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Trends in Health and Mortality Inequalities in the United States

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Trends in Health and Mortality Inequalities in the United States

Abstract

Recent literature has documented a widening gap in mortality in the United States between individuals with high socioeconomic status (SES) and low SES. An important question is whether this trend will continue. In this paper we document trends and inequalities in the health status at ages 54 to 60 of individuals born between 1934 and 1959. We do so by using detailed subjective and objective measures of health in the Health and Retirement Study to examine contributors to mortality inequality and to forecast life expectancy. We found that the health of individuals 54 to 60 years old has generally declined in recent years. In particular, we found large increases in obesity rates, notable increases in diabetes and reported levels of pain, and lower self-reported health and subjective survival probabilities. We also found strong evidence for increasing health inequalities, as the health of individuals in these cohorts with high SES remained largely stable while that for individuals with low SES declined. When we forecast life expectancies using these predictor variables, as well as gender- and SES-specific time trends, we predict overall life expectancy to increase further. However, the increase is concentrated among high SES individuals, suggesting growing mortality inequality. Results are similar among men and women.

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Introduction

There has been a remarkable increase in life expectancy throughout the past century in the United States and other developed nations largely, due to innovations in medical science and technology. There is growing evidence, however, that the longevity gap between richer and poorer individuals (i.e., mortality inequality*)* has also widened in recent decades (Auerbach et al. 2017; Bosworth, Burtless, and Zhang 2016; Case and Deaton 2015; Chetty et al. 2016; Goda, Shoven, and Slavov 2011; Sanzenbacher et al. 2017). Future trends in mortality inequality may be aggravated by similar increases in income and wealth inequalities observed in the past 30 years (Autor, Katz, and Kearney 2008; Burkhauser et al. 2011; Meyer and Sullivan 2017; Piketty and Saez, 2003).

Understanding whether these trends of increasing mortality inequality will continue is important for policymakers and health care professionals. For example, mortality is negatively correlated with both income and wealth. As a result, increases in mortality inequality may result in increases in aggregate Social Security payouts, because individuals with greater annual benefits tend to live longer.

One plausible explanation for the widening gap in mortality comes from individuals' health and health-related behaviors. In particular, the opioid crisis (Gomes et al. 2018; Kolodny et al. 2015), obesity (Flegal et al. 2012; Frederick, Snellman, and Putnam 2014), suicide rates (Rossen et al. 2018, Steelesmith et al. 2019), and smoking (Pernenkil, Wyatt, and Akinyemiju 2017) may each contribute to growing inequality in mortality. While previous research has documented trends in mortality inequality by using mortality data and some education and income measures of SES, it often has not looked at health status directly, partly because the data analyzed (e.g., Census data, Current Population Survey data, Social Security Administration death records) had no or limited information about individuals' health. Moreover, because of the lack of health data, most of the econometric models on mortality relied on extrapolations from past trends to forecast future cohorts' mortality. Such extrapolations may be problematic, because they do not take into account changes in health that may cause changes in trends.

To gain new insights into the causes of widening mortality inequality, this paper first documents trends by SES in various health measures observed in the 1992 to 2016 waves of the Health and Retirement Study (HRS). The HRS is a large, nationally representative panel survey of the U.S. population at least 51 years old and with very detailed health information. We analyze numerous subjective and objective measures of health, such as self-reported health, doctor-diagnosed health conditions (hypertension, diabetes, heart problems, cancer, etc.), limitations with activities of daily living (or ADL, such as walking, eating, dressing), health behaviors, and obesity. We also use individuals' own reported forecasts of their survival chances, collected in the HRS through a probabilistic question format. Because subjective probabilities of survival are forward-looking measures, we go beyond extrapolating survival from past trends. Analysis of such forward-looking measures relies on information known to the individual but not observed in objective indicators.

We use two SES measures: one based on educational level and the other based on individuals' predicted Social Security (SS) wealth (defined as expected lifetime SS benefits). We estimated cohort-specific quantiles of both measures to adjust for cohort trends in these variables over time (Bound et al. 2015).

We find that, with few exceptions (such as decreased rates of smoking), health status, measured at ages 54 to 60, has declined since 1992. We found particularly large increases in rates of obesity, diabetes, and, perhaps surprisingly, self-reported pain levels. We also found that high SES groups have significantly better health than low SES groups, and that health inequalities between these groups has grown substantially over time.

We estimate survival models as functions of detailed health variables, demographics, and SES, and permit the models to have gender- and SES-specific cohort-trends. Despite the documented decline in baseline health status, our preferred models predict increasing life expectancies over time, because the general improvements in mortality offset the negative effects of health. This result is consistent with a model in which individuals' health declines over time due to increasing levels of unhealthy behavior, while improving medical technology helps extend individual lifespans.

Our model suggests life expectancy will stagnate for low SES groups, but it will increase substantially for high SES groups, leading to large future increases in mortality inequality. The growing inequalities in health and health-related behavior are contributing to an increasing mortality gap between richer and poorer Americans.

1. Data and Methods

1.1 The Health and Retirement Study

The HRS is a nationally representative panel survey of Americans at least 51 years old. It started in 1992 and has interviewed respondents every other year since.

Every six years, the HRS enrolls a new birth cohort of individuals 51 to 56 years of age to maintain its representation of the U.S. population older than 50. The latest publicly available data are from 2016.

The HRS is a multidisciplinary survey that has far greater information on health status than is available in the decennial Census, the Current Population Survey, and the Panel Study of Income Dynamics. This, in turn, allows researchers to study the relationship between mortality and its risk factors in greater detail. The HRS collects information about self-reported health, various doctor-diagnosed health problems, ADLs, health behaviors (such as exercising, drinking, smoking, body mass index), mental health, and cognitive function. For this work, we focus on health outcome variables that have been consistently measured since the first wave of HRS.[1]

The HRS makes considerable effort to retain panel members until death. For persons who drop from the sample, the HRS seeks data on survival status and date of death or the last date the respondent was known to be alive.[2] Such observations can be modeled as censored cases in survival models.

A further innovation of the HRS is to ask survey participants about their own survival expectations in a probabilistic format. After reading an introduction about the probability scale, the question reads "`What is the percent chance that you will live to be 75 or more?`" We will sometimes refer to this variable as P75. We use these subjective probabilities in our mortality models. This measure is useful

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[1] There are many additional health measures in the HRS that are either not available in early waves or have been revised substantially over time, as questions about physical exercising, grip strength, and lung function have been.

[2] This information is publicly available in the HRS Tracker File.

because it is a forward-looking measure that incorporates individuals' perceptions of their future course of health and mortality risk. Recent research has demonstrated the validity of the subjective probability of survival. Among 50 to 70 year olds, the average values of expectations are close to life table estimates.[3] Subjective expectations covary with demographic characteristics, health status, parental mortality, smoking behavior, and the onset of new diseases in largely the same way they do in regressions that explain actual mortality (Delavande and Rohwedder 2011; Hudomiet and Willis 2013; Hurd and McGarry 2002). They also predict variation in actual mortality (Gan, Hurd, and McFadden 2005; Hudomiet and Willis 2013; Hurd and McGarry 2002; Hurd, Rohwedder, and Winter 2005). They also predict economic and health outcomes such as consumption, bequests, retirement, and taking medical tests (Gan et al. 2004; Hurd, Smith, and Zissimopoulos 2004; O'Donnell, Teppa, and Doorslaer 2008; Picone, Sloan, and Taylor 2004; Salm 2010).

The HRS oversamples blacks and Hispanics so that race- and ethnicity-specific statistics can be estimated with greater precision. It has survey weights for adjusting the sample's demographic distribution to the American Community Survey.[4]

In this project, we used all 13 survey waves from 1992 to 2016. We restricted the sample to 19,547 individuals who were born between 1934 and 1959, and who were observed in the HRS at least once in the baseline age window of 54 to 60. These individuals were 57 to 82 years old in 2016. Table 1 shows the distribution of the most

[3] At ages older than 70, the average subjective survival probability is above life table survival probabilities due to anchoring bias. Part of our prior research (Hudomiet et al. 2017) has focused on correcting for this bias; we apply those corrections to this research.

[4] In earlier waves, the HRS used the somewhat smaller Current Population Survey to construct the survey weights.

important variables, all measured at the baseline 54 to 60 age range. If an individual appeared in the baseline window more than once, we took the average of his or her values, except for smoking status, the ever-had conditions, and living with moderate to severe pain, in which cases we used the person-specific maximum (i.e., the worst outcome) of the indicator variables from the 54 to 60 age window. Throughout the paper, we report weighted statistics with weights defined as the person-specific mean of the survey waves in the baseline window.

Altogether, about half of the weighted sample is male. Most of the sample has at least some college education. More than three-fourths of the weighted sample is non-Hispanic white.

The sample varies widely in its baseline health status. On average, respondents reported a 63 percent chance of living to age 75, but the standard deviation of this average was 26 percent. On a 1 (best) to 5 scale, respondents rated their health at 2.7, or slightly better than "good" (which was a 3 on the scale). Class 2 obesity, i.e., a body mass index (BMI) exceeding 35, was present for 12 percent of the sample. The most common doctor-diagnosed conditions were arthritis (49 percent) and high blood pressure (49 percent). Moderate to severe pain was reported by 36 percent of the sample. Active smokers were 25 percent of the sample.

White-collar, high-skill jobs, such as management or professional workers, were the most common current or most recent jobs. Blue-collar, low-skill jobs, such as food or cleaning service, were the least common. Nearly three in four respondents lived in metropolitan areas.

Relative to the weighted sample, the unweighted HRS sample is less educated, less white, and more likely to hold blue collar jobs, all because of sampling design. The unweighted sample for analysis also has fewer males, which is the result of differential unit nonresponse and our sample selection.

We use two measures of socioeconomic status in this work. The first is individual Social Security wealth, which is the most relevant measure of SES for the Social Security Administration. Social Security wealth is defined as an individual's expected lifetime Social Security benefits. It is calculated by the HRS as described in Fang and Kapinos (2016),[5] and based on individuals' lifetime earnings observed in linked administrative data from the Social Security Administration. For couples, we use the maximum of the Social Security wealth of the spouses. As a summary measure, we define five equal-size quintiles of Social Security wealth, separately estimated for each of the 13 two-year birth cohorts in our analysis from 1934 to 1935 through 1958 to 1959. By separately measuring the quintiles by cohort, we automatically correct for any population trends in Social Security wealth.

Our second SES measure is based on individuals' years of education. Similar to our calculations for Social Security wealth, we take the maximum educational level of the two spouses (for married persons) and then derive quartiles for each of the 13 birth cohorts. This procedure also automatically corrects for the increasing level of education observed over time (Bound et al. 2015).

Table 1 also shows the number of reported (nonmissing) values in the variables in the first column. For job type and metropolitan status, the fraction of missing answers

[5] The documentation is available at http://hrsonline.isr.umich.edu/modules/meta/xyear/sswealth2010/desc/SSWEALTHP2010.pdf

is shown in the last row of the respective subpanel. Most variables have very few missing entries, well below 0.5 percent of the sample. The only exceptions are 1) Social Security wealth (531 missing cases, 2.7 percent), 2) subjective survival probability (1,020, 5.2 percent), 3) BMI (137, 0.7 percent), and 4) last job type (572, 2.9 percent).

Our preferred method to deal with missing values is imputation. We carried out detailed robustness checks of our main findings. First, we replicated our main models by dropping individuals with missing values. Second, we compared our mortality forecasts to external sources, the SSA cohort life tables. We discuss these results in the results section. The reason we prefer imputation is that we aim to estimate and forecast mortality for the entire United States, and the HRS survey weights are designed for the entire HRS sample rather than a subsample restricted to nonmissing values.

Variables with less than 0.5% few missing values—education, race, self-reported health, ever had conditions, pain, smoking status—were replaced by the mode for each (high-school education, non-Hispanic white, good health, no doctor diagnosed conditions, no pain, nonsmoker). We did not impute values for current or most recent job nor for urban status but added missing flags for these variables to our models. We imputed the three remaining variables — BMI, Social Security wealth, and subjective probabilities of living to age 75 — with regression-based models. Table B1 in the appendix shows the results of the imputation models. We estimated a linear regression of log(BMI), and tobit models of Social Security wealth (censored at 0) and subjective survival (censored at 0% and 100%). We then defined the imputed values as the predicted value of these regressions plus a normally distributed residual drawn from the appropriate distribution. Finally, the tobit values were censored if the imputed values fell outside of the censoring range. The fit of the models was good.[6] As expected, the most important predictors of BMI were time (BMI increases over time) and various health conditions. The most important predictors of SS wealth were time, earnings, and labor history. The strongest predictors of subjective survival were the health conditions.

1.2 Modeling and forecasting survival

Our basic strategy is to fit a Gompertz mortality model to individual data from the cohorts born from 1934 to 1959. The Gompertz hazard function is defined as

$$h_i(t \mid a_i) = \lambda_{0i} \exp(\lambda_1 t), \qquad (1)$$

where $h_i(t \mid a_i)$ refers to the hazard of death of individual *i* at age *t*, whose current age is a_i. Age is measured in months, and therefore the hazards can also be interpreted as monthly death hazards. λ_1 is the scale parameter of the survival function; as previous research does, we assume it is a constant in the population. λ_{0i} is the shape parameter. It depends on covariates in a log-linear fashion:

$$\ln(\lambda_{0i}) = \beta' x_i, \qquad (2)$$

where the x_i refer to mortality predictor variables measured at the baseline ages of 54 to 60, and the β coefficients will be estimated. In our preferred models, we let detailed demographics, health conditions, birth cohorts, and various interaction terms influence the shape parameter of survival, λ_{0i}. The precise specifications will be discussed in the results section.

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[6] The R-squared value of the BMI model was 0.205. McFadden's pseudo-R-squared values of the two Tobit models were relatively low (0.020 for SS wealth, and 0.029 for P75). However, the same models estimated by OLS would produce R-squared values of 0.396 (SS wealth) and 0.239 (P75).

The Gompertz model has been widely used in both demography and biology because its loglinear specification of the mortality hazard aligns closely with observed survival data of humans and other species (Vaupel 1997).

The model is estimated by Maximum Likelihood. Observations with unknown death status, including those who survived to 2016, and those who left the sample earlier, are modeled as censored outcomes where the censoring occurs at the latest age the person was known to be alive.

After estimating the model, we predict mortality for each birth cohort using standard formulas. For example, we estimate the probabilities of surviving from age X to age Y for each individual *i* in our sample using the formula

$$S_i(Y \mid X) = \exp\left\{-\frac{\lambda_{0i}}{\lambda_1}\left[\exp(\lambda_1 Y) - \exp(\lambda_1 X)\right]\right\}. \tag{3}$$

Then we report the cohort and gender specific means of $S_i(Y \mid X)$.

Similarly, we estimate expected age at death conditional on surviving to age X using numerical approximations:

$$E_i(A \mid X) \approx \sum_{t=X+1}^{120} (t-0.5)\left(S_i(t-1 \mid X) - S_i(t \mid X)\right) \tag{4}$$

And again we report the cohort- and gender-specific means of these measures.

2. Results

2.1 Trends and inequalities in mortality risk factors

We first document trends in mortality risks as a function of SES measures. Each risk is measured at the baseline age of 54 to 60. All reported statistics are weighted. We present our results graphically; Appendix A includes table versions of each of our main figures.

Figure 1 shows trends in P75 (the subjective survival probability to age 75) by gender, cohort, and SS wealth. females are presented in the left panel and males in the right, with cohorts on the horizontal axis and Social Security wealth quintiles shown in different color lines.

As previous research has found, we find a very strong SES gradient in P75: Subjective survival probabilities are substantially higher among richer individuals. At the same time, we find that, overall, younger birth cohorts are more pessimistic about their survival chances to age 75. The generational difference is greatest for the least wealthy individuals, suggesting that inequalities in subjective survival have substantially increased for both males and females in recent years.

More specifically, subjective survival probabilities have been stable for the top three quintiles, but have significantly worsened for the bottom two. For example, among males in the bottom quintile, P75 was 58.6% for the 1934-38 birth cohort, but only 50.7% for the 1955-59 cohort, a decrease of 7.9 percentage points, slightly below the 8.8 percentage points predicted by a linear regression on these six points. For the second-lowest quintile, the decrease in subjective survival was 4.8 percentage points, compared to the prediction of 2.4 percentage points in our regression model. Among females in the two bottom quintiles, both the reported and predicted decreases in P75 were about 6 percentage points.

Figure 2 shows P75 by gender, cohort, and education, our other SES measure. Again, the left panel shows females and the right panel shows males, while the horizontal cohorts show birth cohorts and the lines show differing quartiles in educational attainment.

The results in Figure 2 are similar to those in Figure 1. Subjective survival probabilities have been stable for the top two quartiles but have worsened for the bottom two. Subjective survival probability increased slightly for the youngest cohort in the bottom quartile, but this may be a result of sampling variation.

We next consider trends in the objective health measures in the HRS. We show results for a selected list of measures: self-reported health problems, BMI, diabetes, living with pain, number of ADLs, and fraction of smokers. We then present results for an overall health index summarizing all measures: subjective health, eight doctor-diagnosed health conditions, BMI, ADLs, and current-smoker status.

In Figures 3 through 8 we present results for selected health conditions by gender, cohort, and SS wealth. As above, females are in the left panel, males in the right, cohorts on the horizontal axis, and the lines indicate results for differing Social Security wealth quintiles.

Similar to results for the P75 variable, subjective health (Figure 3) worsened in both gender groups and all SES groups (higher numbers mean worse health). Inequalities strongly increased among females, but they remained largely stable among males.

Average BMI (Figure 4) substantially increased in all groups in a roughly parallel fashion. The fraction of the sample with class 2 obesity (BMI greater than 35) increased from about 5% to 15%, with slightly higher rates among females.

The fraction that lives with diabetes (Figure 5) also substantially increased in all groups. Inequalities remained stable among males, but they strongly increased among females.

We found a remarkable pattern in the fraction who report moderate to severe pain (Figure 6): there were enormous differences across the SES groups, a substantial increase over time, and growing inequalities. For example, among males in the top SS wealth quintile, the fraction reporting at least a moderate amount of pain increased from 18.3% to 25.3%, while among those in the bottom quantile the fraction reporting moderate or worse pain increased from 31.6% to 47.0%). Among females, the proportion in the top quintile reporting moderate or worse pain increased from 24.0% to 29.8%, while in the bottom quintile it increased from 42.6% to 64.0%.

The number of ADL limitations (Figure 7) also increased over time, and inequalities across SES groups somewhat widened. The fraction of smokers (Figure 8) decreased, but differences among SES groups increased as those in higher SES groups were less likely to smoke.

Overall, we found that apart from a few exceptions (such as smoking), the health status of individuals in the 54 to 60 age range declined from the 1934 to the 1959 birth cohorts, and the decline was stronger among less educated and poorer Americans.

We sought to summarize these changes and their effects into a single score. Specifically, we sought a health index that could predict mortality. So rather than arbitrarily weighting the health variables, we estimated a Gompertz model of survival for the oldest (1934-38) birth cohort using the health variables as predictors. We then defined the health index as the predicted survival probability from ages 55 to 85 for each individual in the sample. Hence, the weights we applied to each of the health variables are those that optimally predict in-sample mortality in the cohort with the longest observation period. Even though this estimate is a survival probability, we do not use it to forecast mortality trends by cohorts, because this model does not include younger cohorts and trends. Later we will discuss a preferred mortality forecast model. Here, we only aim to summarize objective health status at the baseline age (of 54 to 60).

Figure 9 shows the health index by gender, cohort, and Social Security wealth quintile, while Figure 10 does so for educational attainment quartile. Again, females are on the left, males on the right, cohorts on the horizontal axis, and quintiles or quartiles shown in lines.

As was the case for the P75 variable, SES is a very strong predictor of objective health in all cohorts and both gender groups. Among females, we found a decline in baseline objective health in all SES groups, but the decline was stronger in the low SES groups. For example, in the top SS wealth quintile, the health index decreased from 54.8% in the 1934-38 cohort to 53.5% in the 1955-59 cohort. Among those in the bottom SS wealth quintile, the decrease was from 39% to 31.7%. The patterns are similar when we smoothed these lines by linear regressions.

Among males, the objective baseline health index somewhat improved, but the inequalities also widened. For example, in the top SS wealth quintiles, the index increased from 51.3% to 53.9%, while in the bottom quintile it only increased from 33.9% to 34.7%. When we applied a regression-based smoothing on the six points, we found even larger increases in inequalities. The model predicted an increase from

50.4% to 54.3% in the top quintile and a decrease from 35.1% to 33.6% in the bottom quintile.

2.2 Forecasting survival by SES

We fit Gompertz models to actual mortality as a function of the baseline (ages 54 to 60) characteristics of individuals. In our preferred specification, we use the following predictor variables:

- Demographic covariates (gender, race, marital status interacted with gender, last job type);
- SES measures (education quartiles, SS wealth quintiles);
- Health measures (P75, subjective health, class 2 obesity, all doctor diagnosed conditions, diabetes interacted with gender, number of ADLs, being an active smoker, ever smoked, ever drinks alcohol);
- Linear time trend in birth years;
- Interactions with birth years (gender, education quartiles, SS wealth quintiles).

Our preferred methodology uses a linear time trend in the prediction model. We experimented with more flexible specifications (using higher order polynomials) and the results were similar. In this section, we focus on this preferred specification, but in the next section we briefly discuss alternative versions.

Before we present the SES specific mortality forecasts, we briefly summarize the estimated coefficients of the preferred model in Table 2. Positive coefficients mean worse health (i.e., earlier deaths). Among the demographic predictors we found that, holding other variables (such as health status) constant, women and Hispanics live longer.

We did not find statistical differences among the SES measures, but that is partly due to multicollinearity (we use multiple SES measures interacted with time trends). We found that lower-skilled workers and blue-collar workers died earlier.

Not surprisingly, all the health predictors are very strong predictors of survival. The strongest predictors are self-reported health, ever having cancer, being an active smoker, ever having diabetes, ever having a stroke, ever smoking, and P75.

We found that occasionally drinking alcohol is associated with longer lives. Interestingly, we estimated that other things equal, arthritis and psychological problems at age 54 to 60 are associated with longer lives as well.

The trend coefficient is negative but statistically insignificant, which means that males in the lowest SES quintile only experienced a weak improvement in mortality over time, conditional on health status. The interaction terms between the trend and the SES measures show some increase in mortality inequality: The trend appears to have improved significantly more in the top two SS wealth quintiles.

To illustrate the model's implications for mortality inequality, we estimated the expected age of death for each cohort and gender group. We had observed across cohorts widening differentials as a function of SES in some health measures, so we expected to find widening differentials in mortality inequality. Figures 11 and 12 show the expected ages at death conditional on surviving to age 67 (the current normal retirement age) by SS wealth or education. Figures 13 and 14 show expected ages at death conditional on surviving to age 55 (baseline age).

Average life expectancy improved overall, but the inequalities substantially widened. For example, the expected age of death after age 55 among females in the lowest SS wealth quintile decreased from 81.1 to 80.9, while it increased in the top quintile from 88.5 to 94.1. The patterns were similar when we applied a regression-based smoothing of these lines. The trends were also similar by education quartile.

Among males, we see an improvement in mortality in all SES groups, but the inequalities widened. For example, the expected age of death after age 55 in the lowest SS wealth quintile increased from 77 to 78.3 while that in the top quintile increased from 84.4 to 90.8). Again, the predicted changes were similar when we applied regression-based smoothing. The patterns were also similar for education quartiles.

2.3 Alternative specifications and robustness checks

2.3.1 Alternative SES measures

Our preferred SES measures in this project were based on individuals' educational level and Social Security wealth. In Appendix B, we show trends and inequalities in baseline health (P75 and the health index) by race, latest job type, and the urbanization of the counties where individuals reside. We summarize these findings below.

Regarding race we find whites and blacks are equally optimistic about their survival chances (P75), while Hispanics are significantly more pessimistic, with these differences increasing over time. On our objective health index, whites score highest, followed by Hispanics then blacks, with these differences also increasing over time.

We also find job type is a strong predictor of subjective and objective health. Workers in high-skilled, white-collar jobs are the healthiest, while those in low-skilled, blue-collar jobs are the least healthy. These patterns are not necessarily causal, because individual sorting into different job types is not random. Nevertheless, while P75 and the health index remained largely stable for those in white-collar jobs, it decreased significantly for those in blue-collar jobs, increasing inequalities between occupations.

Urban individuals are slightly more optimistic about their survival (P75) and have slightly better health than rural ones. While their baseline health by cohort remained relatively stable, that for those in other areas decreased, increasing differences by area.

2.3.2 Alternative survival models

Our preferred survival specification uses many health variables as predictors in the econometric model. To test the importance of including all these variables in the model, we re-estimated our main models with two alternative specifications: one excluding all the health predictors except for P75, and the other excluding only P75. Each of these models still includes all the demographic, SES, and trend variables we have analyzed.

Appendix B illustrates our findings. We find similar results with the alternative specifications, excluding some variables or including all. Altogether, adding very detailed health information to the survival models increases precision, but does not appear to be necessary for unbiased estimates of survival chances by SES.

We also investigated the robustness of our main results to our imputation models. Estimating our model with a sample that excluded observations missing P75 and with a sample that excluded individuals with any missing values in the variables used in the prediction model yielded similar results. We conclude that our main results are robust to alternative methods of dealing with missing data. We still prefer using the imputed values, because it allows us to use a larger sample and to consistently use the HRS survey weights.

2.3.3 Internal and external validity

The HRS is a long panel survey, and it allows for testing the accuracy of our Gompertz model to predict survival. Using the model, we estimated the probabilities that individuals would survive to January 2016, and then compared it to the fraction of individuals who actually survived to that date. Appendix B (Table B2) summarizes our results, showing consistency between the model-predicted and the actual survival probabilities for gender and SES groups. That is, the internal consistency of our estimates is high.

To test for external consistency, we compared our estimated life expectancies to published Social Security cohort life tables,[7] the last of which was calculated in 2005 (Table B3). While our results are similar, we estimated slightly higher life expectancies in all groups. For example, for 55-year-old men in the 1934 to1938 cohort, we predicted a life expectancy of 81 years, while the Social Security Administration reported a life expectancy of only 79.4 years (for 55-year-old men in the 1940 birth cohort). Similarly for males in the 1955 to1959 cohort, we predicted a life expectancy of 84.2 years, while the Social Security Administration reported a life expectancy of only 81.1 years (for 55-year-old men in the 1960 birth cohort).

Put another way, we found increases in life expectancy greater than the Social Administration did. At the same time, our estimates are close to those of others, such as

[7] https://www.ssa.gov/oact/NOTES/as120/LifeTables_Body.html

Chetty et al. (2016) or Sanzenbacher et al. (2017). Among the possible explanations for the differences in our estimates and that of the Social Security Administration are differences in the samples and the fact that the Social Security Administration estimates were made 14 years ago.

3. Conclusions

In this paper, we documented trends and inequalities in health among 54- to-60-year-old Americans using the 1992 to 2016 waves of the HRS. We found that, with few exceptions (such as decreased rates of smoking), the health of these cohorts has declined over time. Because these changes have been uneven by socioeconomic status, they have led to greater increases in health inequality.

We used two measures of socioeconomic status: one based on education and one based on Social Security wealth. Measures based on education are more typical in the literature, because it is easier to measure and interpret them. Nevertheless, we found that SS wealth more strongly correlated with mortality and showed a more pronounced increase in mortality inequality over time. This may not be surprising, given that SS wealth, which is a function of individuals' lifetime earnings, is based on far more and more up-to-date information than educational attainment is.

In the second part of the paper, we estimated Gompertz mortality models using detailed health variables, demographics, SES, and cohort-trends as predictor variables. Similar to health inequality, we found large increases in (forecasted) mortality inequality. For example, the expected age of death, conditional on survival to age 55, among females in the lowest SS wealth quintile decreased by 0.2 years, while for those in the top quintile it increased by 5.6 years. Among males in the bottom quintile, life expectancy increased 1.3 years, while for those in the top quintile it increased 6.4 years.

Even though we documented significant declines in health status, our forecasting models consistently predicted increasing life expectancies over time, due to the included “trend” variables in the econometric specifications. There are two possible explanations for this. First, mortality is a byproduct of middle-aged health status and medical technology to treat old or sick individuals. It may be that the health of individuals in their late 50s declined over time due to increasing levels of unhealthy behavior, but that continually improving medical technology has offset these behaviors. Second, it may be that mortality forecasts for the youngest birth cohorts are biased downward, because they are based on extrapolations from past survival trends. The observed declines in middle-aged health may eventually translate into decreased life expectancy. Both of these explanations are plausible, but further research and more waves of HRS data are required to analyze them separately.

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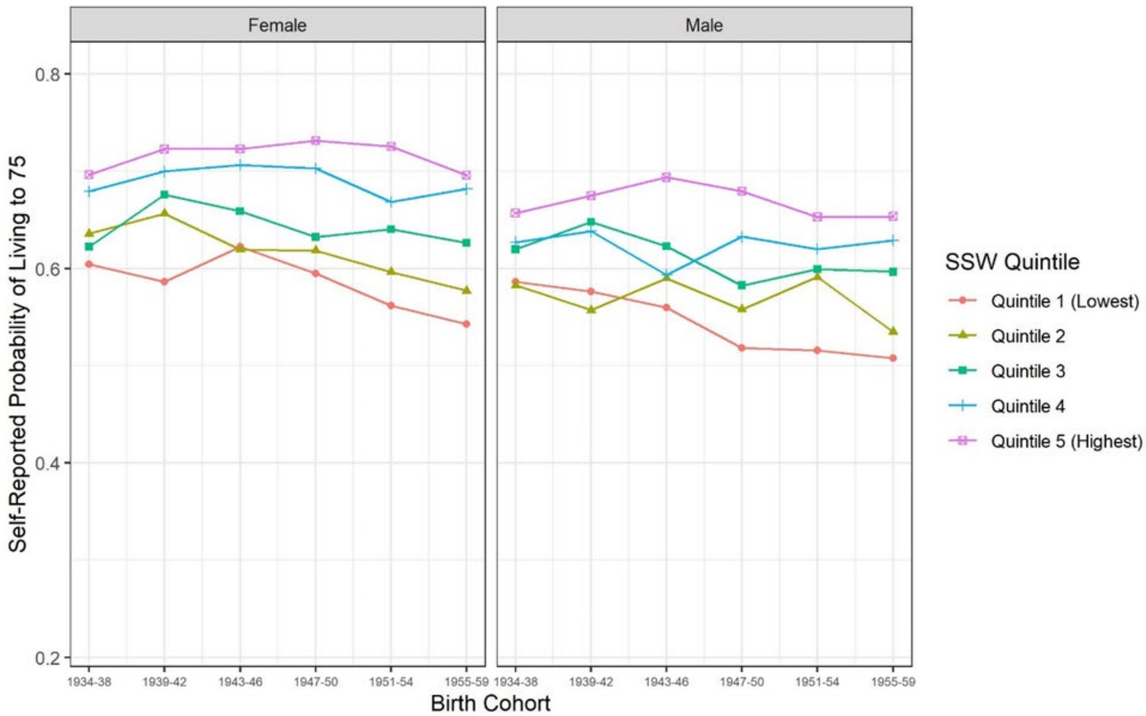
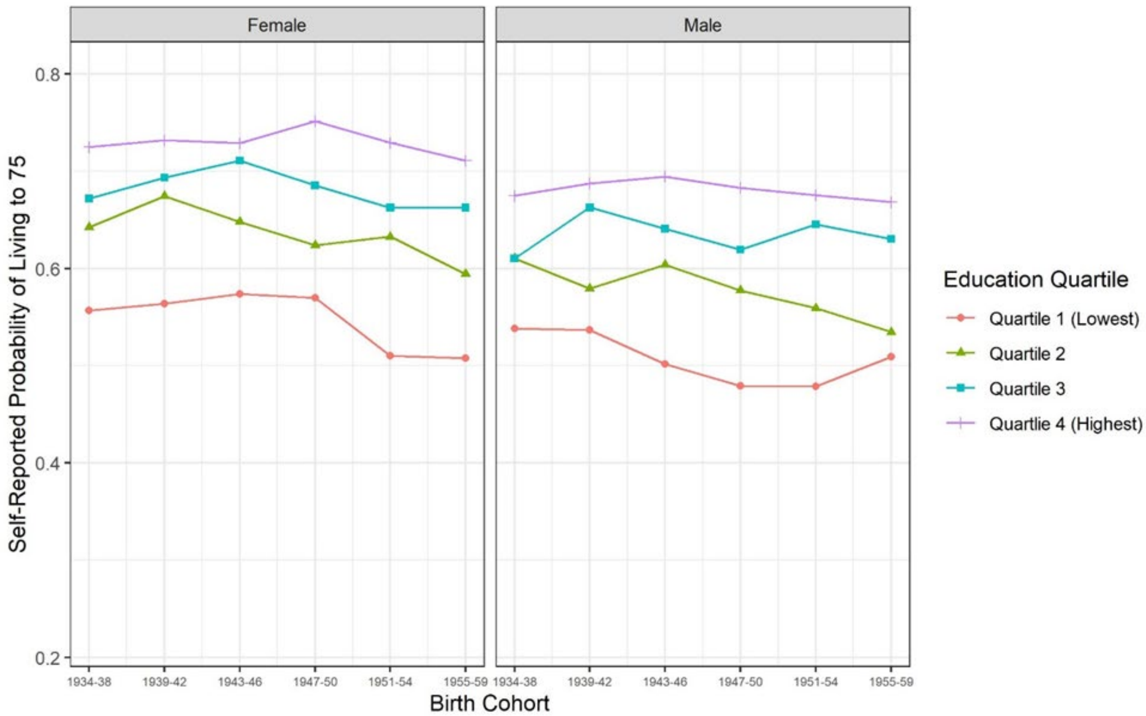
Figures and tables

Figure 1. Subjective survival probability by gender, cohort, and SS wealth



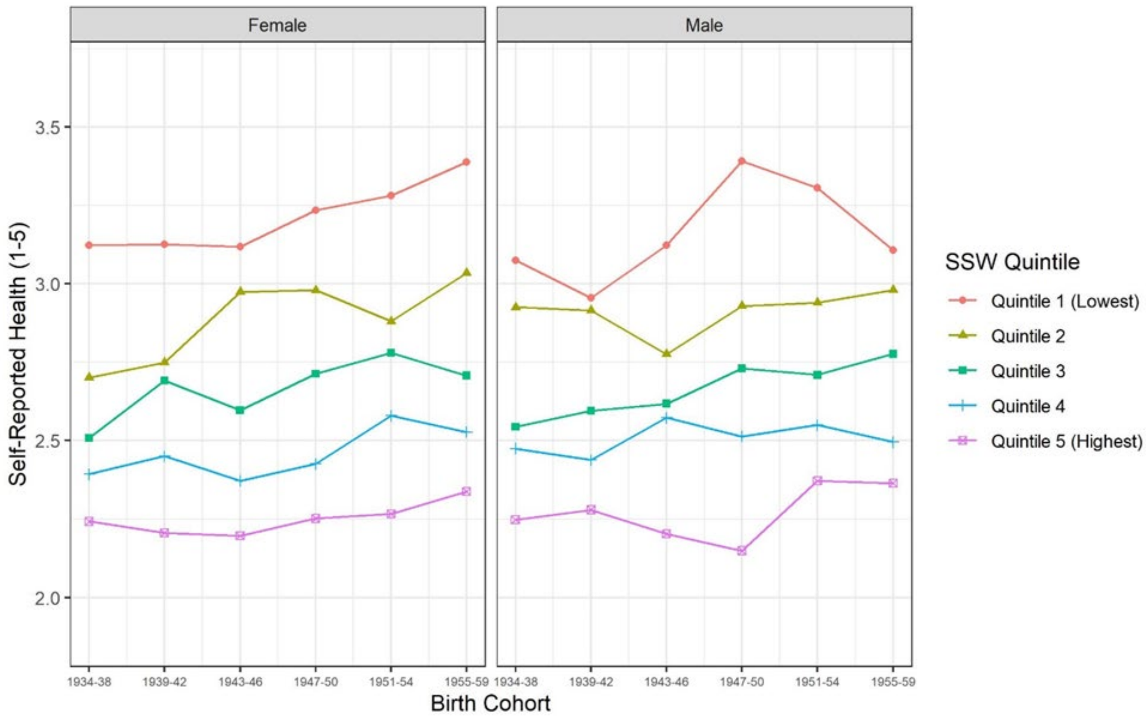
Notes: HRS, 1992 to 2016, ages 54 to 60. SS wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

Figure 2. Subjective survival probability by gender, cohort, and education



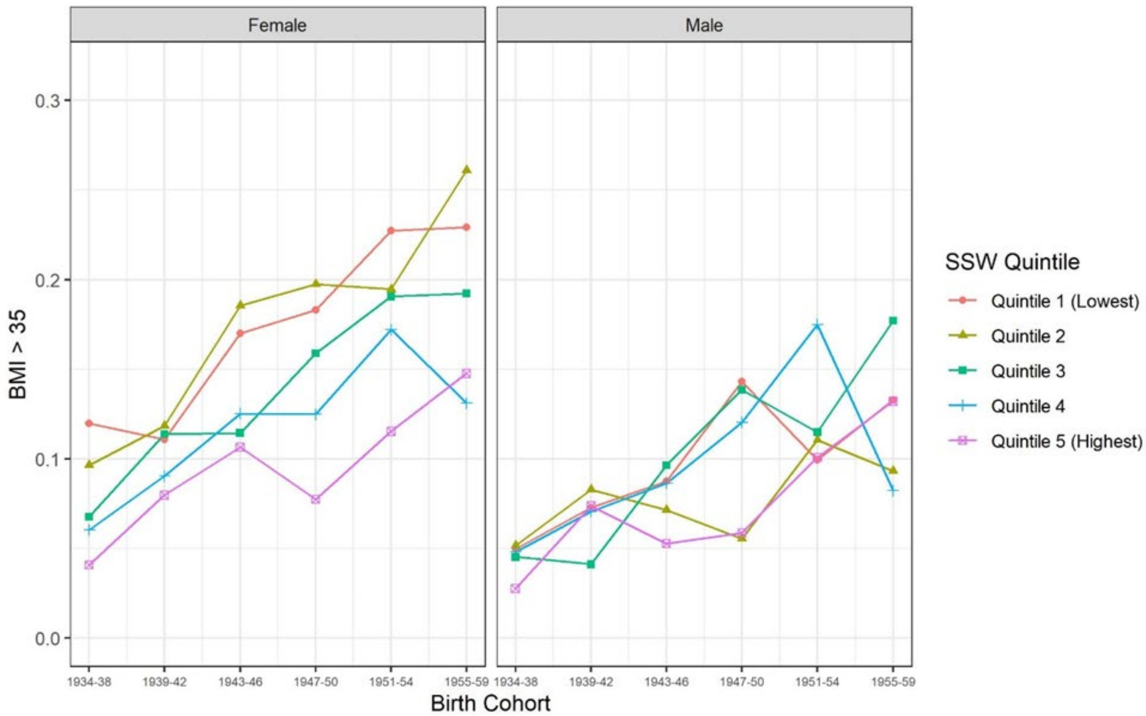
Notes: See Figure 1 notes about sample definitions. Education quartiles are cohort-specific quartiles of household education (maximum of husbands' and wives' years of education).

Figure 3. Self-reported health problems by gender, cohort, and SS wealth



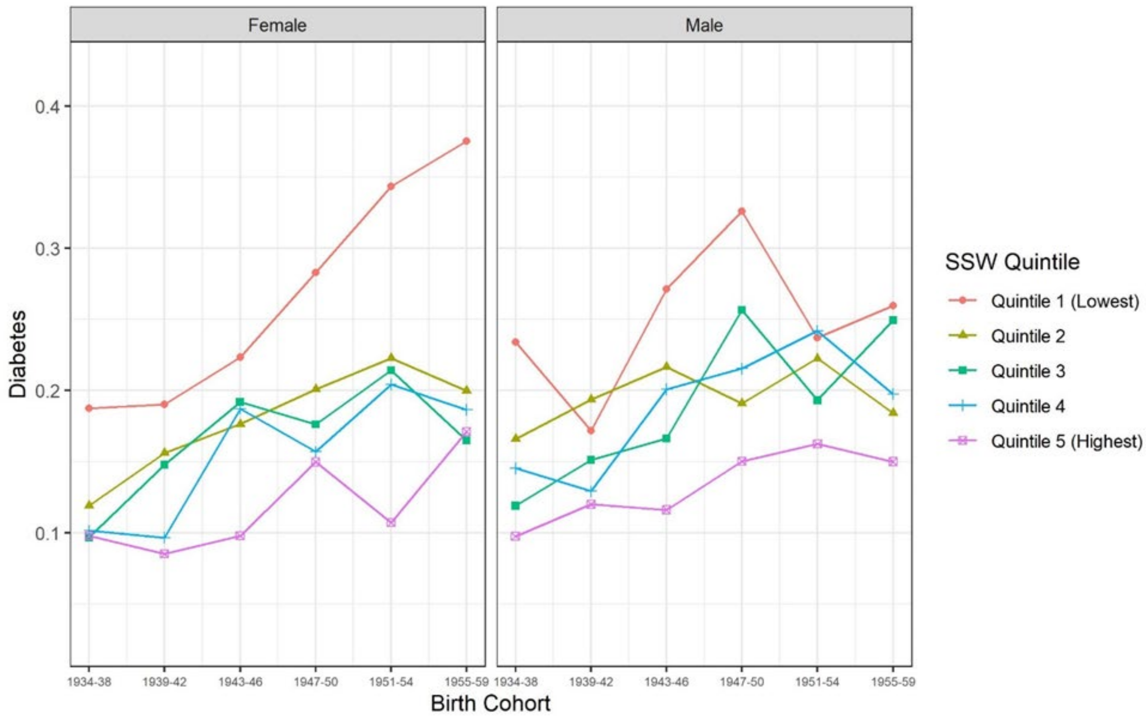
Notes: See Figure 1 notes about sample and SSW quintile definitions. The health measures individuals' own assessment of their health from a scale of 1. Excellent, to 5. Poor.

Figure 4. BMI by gender, cohort, and SS wealth



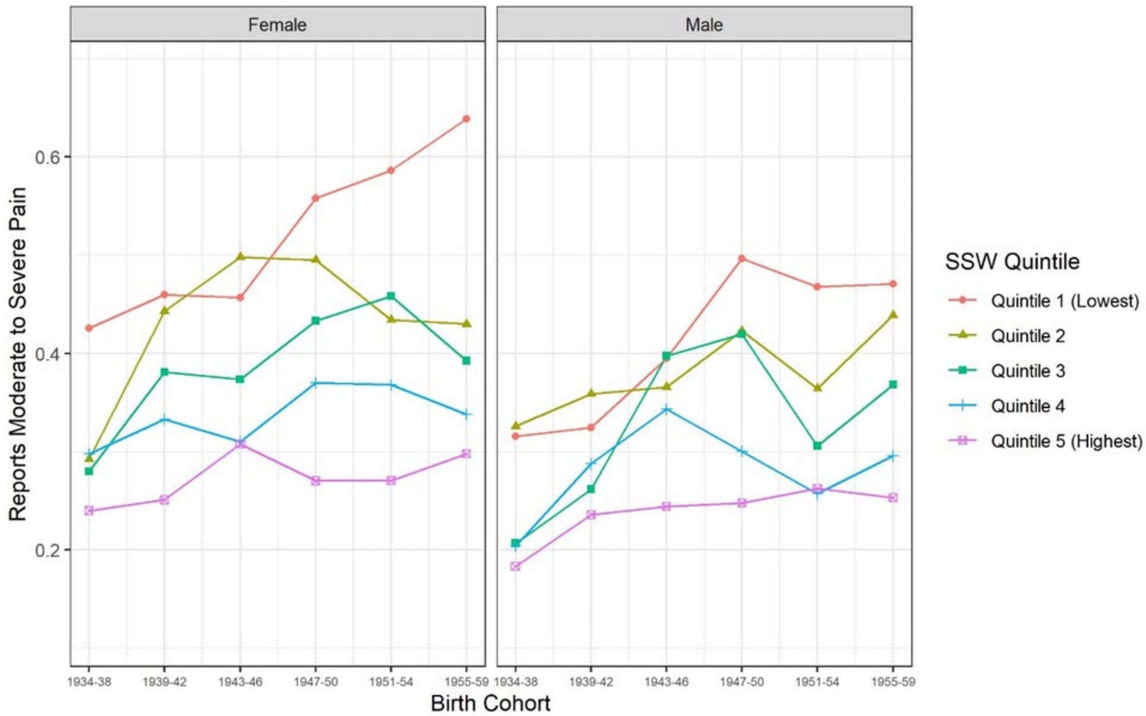
Notes: See Figure 1 notes about sample and SSW quintile definitions.

Figure 5. Fraction ever had diabetes by gender, cohorts, and SS wealth



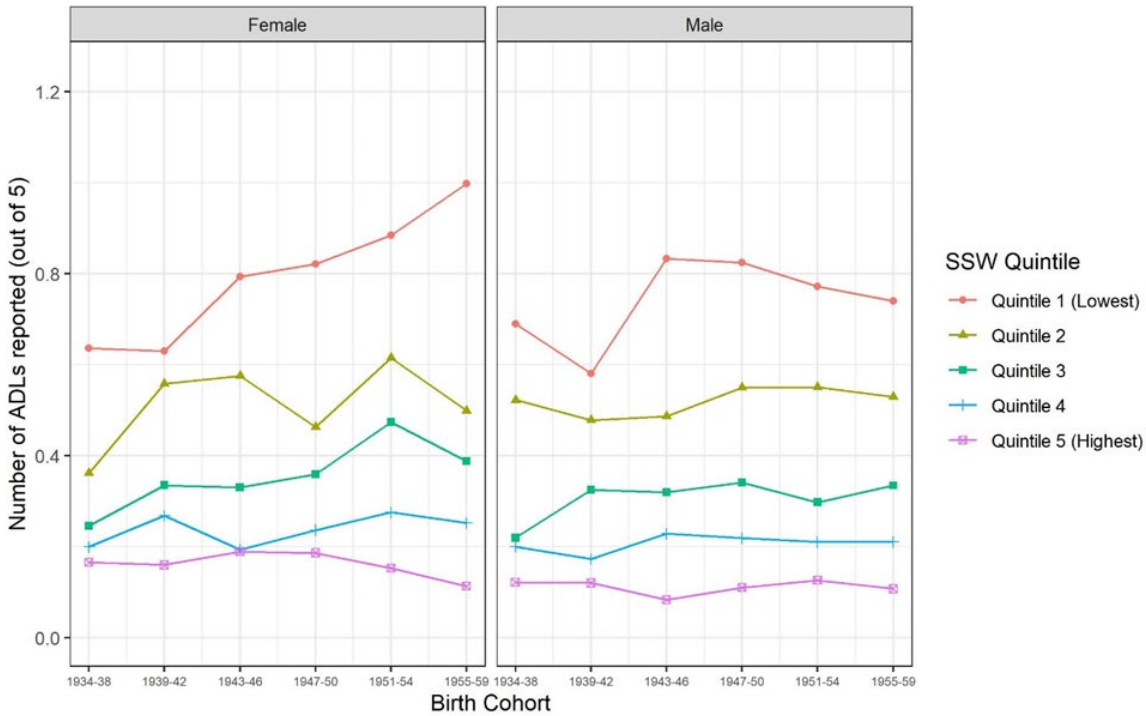
Notes: See Figure 1 notes about sample and SSW quintile definitions.

Figure 6. Fraction living with moderate to severe pain by gender, cohort, and SS wealth



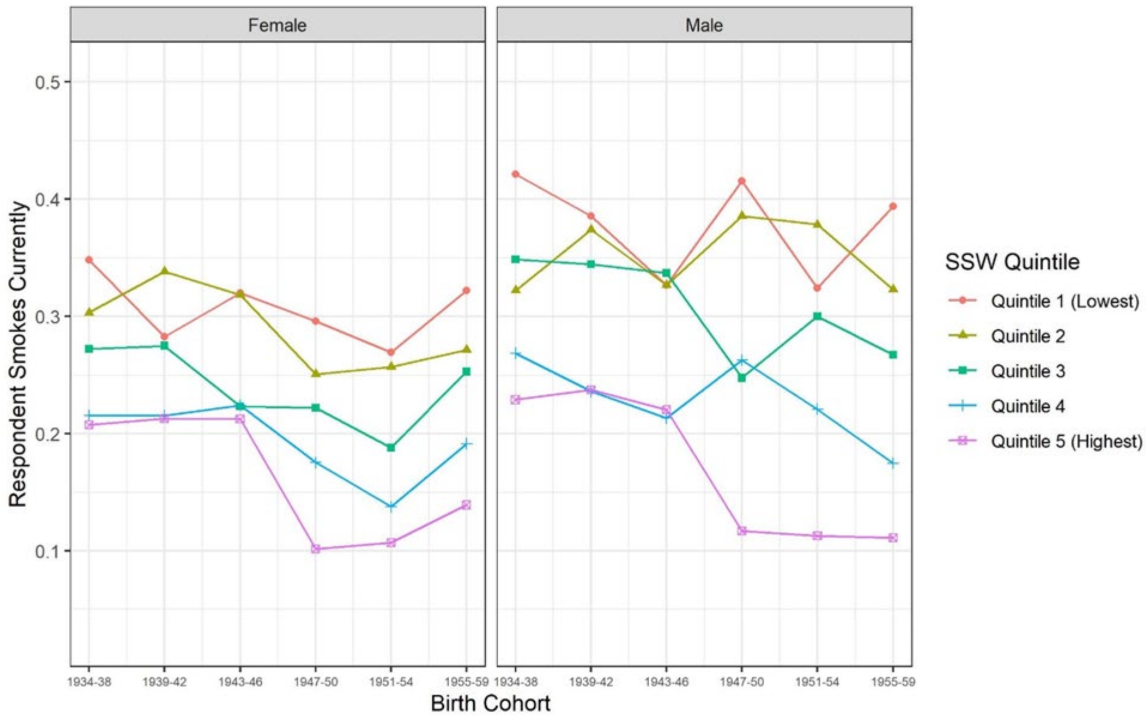
Notes: See Figure 1 notes about sample and SSW quintile definitions.

Figure 7. Number of ADL limitations by gender, cohort, and SS wealth



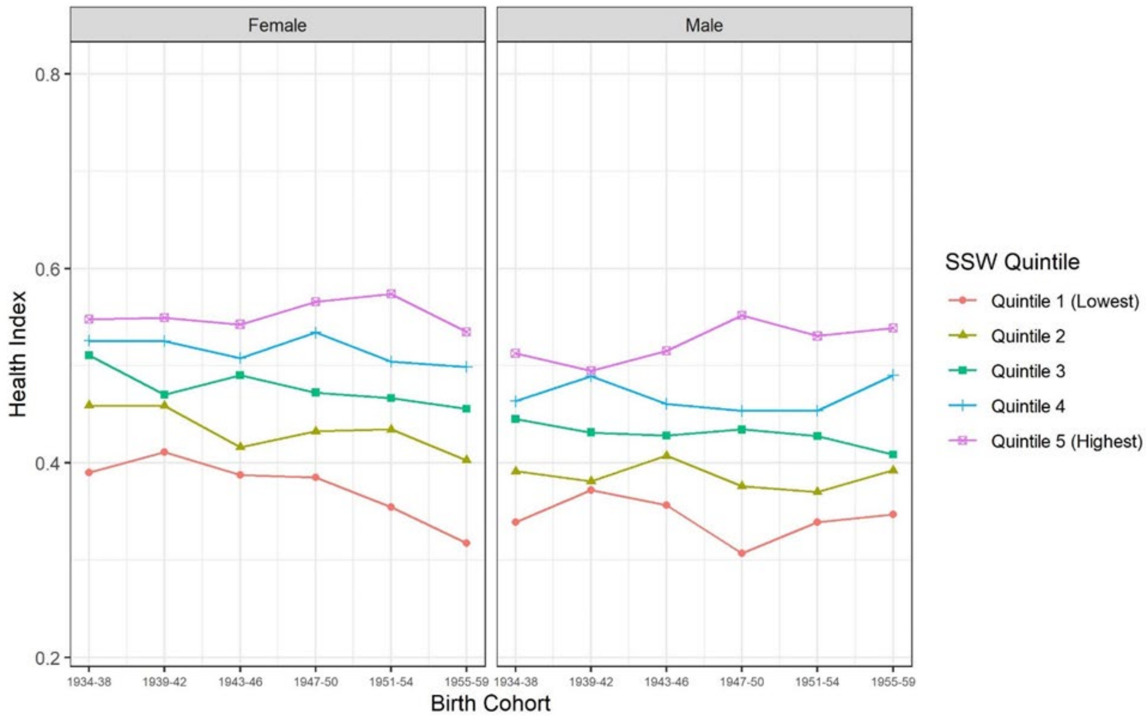
Notes: See Figure 1 notes about sample and SSW quintile definitions.

Figure 8. Fraction of smokers by gender, cohort, and SS wealth



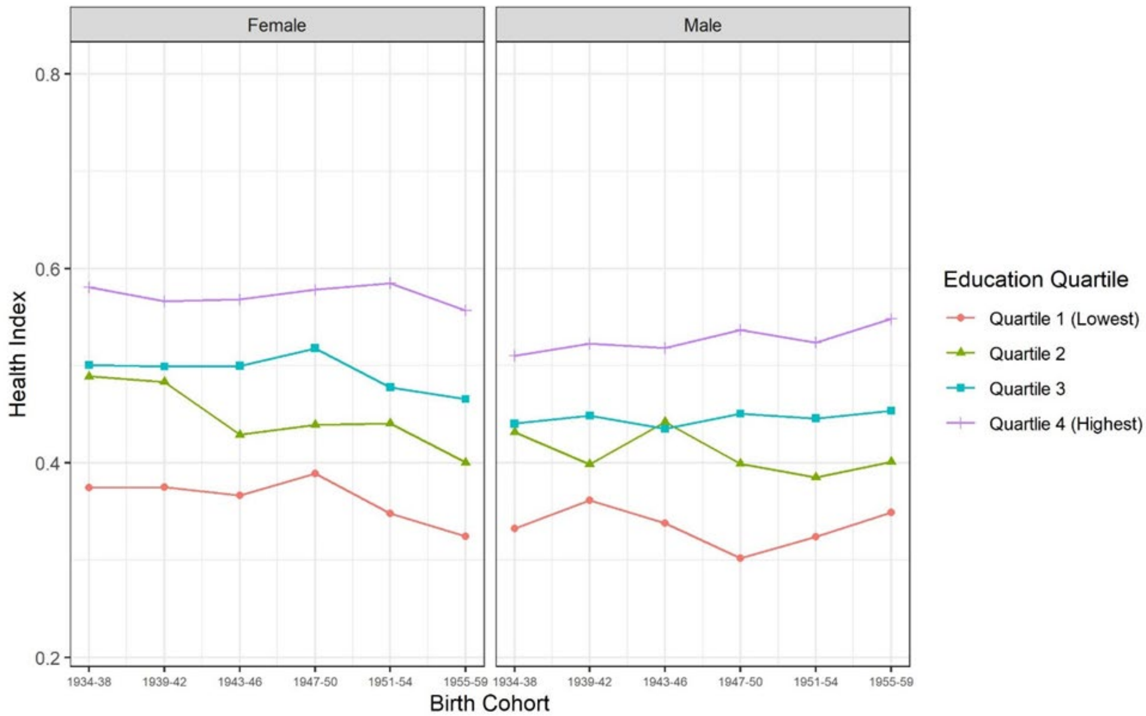
Notes: See Figure 1 notes about sample and SSW quintile definitions.

Figure 9. Health index by gender, cohort, and SS wealth



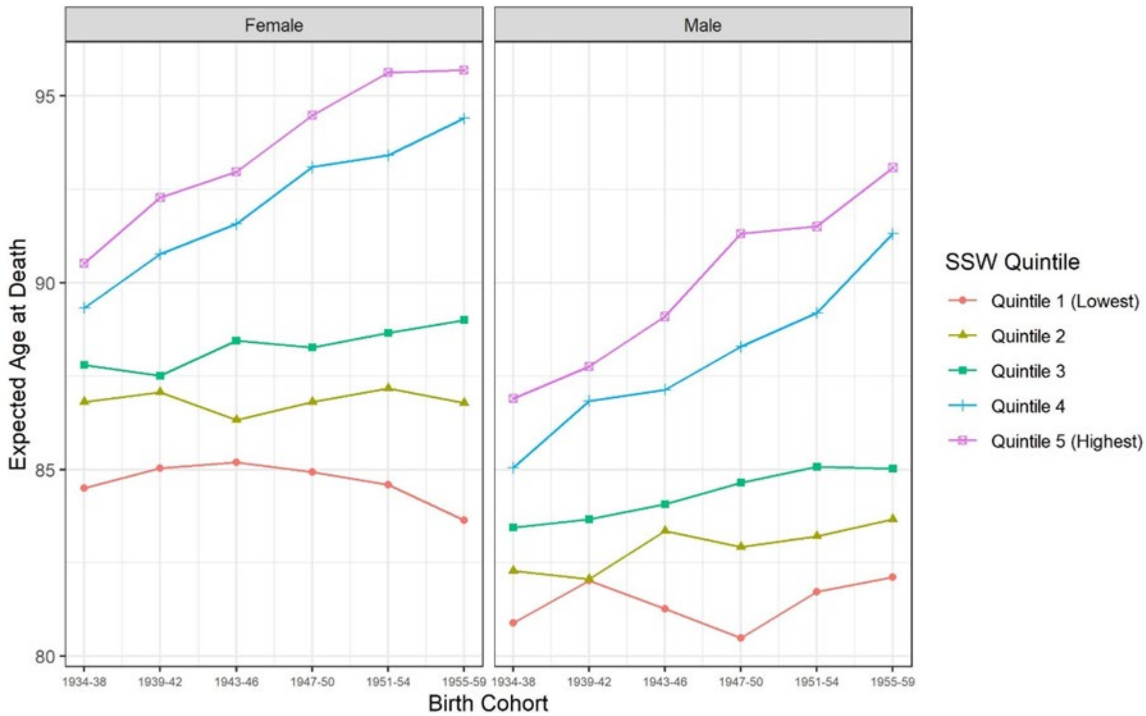
Notes: See Figure 1 notes about sample and SSW quintile definitions. The Health index is a predicted probability of survival from age 55 to 85 as a function of all objective health measures. Model estimated on the 1934-38 cohort.

Figure 10. Health index by gender, cohort, and education



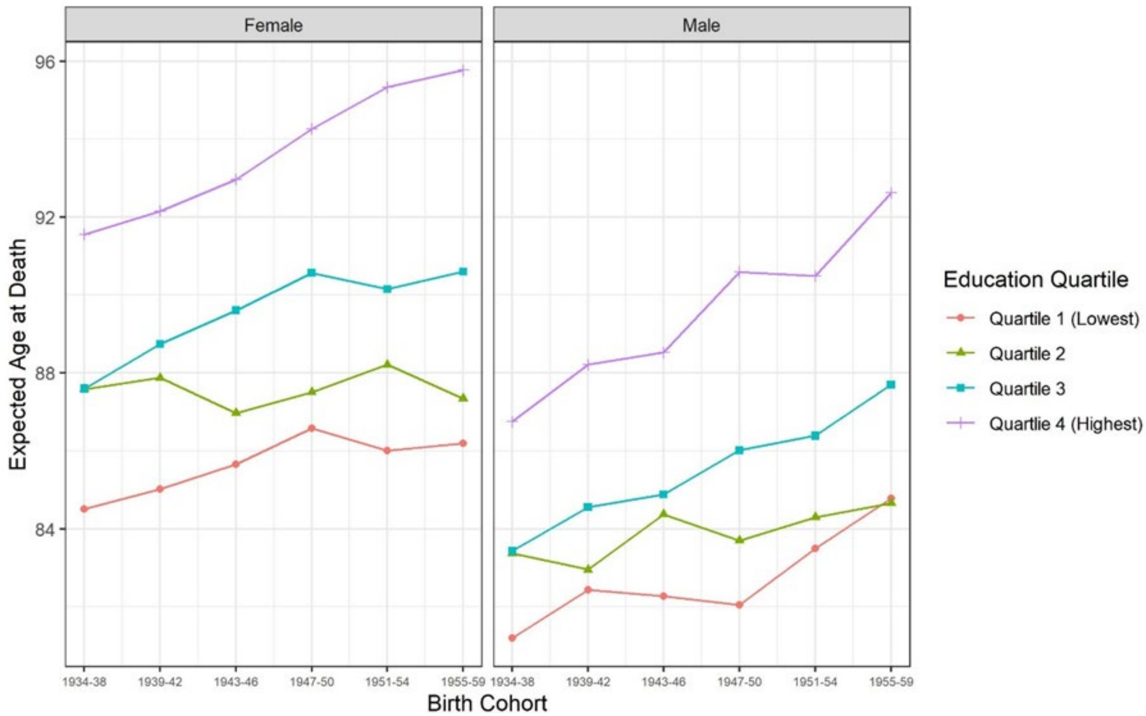
Notes: See Figure 2 & 3 notes about definitions.

Figure 11. Expected age at death from age 67 by gender, cohort, and SS wealth



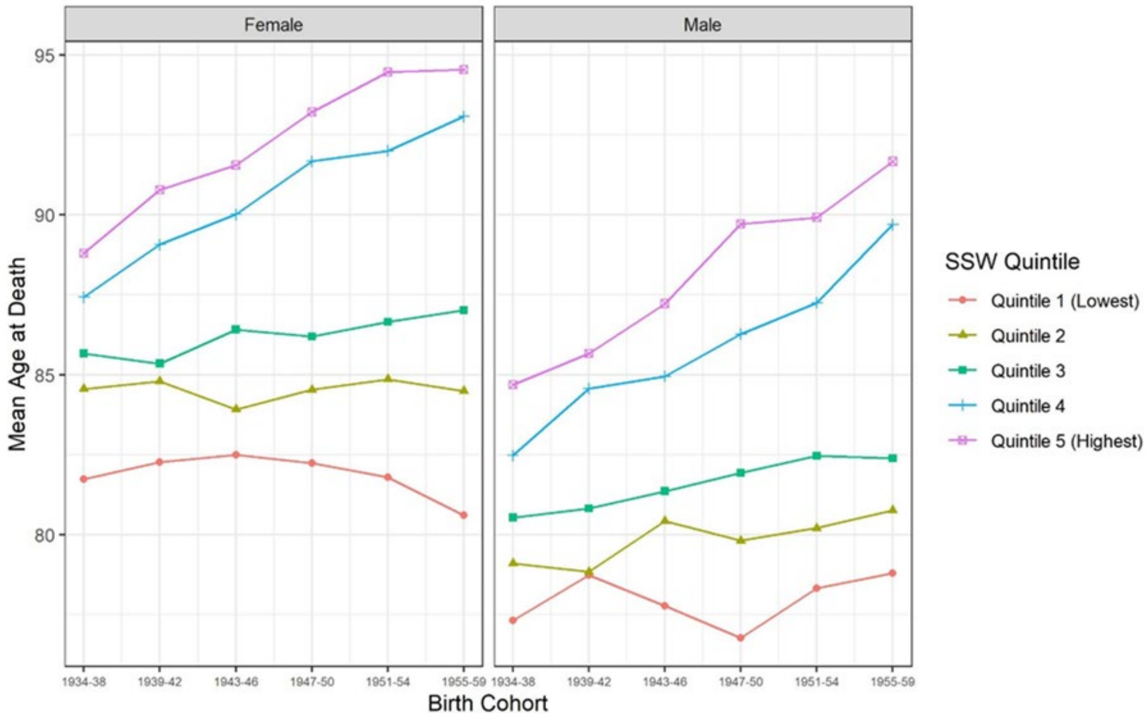
Notes: See Figure 1 notes about sample and SSW quintile definitions. Model estimates based on our preferred specification.

Figure 12. Expected age at death from age 67 by gender, cohort, and education



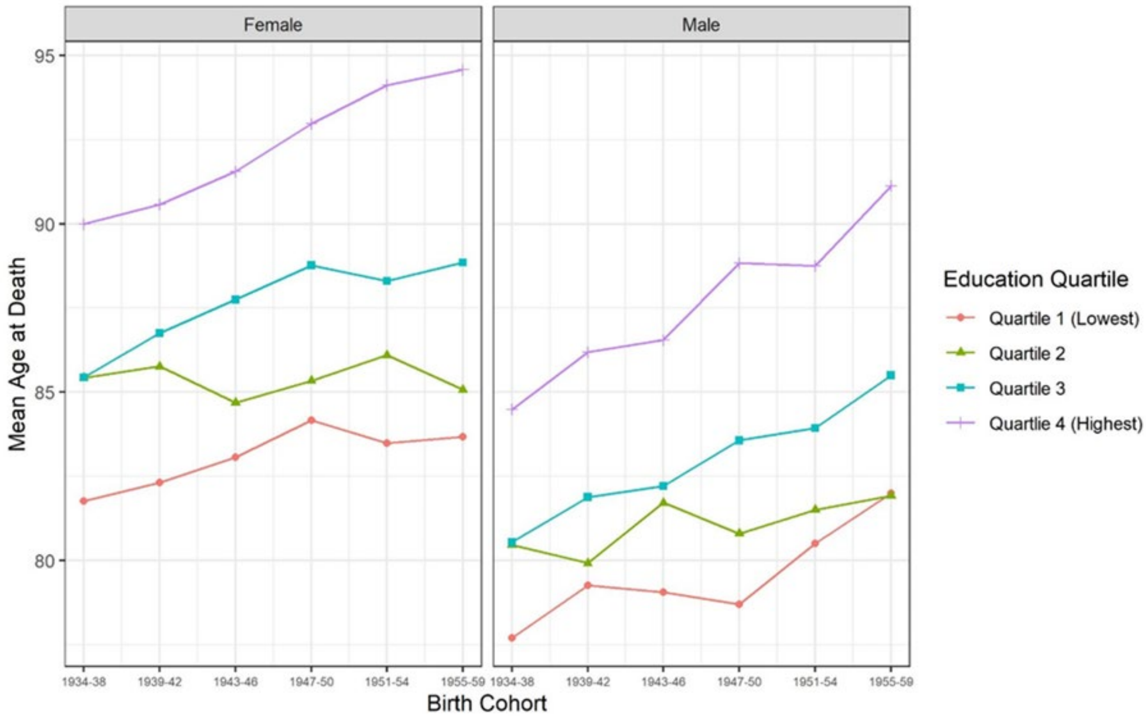
Notes: See Figure 2 notes about sample and education quartile definitions. Model estimates based on our preferred specification.

Figure 13. Expected age at death conditional on survival to age 55 by gender, birth cohorts, and SS wealth



Notes: See Figure 1 notes about sample and SSW quintile definitions. Model based estimates.

__Figure 14. Expected age at death conditional on survival to age 55 by gender, birth cohorts, and education__



Notes: See Figure 2 notes about sample and education quartile definitions. Model based estimates.

Table 1. Baseline characteristics in the sample

	N	Weighted Mean	Weighted SD	Unweighted Mean	Unweighted SD
Male	19,547	0.486	0.500	0.445	0.497
Birth Year	19,547	1948.4	7.2	1946.1	7.9
Education	19,537				
HS dropout		0.138	0.344	0.197	0.398
HS degree or GED		0.324	0.468	0.340	0.474
Some college		0.265	0.442	0.247	0.431
College+		0.273	0.446	0.216	0.411
Race	19,532				
Non-Hispanic white		0.761	0.426	0.634	0.482
Non-Hispanic black		0.111	0.314	0.201	0.401
Non-Hispanic other race		0.038	0.190	0.033	0.178
Hispanic		0.090	0.286	0.132	0.338
Social Security Wealth	19,016	198,738	80,235	188,132	80,154
Subjective survival probability to 75	18,527	63.11	25.58	62.66	26.35
Self-reported health (1-5)	19,545	2.673	1.026	2.761	1.044
BMI > 35	19,410	0.123	0.328	0.121	0.326
Ever had diabetes	19,532	0.186	0.389	0.197	0.398
Ever had high blood pressure	19,505	0.491	0.500	0.513	0.500
Ever had cancer	19,538	0.096	0.294	0.091	0.288
Ever had lung disease	19,539	0.096	0.294	0.100	0.300
Ever had heart problems	19,544	0.170	0.376	0.174	0.379
Ever had stroke	19,547	0.043	0.204	0.051	0.219
Ever had psychiatric problems	19,533	0.213	0.409	0.206	0.404
Ever had arthritis	19,513	0.494	0.500	0.505	0.500
Under moderate to severe pain	19,514	0.357	0.479	0.358	0.479
# of ADLs (0-5)	19,547	0.372	0.941	0.417	0.998
Current smoker	19,521	0.249	0.432	0.268	0.443
Last job type	19,547				
White collar, high skill		0.330	0.470	0.284	0.451
White collar, low skill		0.236	0.425	0.228	0.419
Blue collar, high skill		0.210	0.407	0.207	0.405
Blue collar, low skill		0.164	0.371	0.205	0.404
Never worked		0.031	0.174	0.042	0.202
Missing		*0.029*	*0.168*	*0.034*	*0.182*
Metropolitan county	19,547				
Urban		0.518	0.500	0.531	0.499
Suburban		0.219	0.413	0.217	0.412
Rural		0.260	0.438	0.247	0.431
Missing		*0.004*	*0.062*	*0.005*	*0.072*

Notes: HRS, 1992 to 2016, age 54 to 60.

Table 2. Output of the preferred mortality model

Coefficients in ln(γ_{0i})	coef.	s.e.
Female	-0.601	[0.094]***
Non-Hispanic black	0.010	[0.044]
Non-Hispanic other race	-0.304	[0.113]***
Hispanic	-0.520	[0.064]***
Married	-0.243	[0.059]***
Female-married interaction	0.168	[0.077]**
2nd education quartile	-0.019	[0.093]
3rd education quartile	0.077	[0.096]
highest education quartile	0.000	[0.113]
2nd SSW quintile	-0.033	[0.098]
3rd SSW quintile	0.022	[0.104]
4th SSW quintile	0.010	[0.113]
Highest SSW quintile	-0.067	[0.121]
White collar, low skill	0.108	[0.056]*
Blue collar, high skill	0.092	[0.059]
Blue collar, low skill	0.127	[0.056]**
Never worked	0.370	[0.088]***
Jog type missing	0.335	[0.084]***
Subjective survival probability	-0.218	[0.071]***
Self-reported health	0.423	[0.024]***
BMI > 35	0.145	[0.053]***
Ever had diabetes	0.381	[0.054]***
Female X diabetes	0.161	[0.074]**
Ever had high blood pressure	0.073	[0.037]**
Ever had cancer	0.587	[0.048]***
Ever had lung disease	0.164	[0.047]***
Ever had heart problems	0.212	[0.040]***
Ever had stroke	0.309	[0.059]***
Ever had psychiatric problems	-0.134	[0.043]***
Ever had arthritis	-0.256	[0.038]***
Ever smoked	0.280	[0.046]***
Currently smokers	0.568	[0.041]***
Ever drinks	-0.095	[0.036]***
Under moderate to severe pain	-0.156	[0.042]***
# of ADLs	0.056	[0.017]***
Birth year (minus 1930)	-0.010	[0.007]
Female-birth year interaction	0.003	[0.006]
2nd educ-birth year interaction	0.008	[0.007]
3rd educ-birth year interaction	0.002	[0.008]
4th educ-birth year interaction	-0.002	[0.009]
2nd SSW-birth year interaction	-0.001	[0.008]
3rd SSW-birth year interaction	-0.007	[0.008]
4th SSW-birth year interaction	-0.025	[0.010]***
5th SSW-birth year interaction	-0.021	[0.010]**
Constant	-13.712	[0.262]***
γ_1	0.008	[0.000]***

Log likelihood	-26060.216
N	19547

Notes: HRS, 1992-2016, Age 54-60. γ_{0i} refers to the shape parameter and γ_1 refers to the scale parameter of the Gompertz model.

Appendix A: Table versions of the main figures

Table A1. Subjective survival probability by gender, cohort, and SS wealth

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	0.586	0.576	0.560	0.518	0.516	0.507
Quintile 2	0.583	0.557	0.590	0.558	0.591	0.535
Quintile 3	0.620	0.648	0.623	0.582	0.599	0.597
Quintile 4	0.627	0.638	0.593	0.632	0.620	0.629
Quintile 5 (Highest)	0.657	0.675	0.694	0.679	0.653	0.653
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	0.604	0.586	0.623	0.595	0.562	0.542
Quintile 2	0.636	0.656	0.619	0.618	0.597	0.578
Quintile 3	0.622	0.676	0.659	0.632	0.640	0.626
Quintile 4	0.679	0.700	0.706	0.703	0.669	0.682
Quintile 5 (Highest)	0.696	0.723	0.723	0.731	0.725	0.696

Table A2. Subjective survival probability by gender, cohort, and education

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quartile 1 (Lowest)	0.538	0.537	0.502	0.479	0.479	0.509
Quartile 2	0.611	0.579	0.604	0.577	0.559	0.535
Quartile 3	0.610	0.663	0.641	0.619	0.645	0.630
Quartile 4 (Highest)	0.675	0.687	0.695	0.683	0.675	0.668
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quartile 1 (Lowest)	0.557	0.564	0.574	0.569	0.510	0.508
Quartile 2	0.642	0.674	0.648	0.624	0.633	0.594
Quartile 3	0.672	0.693	0.711	0.685	0.663	0.663
Quartile 4 (Highest)	0.725	0.732	0.729	0.752	0.729	0.711

Table A3. Health index by gender, cohort, and SS wealth

	Male					
	1934-38	1939-42	1943-46	1947-50	1951-54	1955-59
Quintile 1 (Lowest)	0.339	0.372	0.357	0.307	0.339	0.347
Quintile 2	0.392	0.381	0.407	0.376	0.370	0.392
Quintile 3	0.445	0.431	0.428	0.434	0.428	0.409
Quintile 4	0.464	0.489	0.461	0.454	0.454	0.490
Quintile 5 (Highest)	0.513	0.495	0.515	0.552	0.531	0.539
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	0.390	0.411	0.388	0.385	0.355	0.317
Quintile 2	0.459	0.459	0.416	0.433	0.435	0.403
Quintile 3	0.511	0.470	0.490	0.472	0.467	0.456
Quintile 4	0.526	0.525	0.508	0.534	0.504	0.499
Quintile 5 (Highest)	0.548	0.549	0.542	0.566	0.574	0.535

Table A4. Health index by gender, cohort, and education

	Male					
	1934-38	1939-42	1943-46	1947-50	1951-54	1955-59
Quartile 1 (Lowest)	0.333	0.362	0.338	0.302	0.324	0.349
Quartile 2	0.432	0.399	0.442	0.399	0.385	0.401
Quartile 3	0.440	0.449	0.435	0.451	0.446	0.454
Quartile 4 (Highest)	0.510	0.523	0.518	0.537	0.524	0.548
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quartile 1 (Lowest)	0.374	0.375	0.367	0.389	0.348	0.325
Quartile 2	0.489	0.483	0.429	0.439	0.441	0.401
Quartile 3	0.501	0.499	0.500	0.518	0.478	0.466
Quartile 4 (Highest)	0.581	0.566	0.568	0.578	0.585	0.557

Table A5. Subjective health by gender, cohort, and SS wealth

	Male					
	1934-38	1939-42	1943-46	1947-50	1951-54	1955-59
Quintile 1 (Lowest)	3.075	2.956	3.123	3.392	3.306	3.109
Quintile 2	2.926	2.915	2.775	2.929	2.940	2.980
Quintile 3	2.544	2.596	2.618	2.731	2.710	2.776
Quintile 4	2.475	2.438	2.573	2.513	2.550	2.496
Quintile 5 (Highest)	2.248	2.280	2.203	2.149	2.372	2.364
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	3.122	3.126	3.118	3.235	3.281	3.391
Quintile 2	2.701	2.749	2.974	2.980	2.881	3.032
Quintile 3	2.509	2.692	2.596	2.713	2.781	2.708
Quintile 4	2.393	2.451	2.372	2.426	2.579	2.528
Quintile 5 (Highest)	2.242	2.206	2.196	2.252	2.267	2.338

Table A6. BMI by gender, cohort, and SS wealth

	Male					
	1934-38	1939-42	1943-46	1947-50	1951-54	1955-59
Quintile 1 (Lowest)	0.050	0.073	0.088	0.143	0.100	0.131
Quintile 2	0.052	0.083	0.072	0.056	0.111	0.095
Quintile 3	0.045	0.041	0.097	0.139	0.115	0.177
Quintile 4	0.048	0.071	0.087	0.120	0.175	0.082
Quintile 5 (Highest)	0.028	0.074	0.053	0.059	0.101	0.132
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	0.120	0.111	0.170	0.183	0.227	0.231
Quintile 2	0.097	0.119	0.186	0.198	0.195	0.260
Quintile 3	0.068	0.114	0.115	0.159	0.191	0.192
Quintile 4	0.060	0.091	0.125	0.125	0.172	0.131
Quintile 5 (Highest)	0.041	0.080	0.107	0.078	0.115	0.148

Table A7. Fraction ever had diabetes by gender, cohorts, and SS wealth

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	0.234	0.172	0.272	0.326	0.237	0.259
Quintile 2	0.166	0.194	0.217	0.191	0.223	0.185
Quintile 3	0.119	0.151	0.166	0.257	0.193	0.250
Quintile 4	0.145	0.129	0.201	0.215	0.242	0.198
Quintile 5 (Highest)	0.098	0.120	0.116	0.150	0.162	0.150
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	0.188	0.190	0.223	0.283	0.344	0.377
Quintile 2	0.119	0.156	0.176	0.201	0.223	0.198
Quintile 3	0.097	0.148	0.192	0.176	0.214	0.165
Quintile 4	0.101	0.097	0.187	0.157	0.204	0.187
Quintile 5 (Highest)	0.098	0.085	0.098	0.150	0.107	0.171

Table A8. Fraction living with moderate to severe pain by gender, cohort, and SS wealth

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	0.316	0.325	0.395	0.497	0.468	0.470
Quintile 2	0.326	0.359	0.366	0.423	0.364	0.440
Quintile 3	0.207	0.262	0.398	0.420	0.306	0.368
Quintile 4	0.204	0.288	0.343	0.301	0.257	0.296
Quintile 5 (Highest)	0.183	0.236	0.244	0.248	0.263	0.253
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	0.426	0.460	0.457	0.558	0.587	0.640
Quintile 2	0.292	0.443	0.498	0.495	0.434	0.429
Quintile 3	0.280	0.381	0.374	0.433	0.459	0.393
Quintile 4	0.298	0.333	0.310	0.370	0.368	0.338
Quintile 5 (Highest)	0.240	0.251	0.308	0.270	0.271	0.298

Table A9. Number of ADL limitations by gender, cohort, and SS wealth

	Male					
	1934-38	1939-42	1943-46	1947-50	1951-54	1955-59
Quintile 1 (Lowest)	0.689	0.581	0.833	0.824	0.773	0.738
Quintile 2	0.523	0.478	0.487	0.550	0.551	0.532
Quintile 3	0.220	0.326	0.320	0.341	0.298	0.335
Quintile 4	0.201	0.173	0.229	0.219	0.211	0.211
Quintile 5 (Highest)	0.122	0.121	0.084	0.110	0.127	0.108
	Female					
	1934-38	1939-42	1943-46	1947-50	1951-54	1955-59
Quintile 1 (Lowest)	0.637	0.630	0.793	0.821	0.884	1.005
Quintile 2	0.362	0.559	0.575	0.463	0.615	0.492
Quintile 3	0.246	0.335	0.331	0.359	0.474	0.388
Quintile 4	0.200	0.268	0.194	0.237	0.276	0.252
Quintile 5 (Highest)	0.166	0.160	0.190	0.187	0.154	0.114

Table A10. Fraction of smokers by gender, cohort, and SS wealth

	Male					
	1934-38	1939-42	1943-46	1947-50	1951-54	1955-59
Quintile 1 (Lowest)	0.421	0.386	0.327	0.416	0.324	0.395
Quintile 2	0.322	0.374	0.327	0.386	0.378	0.322
Quintile 3	0.349	0.345	0.337	0.248	0.300	0.267
Quintile 4	0.269	0.236	0.213	0.263	0.221	0.175
Quintile 5 (Highest)	0.229	0.237	0.221	0.117	0.113	0.111
	Female					
	1934-38	1939-42	1943-46	1947-50	1951-54	1955-59
Quintile 1 (Lowest)	0.348	0.283	0.320	0.296	0.269	0.322
Quintile 2	0.303	0.339	0.318	0.251	0.257	0.271
Quintile 3	0.272	0.275	0.223	0.222	0.188	0.253
Quintile 4	0.216	0.215	0.224	0.175	0.138	0.191
Quintile 5 (Highest)	0.208	0.213	0.213	0.102	0.107	0.139

Table A11. Expected age at death from age 67 by gender, cohort, and SS wealth

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	80.68	81.31	81.23	80.74	81.38	81.71
Quintile 2	82.05	82.13	83.26	82.98	82.94	83.73
Quintile 3	83.44	83.58	84.04	84.70	84.81	84.97
Quintile 4	85.00	86.48	87.30	88.18	89.20	90.76
Quintile 5 (Highest)	86.63	87.43	89.07	90.99	91.11	92.29
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	84.00	84.55	85.36	84.45	84.07	83.88
Quintile 2	86.68	86.92	86.31	86.89	86.39	86.21
Quintile 3	87.65	87.27	88.27	88.47	88.01	88.54
Quintile 4	89.18	90.67	91.66	93.23	93.02	93.92
Quintile 5 (Highest)	90.27	91.74	92.62	94.16	94.84	95.31

Table A12. Expected age at death from age 67 by gender, cohort, and education

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quartile 1 (Lowest)	81.30	82.12	82.50	82.12	83.26	84.20
Quartile 2	83.22	82.85	84.45	83.68	84.01	83.92
Quartile 3	83.27	84.33	84.71	85.91	85.91	87.17
Quartile 4 (Highest)	86.46	87.91	88.54	90.18	90.37	91.68
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quartile 1 (Lowest)	84.45	84.90	85.59	86.17	85.63	86.22
Quartile 2	87.19	87.36	87.14	87.35	87.32	87.04
Quartile 3	87.42	88.60	89.41	90.44	89.08	89.76
Quartile 4 (Highest)	91.29	91.91	92.89	94.17	94.56	95.03

Table A13. Expected age at death from age 55 by gender, cohort, and SS wealth

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	77.05	77.82	77.74	77.09	77.89	78.35
Quintile 2	78.81	78.91	80.32	79.86	79.90	80.83
Quintile 3	80.54	80.72	81.31	82.01	82.15	82.36
Quintile 4	82.43	84.16	85.14	86.15	87.26	89.08
Quintile 5 (Highest)	84.38	85.30	87.20	89.35	89.46	90.79
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quintile 1 (Lowest)	81.12	81.74	82.72	81.65	81.19	80.91
Quintile 2	84.40	84.64	83.88	84.62	83.95	83.82
Quintile 3	85.50	85.06	86.21	86.43	85.90	86.50
Quintile 4	87.26	88.96	90.11	91.83	91.57	92.56
Quintile 5 (Highest)	88.52	90.16	91.16	92.86	93.60	94.11

Table A14. Expected age at death from age 55 by gender, cohort, and education

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quartile 1 (Lowest)	77.82	78.85	79.35	78.80	80.23	81.36
Quartile 2	80.27	79.80	81.80	80.76	81.14	81.03
Quartile 3	80.35	81.61	82.01	83.44	83.38	84.90
Quartile 4 (Highest)	84.14	85.83	86.57	88.37	88.62	90.07
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Quartile 1 (Lowest)	81.69	82.20	83.02	83.70	83.06	83.72
Quartile 2	84.96	85.16	84.88	85.13	85.03	84.69
Quartile 3	85.24	86.59	87.51	88.64	87.05	87.86
Quartile 4 (Highest)	89.69	90.32	91.45	92.85	93.25	93.76

Appendix B: Additional tables and figures

Figure B1. Subjective survival probability by gender, birth cohorts, and race

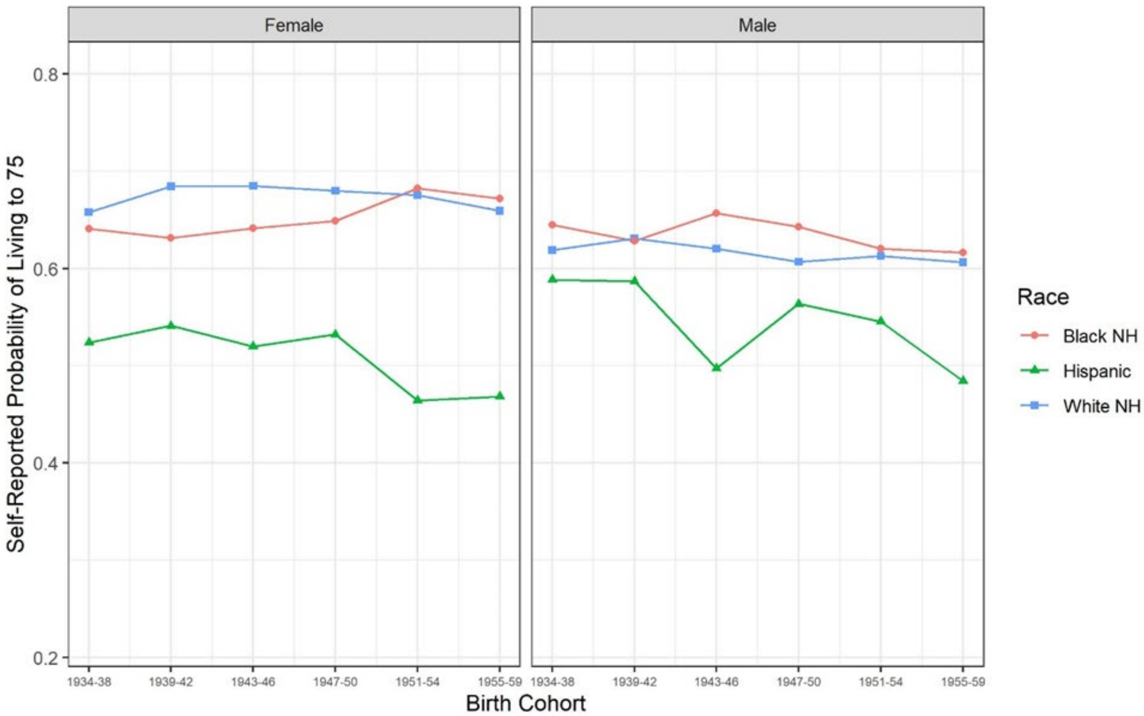


Figure B2. Health index by gender, birth cohorts, and race

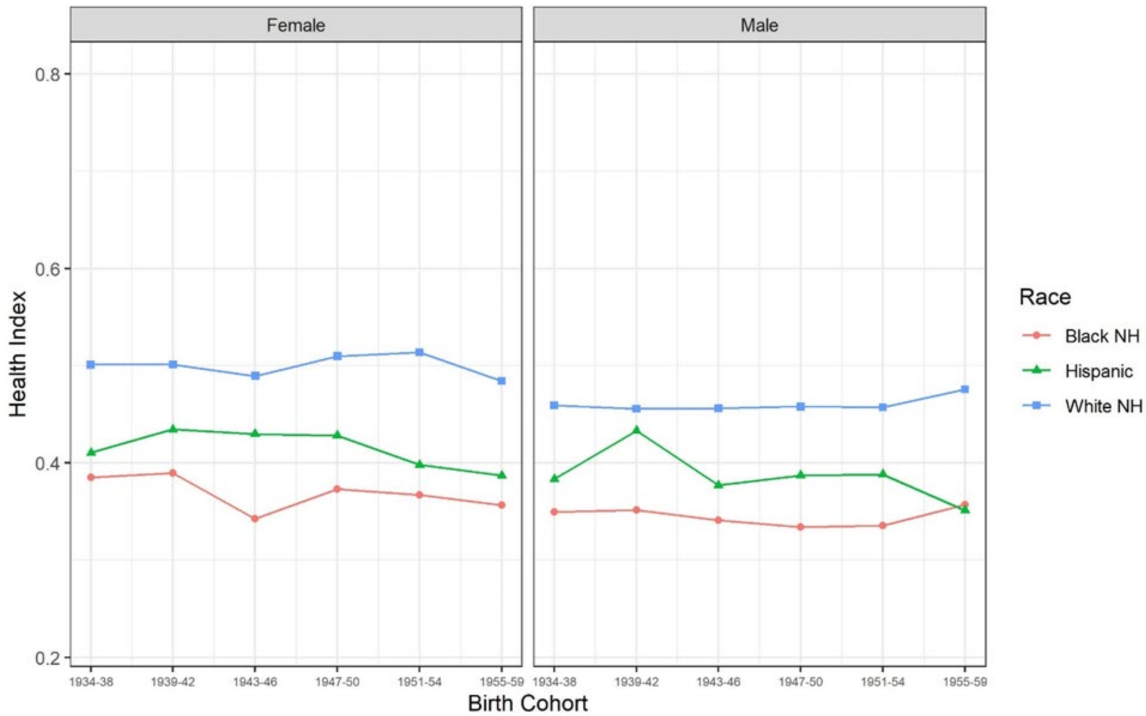


Figure B3. Subjective survival probability by gender, birth cohorts, and job type

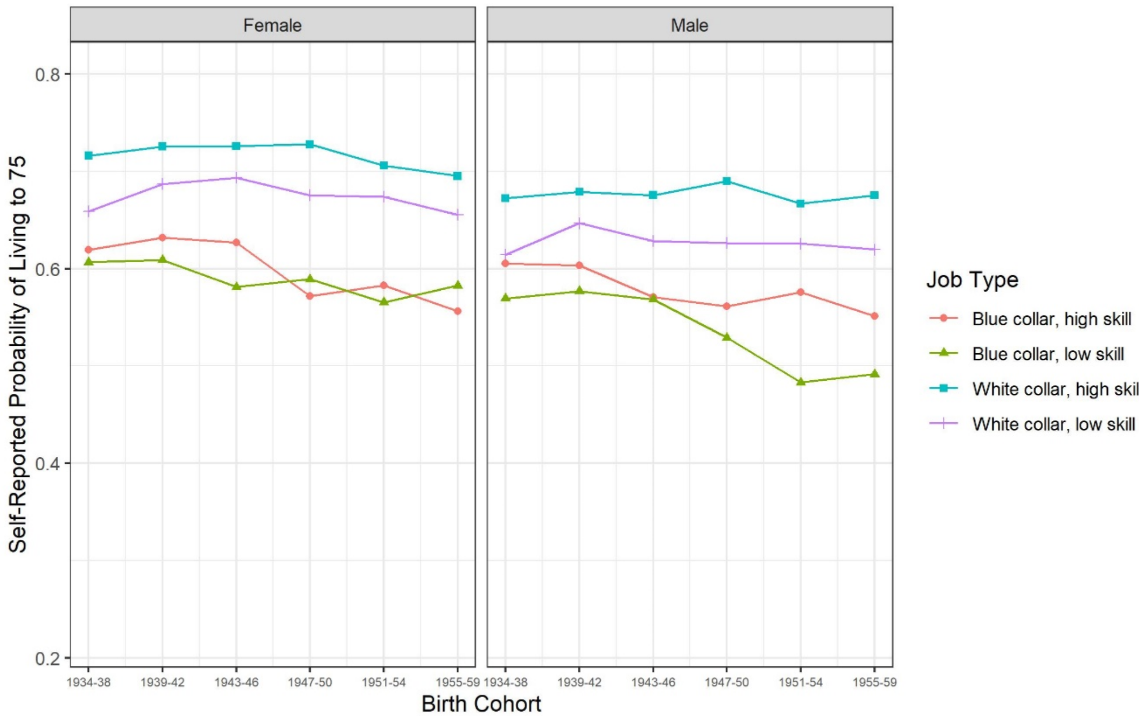


Figure B4. Health index by gender, birth cohorts, and job type

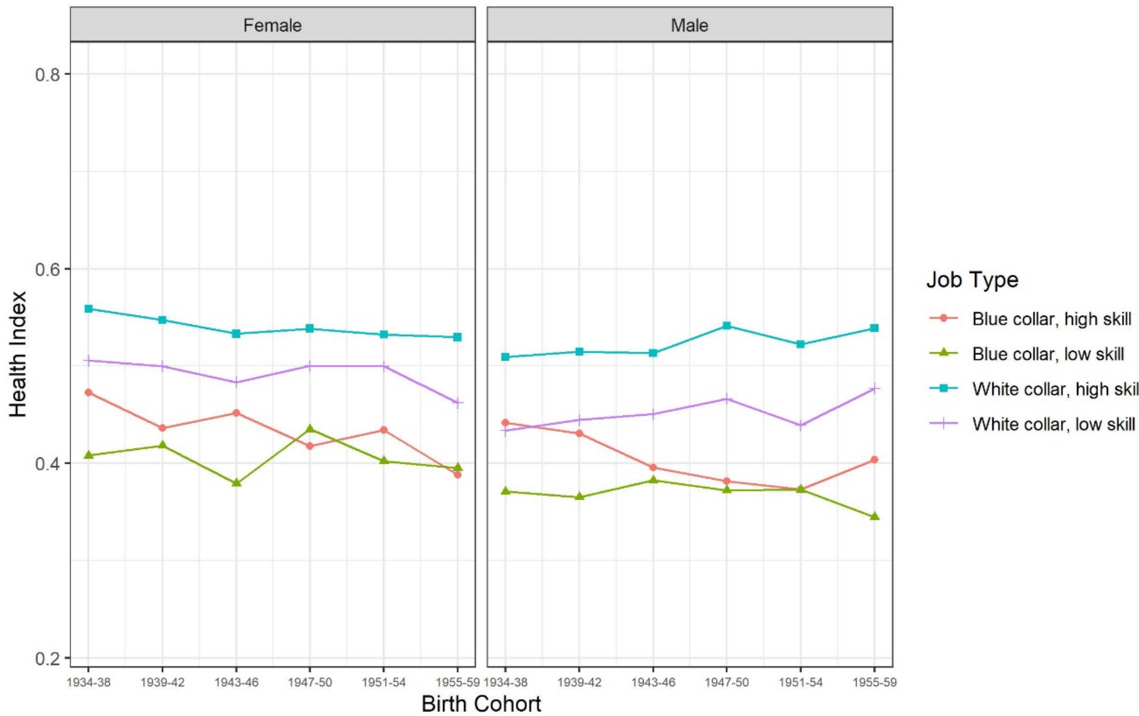


Figure B5. Subjective survival probability by gender, birth cohorts, and urbanization

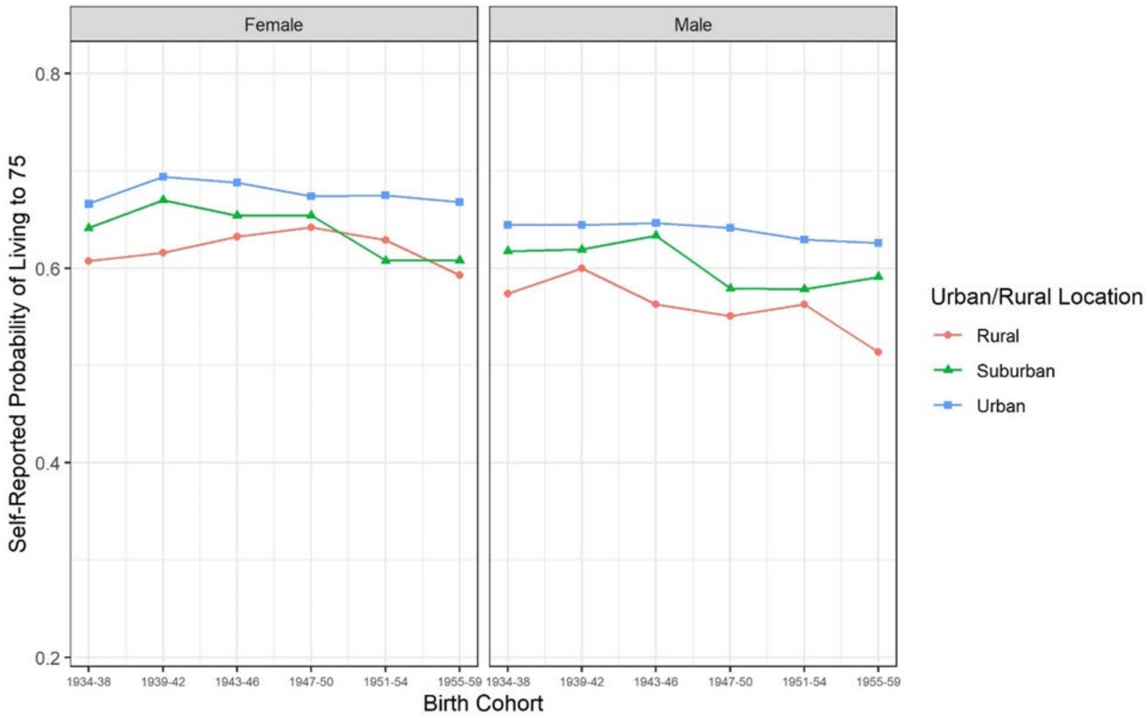


Figure B6. Health index by gender, birth cohorts, and urbanization

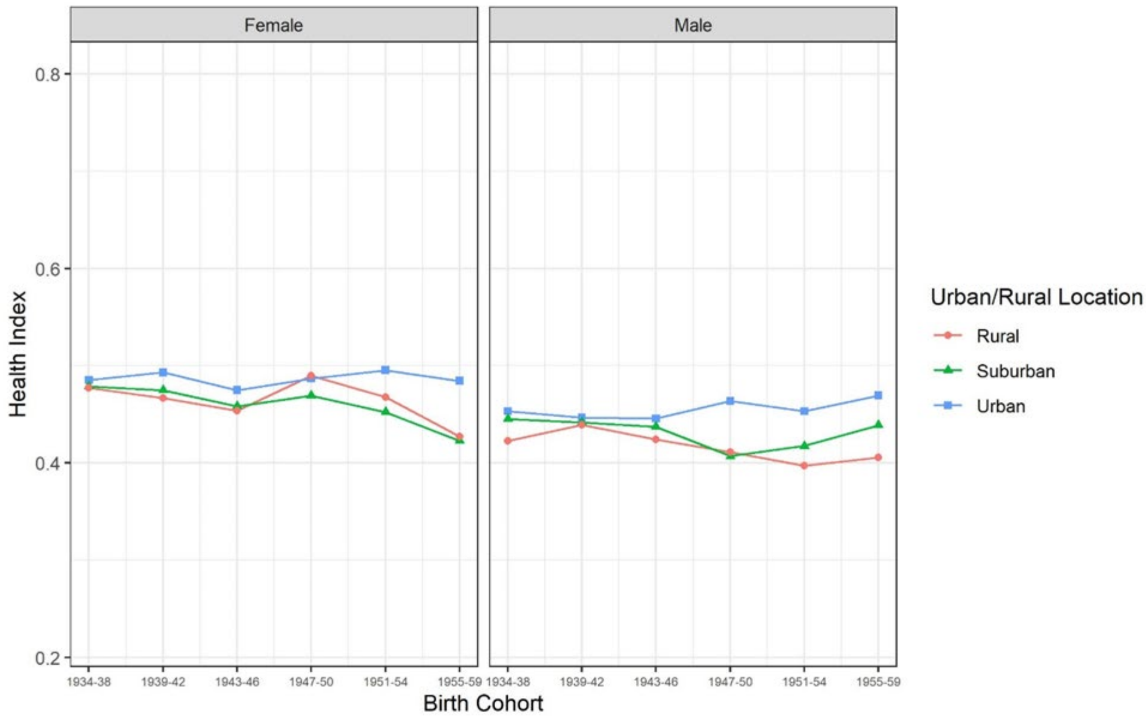


Figure B7. Expected age at death conditional on survival to age 55 by gender, birth cohorts, and SS wealth, specification without objective health measures

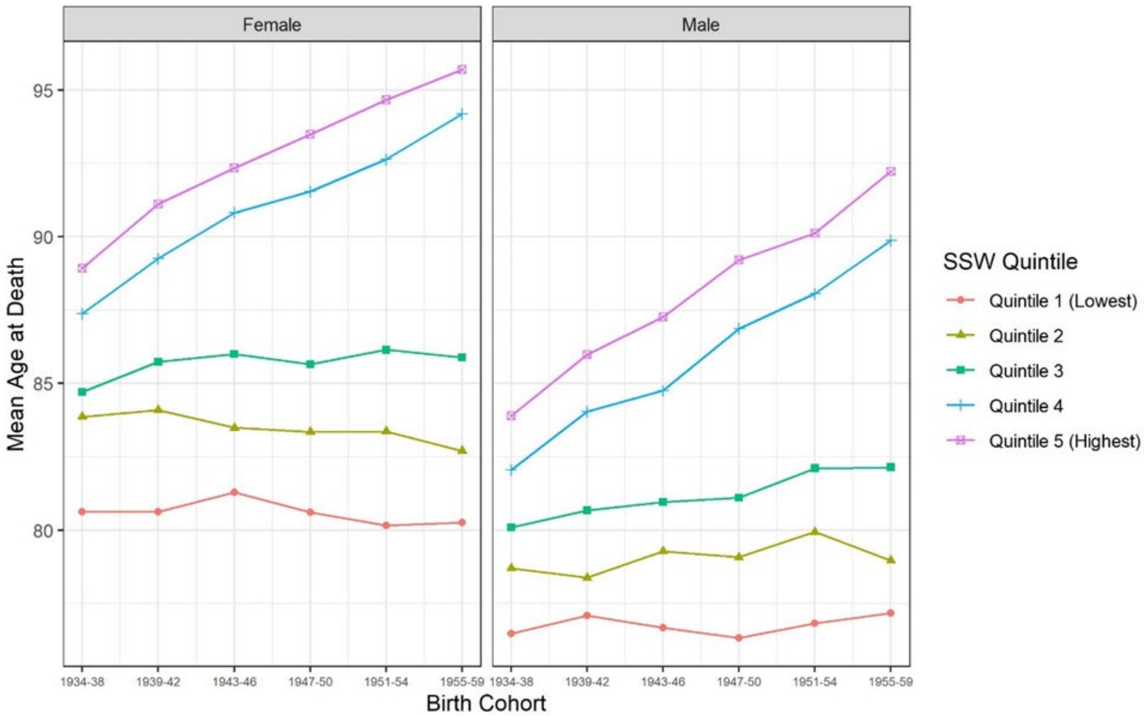


Figure B8. Expected age at death conditional on survival to age 55 by gender, birth cohorts, and SS wealth, specification without P75

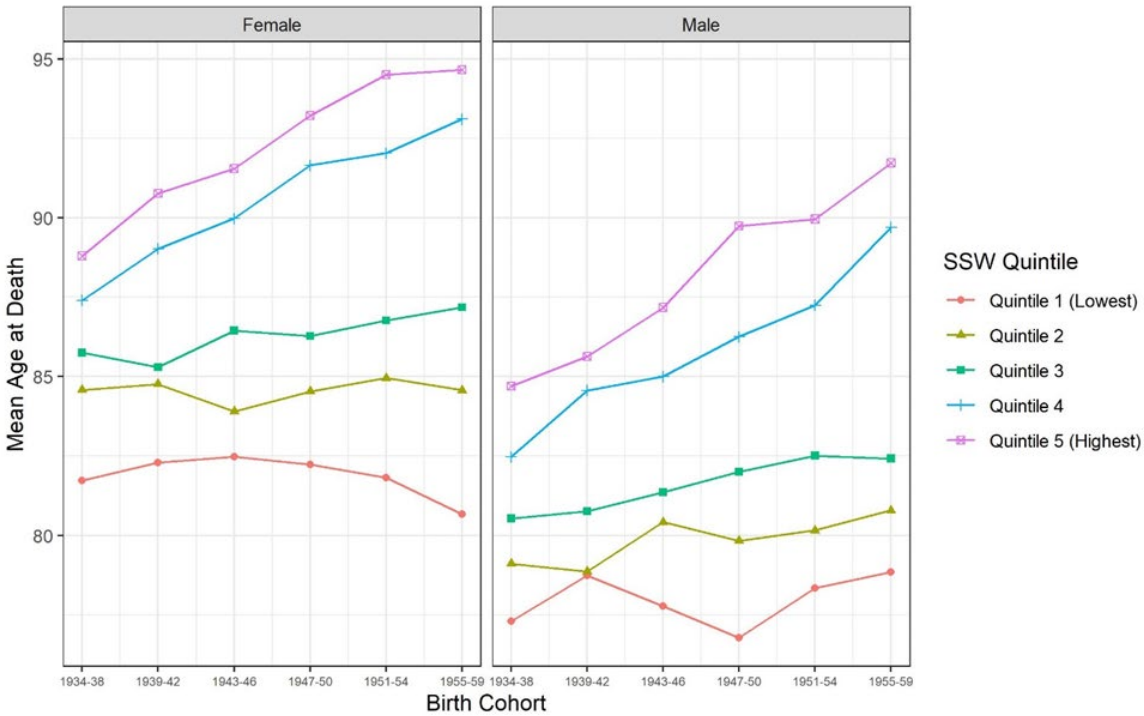


Figure B9. Expected age at death conditional on survival to age 55 by gender, birth cohorts, and SS wealth, excluding observations with missing P75

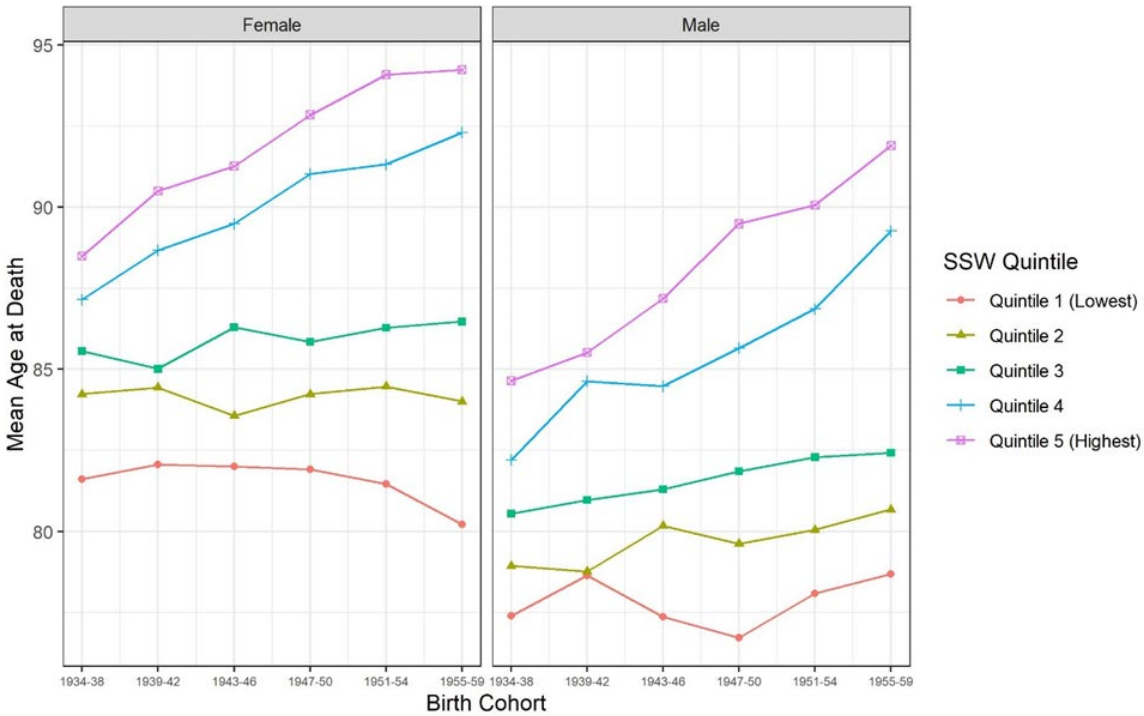


Figure B10. Expected age at death conditional on survival to age 55 by gender, birth cohorts, and SS wealth, excluding observations with any missing values

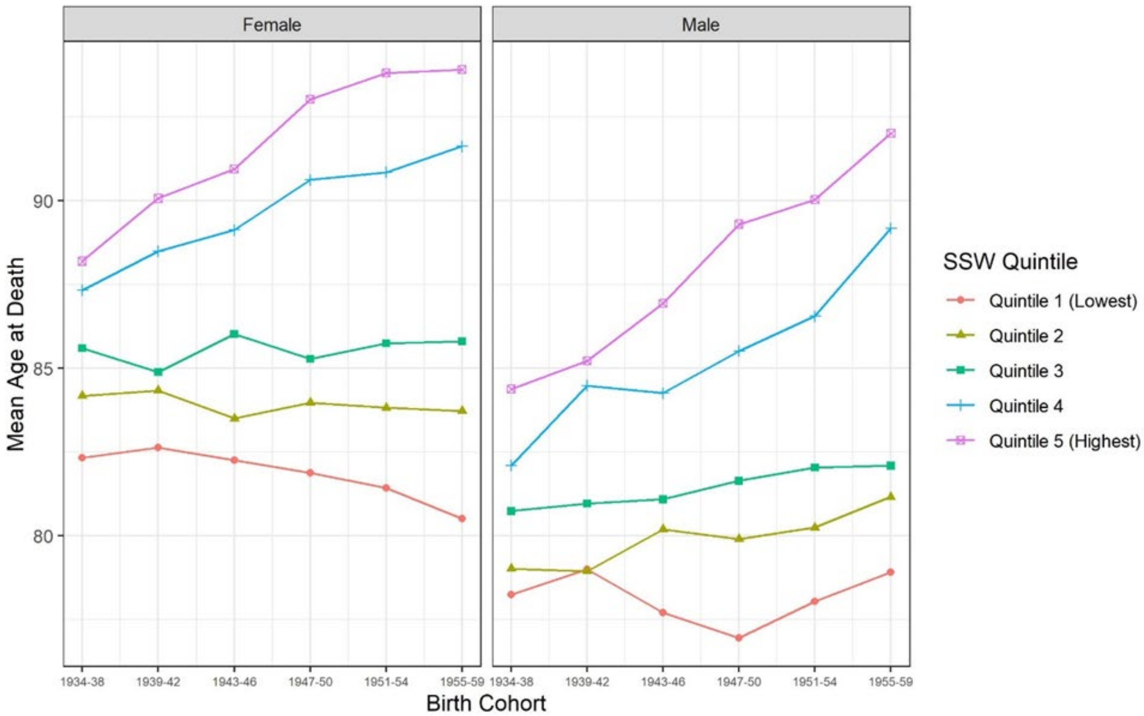


Table B1. Imputation models of BMI, SS wealth, and subjective survival probability

	ln(bmi)		SS wealth		Subjective survival	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
	[1]	[2]	[3]	[4]	[5]	[6]
Male	-0.001	0.003	12748***	1199	-3.79***	0.45
Married	-0.004	0.004	-8074***	1452	-2.62***	0.54
Born 1934-1935	ref.	ref.	ref.	ref.	ref.	ref.
1936-1937	-0.003	0.006	645	2387	-0.01	0.88
1938-1940	0.014*	0.006	-8794***	2359	0.36	0.88
1940-1941	0.020***	0.006	11586***	2371	0.78	0.88
1942-1943	0.027***	0.007	10708***	2670	0.36	1.00
1944-1945	0.030***	0.007	9043**	2840	0.15	1.07
1946-1947	0.033***	0.007	19484***	2775	0.97	1.04
1948-1949	0.040***	0.007	17299***	2659	0.31	1.00
1950-1951	0.053***	0.006	15270***	2539	0.13	0.95
1952-1953	0.054***	0.006	9774***	2514	-0.14	0.93
1954-1955	0.056***	0.006	12093***	2540	-0.33	0.93
1956-1957	0.069***	0.006	8233**	2541	-1.04	0.93
1958-1959	0.090***	0.006	-1517	2588	-2.15*	0.95
Education quartiles						
Lowest	0.006	0.004	-5490***	1621	-4.11***	0.60
2nd	0.005	0.004	-1547	1464	-2.05***	0.54
3rd	ref.	ref.	ref.	ref.	ref.	ref.
Highest	-0.016***	0.004	438	1525	0.42	0.57
Self-reported health	0.016***	0.002	52	719	-10.09***	0.27
Ever had high blood pressure	0.067***	0.003	982	1115	-0.19	0.42
Ever had diabetes	0.082***	0.003	-2108	1414	-1.44**	0.52
Ever had cancer	-0.017***	0.004	2742	1794	-3.07***	0.66
Ever had lung disease	0.004	0.004	-1855	1833	-3.08***	0.67
Ever had heart problems	-0.001	0.004	-936	1456	-2.91***	0.53
Ever had stroke	-0.028***	0.006	-1562	2471	-1.14	0.90
Ever had psychiatric problems	-0.016***	0.003	-1307	1403	-1.42**	0.51
Ever had arthritis	0.030***	0.003	-559	1157	1.29**	0.43
# of ADLs	0.011***	0.002	1013	672	-1.08***	0.24
Urban county	ref.	ref.	ref.	ref.	ref.	ref.
Suburban	0.002	0.003	-2794*	1312	-2.86***	0.49
Rural	-0.004	0.003	-6971***	1323	-4.67***	0.49
Missing metro	-0.021	0.019	9555	8591	0.13	3.19
White collar, high skill	-0.006	0.004	12066***	1693	1.29*	0.63
White collar, low skill	-0.008*	0.004	2155	1657	0.63	0.62
Blue collar, high skill	ref.	ref.	ref.	ref.	ref.	ref.
Blue collar, low skill	-0.006	0.004	-7792***	1632	-0.07	0.61

Never worked	-0.004	0.008	-8561*	3511	-2.56*	1.17
Missing	-0.002	0.008	-5405	3576	1.00	1.24
Lives northeast U.S.	0.005	0.004	7401***	1520	0.00	0.56
Midwest	0.018***	0.003	4969***	1354	-0.81	0.50
South	ref.	ref.	ref.	ref.	ref.	ref.
West	-0.012**	0.004	-1257	1439	0.02	0.53
Other	-0.124**	0.048	27069	17590	-5.71	7.13
Number of years worked	0.001***	0.000	1443***	54	-0.02	0.02
Earnings lowest quintile	-0.006	0.005	-23741***	1951	-0.54	0.73
2nd	-0.008	0.004	-20110***	1781	-0.65	0.67
3rd	ref.	ref.	ref.	ref.	ref.	ref.
4th	0.010*	0.004	19328***	1652	-0.40	0.63
Highest	0.023***	0.005	41558***	1906	-1.10	0.72
HH income lowest quintile	-0.002	0.005	-13604***	2047	-2.01**	0.77
2nd	0.001	0.004	-4937**	1675	-0.44	0.63
3rd	ref.	ref.	ref.	ref.	ref.	ref.
4th	-0.013**	0.004	-74	1655	0.89	0.62
Highest	-0.031***	0.005	1397	1848	1.52*	0.70
U.S. born	0.032***	0.004	8331***	1641	6.72***	0.61
Currently works	0.009	0.005	5146**	1838	-1.10	0.69
Has back pain	-0.001	0.003	-218	1156	0.26	0.43
No pain	ref.	ref.	ref.	ref.	ref.	ref.
Mild pain	0.013**	0.004	-99	1724	-1.01	0.64
Moderate pain	0.020***	0.004	132	1475	0.77	0.55
Sever pain	0.014**	0.005	-7548***	2095	2.33**	0.77
Currently smokes	-0.084***	0.003	-5472***	1389	-4.80***	0.51
Ever smoked	0.007*	0.003	1891	1219	0.97*	0.45
Ever drinks	-0.014***	0.003	6519***	1167	0.89*	0.43
Number of children	0.004***	0.001	-756**	259	0.47***	0.10
BMI			99	98	0.08*	0.04
SS wealth lowest quintile					1.72**	0.66
2nd					0.31	0.61
3rd					ref.	ref.
4th					-0.12	0.60
Highest					-0.82	0.63
Constant	3.157***	0.011	92668***	5100	90.99***	1.92
sigma			68322***	362	25.31***	0.14
(Pseudo) R-squared	0.205		0.020		0.029	
N	19410		18274		18527	

Notes: HRS, 1992-2016, Age 54-60. The BMI model is a linear regression. SS wealth is a tobit, censored at zero. The subjective survival model is a tobit censored at 0% and 100%.

Table B2. Actual and predicted probabilities to survive to 2016 January by gender, cohort, and SS wealth

	Male					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Total sample, predicted	54.76	67.47	78.80	86.58	92.87	97.10
Total sample, actual	53.51	64.96	78.87	88.58	92.81	96.57
1st SSW, predicted	41.65	55.94	67.45	77.11	88.07	95.06
1st SSW, actual	39.06	51.39	62.10	77.50	88.00	94.33
2nd SSW, predicted	47.79	59.98	74.75	82.12	90.88	96.10
2nd SSW, actual	46.01	53.26	73.65	85.43	90.10	95.07
3rd SSW, predicted	54.08	65.85	78.41	85.94	92.78	97.04
3rd SSW, actual	52.12	62.36	80.00	90.32	93.31	96.63
4th SSW, predicted	59.76	74.26	84.01	91.85	95.61	98.59
4th SSW, actual	58.74	74.37	82.47	89.50	96.12	99.20
5th SSW, predicted	64.82	76.64	87.34	93.84	96.52	98.76
5th SSW, actual	64.73	75.87	91.23	97.25	95.80	97.48
	Female					
	1934-38	**1939-42**	**1943-46**	**1947-50**	**1951-54**	**1955-59**
Total sample, predicted	65.67	76.40	84.47	91.03	94.82	97.84
Total sample, actual	64.60	74.46	84.42	91.70	94.44	98.09
1st SSW, predicted	54.60	66.15	77.79	85.08	91.37	95.86
1st SSW, actual	54.98	60.90	81.18	85.86	90.81	95.76
2nd SSW, predicted	64.99	74.17	80.21	89.18	93.36	97.34
2nd SSW, actual	62.65	72.93	78.54	89.96	94.41	98.18
3rd SSW, predicted	67.56	75.96	84.80	91.25	94.94	97.95
3rd SSW, actual	65.70	75.00	84.93	92.98	92.73	98.40
4th SSW, predicted	71.69	82.98	90.51	94.70	97.09	98.97
4th SSW, actual	70.89	81.37	91.45	93.08	97.02	99.76
5th SSW, predicted	74.91	84.85	91.06	95.55	97.77	99.10
5th SSW, actual	74.18	84.26	86.85	96.96	97.50	98.49

Table B3. Expected life expectancy by gender and cohorts, own estimates vs. SS cohort life tables

	Males		**Females**	
Panel A: Own estimates	**From age 55**	**From age 67**	**From age 55**	**From age 67**
1934-1938 cohort	81.0	83.8	85.0	87.2
1955-1959 cohort	84.2	86.6	87.6	89.6
Total change	3.2	2.8	2.6	2.4
Annual change	0.15	0.13	0.12	0.11

	Males		**Females**	
Panel B: SSA cohort life tables	**From age 55**	**From age 67**	**From age 55**	**From age 67**
1940 cohort	79.4	82.6	82.8	85.2
1960 cohort	81.1	83.8	84.2	86.3
Total change	1.7	1.2	1.4	1.2
Annual change	0.09	0.06	0.07	0.06