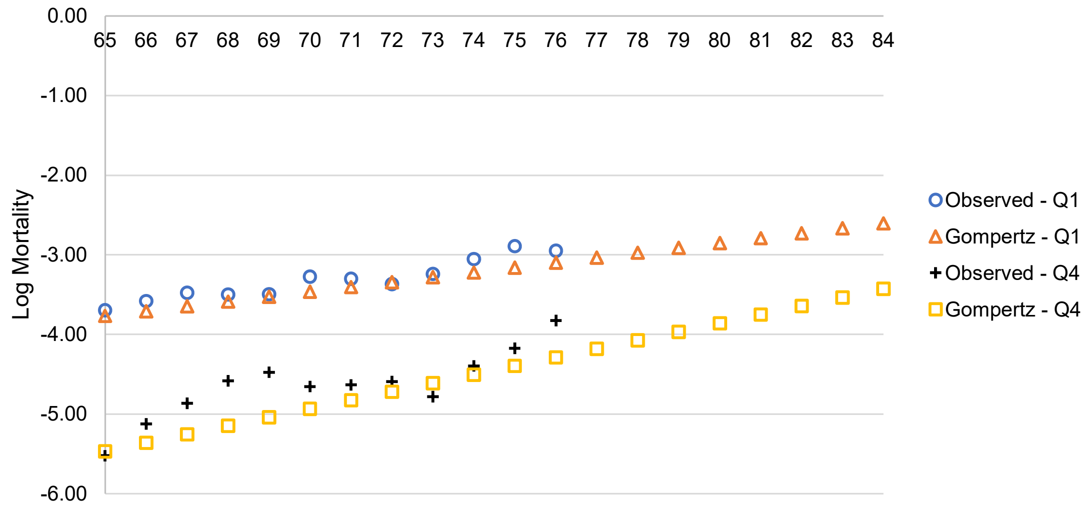
(a) Log Mortality



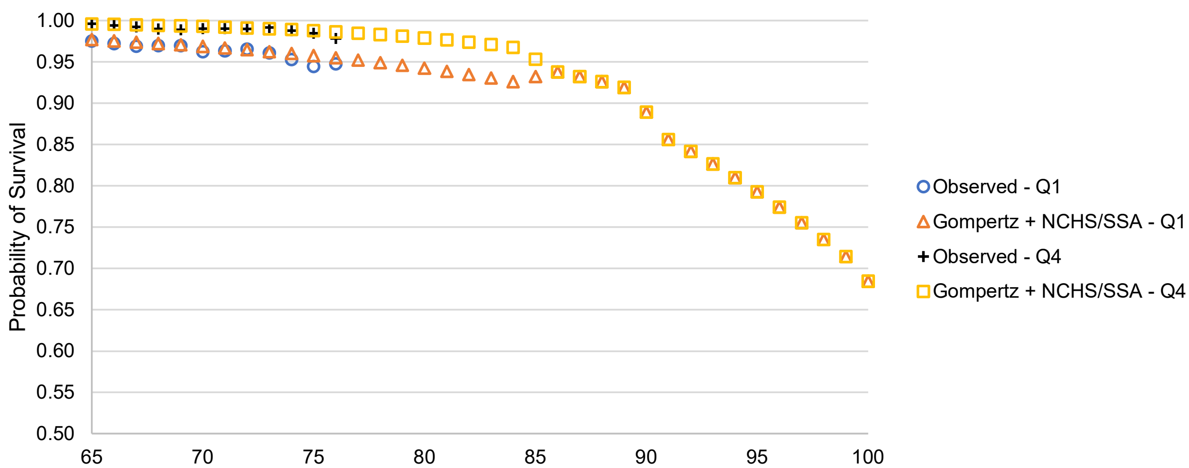
(b) Survival Probabilities

Notes: Figure depicts log mortality and the survival curve for men in our sample. In Panel (a), we depict the natural log of the mortality rate at each age on the x-axis. We depict this value for the first and fourth wealth quartiles with observed and Gompertz estimates, based on the key, through age 76. At age 77, we lack enough data and so we turn to Gompertz approximation after that. In Panel (b), we estimate the probability of survival by age. This panel highlights the usage of observed data through age 76, Gompertz through age 89 (without wealth variaton after age 85), 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 1992-2012 (for life expectancy through age 89) where we pool (with wealth variation) before age 66 and after age 74 and without wealth variation after age 84, plus NCHS data for ages 90-99 and SSA data for ages 100+.

Figure A.2: Gompertz Results for Women



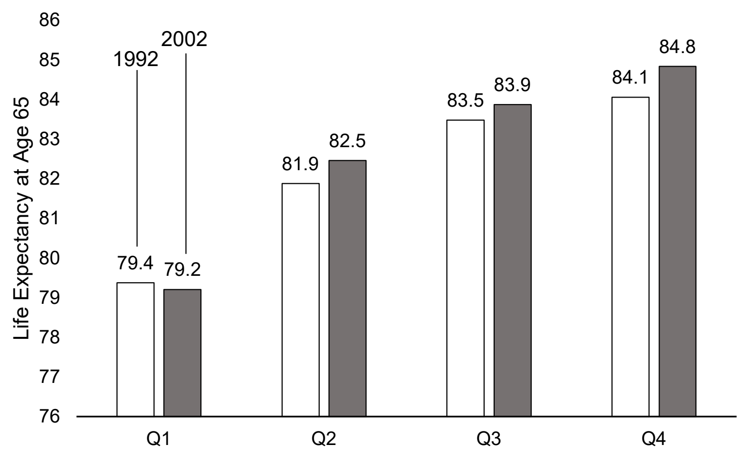
(a) Log Mortality



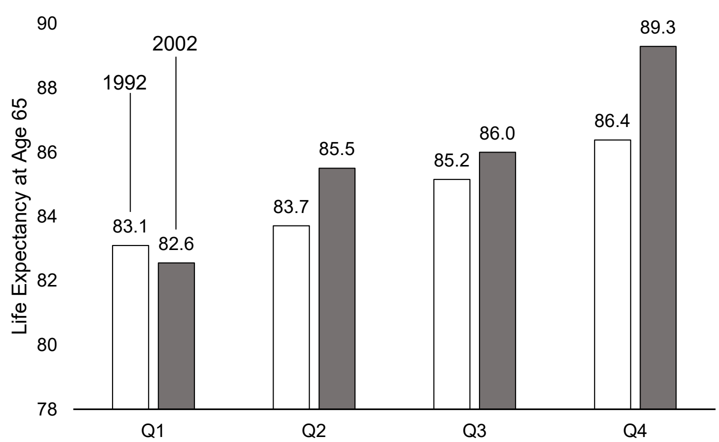
(b) Survival Probabilities

Notes: Figure depicts log mortality and the survival curve for women in our sample. In Panel (a), we depict the natural log of the mortality rate at each age on the x-axis. We depict this value for the first and fourth wealth quartiles with observed and Gompertz estimates, based on the key, through age 76. At age 77, we lack enough data and so we turn to Gompertz approximation after that. In Panel (b), we estimate the probability of survival by age. This panel highlights the usage of observed data through age 76, Gompertz through age 89 (without wealth variaton after age 85), 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 1992-2012 (for life expectancy through age 89) where we pool (with wealth variation) before age 66 and after age 74 and without wealth variation after age 84, plus NCHS data for ages 90-99 and SSA data for ages 100+.

Figure A.3: Life Expectancy at Age 65 by Wealth Quartile



(a) Men



(b) Women

Notes: Figure shows life expectancy estimates, at age 65, for men and women of each wealth quartile (horizontal axis) in 1992 (left bar) and 2002 (right bar). Life expectancy estimates were derived as described in the text. Source: HRS data 1992-2012 (for life expectancy through age 89) where we pool (with wealth variation) before age 66 and after age 74 and without wealth variation after age 84, plus NCHS data for ages 90-99 and SSA data for ages 100+.

B Other Appendix Tables and Figures

Below, in Table B.1, we provide additional empirical results. In column 1, we present the results of a logit model where the dependent variable is working. This model is the same in all respects, with the exception of being a logit instead of a linear probability model, as the one specified in the main text of our analysis. We present this here to highlight the specification we used with concerns of the probability of working becoming negative at extreme older ages, when data was limited.

In column 2, we present the results of a tobit regression of hours worked on all of the same covariates we have used in prior analyses. Largely, these results highlight the same story we have told about working itself - though the difference in hours worked is not distinguishable or statistically significant for the wealthiest quartile compared to the poorest quartile in 1992 (yet, the coefficient is still positive), we certainly recognize temporal changes in the amount in which people work. In fact, the coefficient changes, within wealth quartile, are all statistically significant (at least at the 5% level, except the second quartile, which has probability of exceeding the F-value of 0.0536) while the first quartile's difference is not. Thus, our story of increasing returns to wealth in quantity of work holds here, too.

Below, in Table B.2, we provide distributional information related to wealth-at-65 for individuals in 1992 and in 2002. In Table B.3, we repeat the regression results reported in Table 2 (main text), but we set wealth quartiles to be based, for both cohorts, on the 1992 wealth distribution.

Table B.1: Results from Nonlinear Estimation Models

	Logit	Tobit
	(1)	(2)
Dependent variable:	Working?	Hours Worked
Wealth quartile:		
1–1992 (most poor)	reference group	
2–1992	0.488**	8.680**
	(0.201)	(4.313)
3–1992	-0.0444	-1.992
	(0.203)	(4.407)
4–1992 (most rich)	0.440**	7.668*
	(0.191)	(4.177)
1–2002 (most poor)	0.230	5.015
	(0.179)	(3.874)
2–2002	0.723***	14.42***
	(0.178)	(3.837)
3–2002	0.846***	16.69***
	(0.177)	(3.832)
4–2002 (most rich)	0.669***	13.06***
	(0.177)	(3.835)
Age-Sex Dummies	✓	✓
Time-to-Death Dummy	✓	✓
Reference Group Mean	0.1212	3.3595
Observations	18254	18097

Notes: This table presents regression results with different dependent variables and specifications, as indicated by each column heading. Standard errors are in parentheses. In each regression, we include dummy variables for time-to-death and age-sex groups. In these regressions, we omit HRS waves 10 and 11 (2010 and 2012) and weight values based on HRS weights provided. For the logit regression, the model follows the same design as Equation 2 and the second column of Table 2. For the tobit regression, the lower limit is set to 0, and we set hours worked to 0 if a respondent was alive but not working. In each instance, the reference group is the first wealth quartile in 1992. Source: HRS respondents aged 64-66 in 1992 and 2002 for working prevalence and hours worked. Significance is given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Wealth Distribution Details

	1992	2002
First Quartile	89,042	59,058
Second Quartile	221,040	201,536
Third Quartile	463,611	530,555
Mean	404,305	505,210

Notes: This table presents distributional values for respondent wealth-at-65 in each of our two cohort years, 1992 and 2002, rounded to the nearest dollar. Wealth is in 2012 USD. Source: HRS respondents aged 64-66 in 1992 and 2002, with a wealth quartile in the given year.

Table B.3: Regression Results Using 1992 Wealth Quartile Cutoffs

	Objective		Subjective	
	(1) Disabled?	(2) Working?	(3) Pr(Live to 75)	(4) Pr(Work Lim. Health Cond. in Next 10yrs)
Wealth quartile:				
1–1992 (most poor)	reference group		reference group	
2–1992	-0.0759***	0.0613**	0.0944***	-0.0235
	(0.0292)	(0.0265)	(0.0242)	(0.0260)
3–1992	-0.129***	-0.00669	0.114***	-0.00410
	(0.0276)	(0.0237)	(0.0227)	(0.0252)
4–1992 (most rich)	-0.151***	0.0557**	0.154***	-0.0282
	(0.0257)	(0.0243)	(0.0220)	(0.0258)
1–2002 (most poor)	-0.0238	0.0365	0.0435**	-0.0188
	(0.0251)	(0.0237)	(0.0194)	(0.0227)
2–2002	-0.124***	0.123***	0.0719***	-0.0423*
	(0.0249)	(0.0241)	(0.0196)	(0.0230)
3–2002	-0.154***	0.149***	0.110***	-0.0840***
	(0.0247)	(0.0242)	(0.0193)	(0.0224)
4–2002 (most rich)	-0.180***	0.109***	0.161***	-0.0995***
	(0.0244)	(0.0236)	(0.0186)	(0.0218)
Age-Sex Dummies	✓	✓	✓	✓
Time-to-Death Dummy	✓	✓	✓	✓
Reference Group Mean	0.2984	0.1212	0.5441	0.4616
Observations	18265	18258	8925	5908
R^2	0.0608	0.153	0.0378	0.0306

Notes: This table depicts regression results with different dependent variables, as indicated by each column heading, portraying Equation 2 for disability and work (grouped as objective), plus the same model for the subjective questions in columns (3) and (4). Here, wealth quartiles are set, in both cohorts, using the 1992 wealth distribution (i.e., inequality is fixed at the 1992 level). Standard errors are in parentheses. In each regression, we include dummy variables for time-to-death and age-sex groups. In these regressions, we omit HRS waves 10 and 11 (2010 and 2012) and weight values based on HRS weights provided. In each instance, the reference group is the first wealth quartile in 1992. Subjective answers were originally given on a 0-100 scale, and so we scale those down by 100 to provide values between 0 and 1. Source: HRS respondents aged 64-66 in 1992 and 2002 for disability and work prevalence, and those aged 60-65 in 1992 and 2002 for the subjective questions. Significance is given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.