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Péter Hudomiet, Michael D. Hurd, and Susann Rohwedder

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Péter Hudomiet
RAND

Michael D. Hurd
RAND, NBER, NETSPAR

Susann Rohwedder
RAND, NETSPAR

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Michigan Retirement and Disability Research Center, University of Michigan, P.O. Box 1248. Ann Arbor, MI 48104, mrdrc.isr.umich.edu, (734) 615-0422

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Abstract

The prevalence of obesity, diabetes, and other health problems has increased in recent decades in the United States, and there is a growing gap between the health and longevity of individuals with high socioeconomic status (SES) and low SES. These trends likely have implications for Social Security's financial position in the coming decades. Because high-SES individuals tend to receive higher annual benefits and live longer, increases in health and mortality inequalities may result in increases in aggregate Social Security payouts. This paper uses data from the Health and Retirement Study, and a microsimulation model of health, mortality, and Social Security benefits, to forecast lifetime Social Security benefits of the 1934 to 1959 birth cohorts in the U.S. We compare alternative assumptions about the future course of mortality. We find that accounting for health and mortality inequalities is important. In a baseline model that ignores trends in mortality inequalities, we estimate that lifetime Social Security benefits would grow by 26% in real terms between the 1934 and 1959 birth cohorts due to increasing benefit levels and improvements in average mortality. When we account for mortality inequalities, we find an increase of 28% to 38% in average lifetime benefits, depending on the assumptions of the model. We also forecast lifetime benefits using the alternative assumption that improvements in population mortality will slow for younger birth cohorts.

Citation

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Introduction

Life expectancy has increased substantially in the Unites States and most other countries in the past few centuries due to innovations in medical science and technology and improving population health. More recently, however, there is growing evidence that some important health outcomes in the U.S. have stopped improving or even begun to deteriorate. Notable examples include the opioid crisis and related increases in middle-aged mortality (Gomes et al. 2018; Kolodny et al. 2015), increasing trends in obesity and diabetes (Flegal et al. 2012; Frederick et al. 2014; Hudomiet et al. 2019), and surging suicide rates (Rossen et al. 2018; Steelesmith et al. 2019). In Hudomiet et al. (2019) we analyzed a large number of health outcomes for 54- to 60-year-old individuals between 1992 and 2016 using a nationally representative U.S. survey, the Health and Retirement Study (HRS). We found that, with few exceptions (such as decreased rates of smoking), health status has declined since 1992. We found particularly large increases in rates of obesity, diabetes, and self-reported levels of pain.

We also found that high-SES groups have significantly better health than low-SES groups, and that health inequalities between SES groups have grown substantially since 1992 (Hudomiet et al. 2019). This finding goes hand-in-hand with mounting evidence that the gap between richer and poorer individuals' lifespans (i.e. mortality inequality) has noticeably widened in recent decades (Auerbach et al. 2017; Bosworth et al. 2016; Case and Deaton 2015; Chetty et al. 2016; Goda, Shoven, and Slavov 2011; Sanzenbacher et al. 2017). Health and mortality inequalities, thus, grew markedly, and similarly to income and wealth inequalities, over the past 30 years (Autor et al. 2008; Burkhauser et al. 2011; Meyer and Sullivan 2017; Piketty and Saez 2003).

Trends and inequalities in income, health, and mortality have important implications for government programs that serve the older population. For example, trends in mortality inequalities may affect the future position of the Social Security system. High-SES individuals receive higher lifetime Social Security benefits than low-SES individuals because their monthly benefit levels are higher and because they receive benefits longer. Because of the positive correlation between benefits and longevity, the expected cumulative payout from the Social Security system is directly related to the survival chances of different SES groups (i.e., mortality inequality). Forecasting the financial position of the Social Security system, therefore, critically depends on the accuracy of mortality forecasts, including the estimated SES gradient in mortality. The 2015 report of the Technical Panel on Assumptions and Methods to the Social Security Advisory Board (Munnell et al. 2015, pp. 20) explicitly called for more research on the implications of mortality inequality for Social Security.

This paper investigates the implications of growing health and mortality inequalities for expected future Social Security payouts using a microsimulation framework. The starting point of our investigation is a mortality model in which survival depends on gender- and SES-specific cohort trends but also on detailed health variables and demographics. Despite the decline in baseline health status documented by Hudomiet et al. (2019), our preferred models predict increasing life expectancies over time because the general improvements in mortality offset the negative effects of health. More importantly, our preferred model predicts a substantial increase in mortality inequalities between the 1934 and 1959 birth cohorts: While life expectancy will stagnate for low-SES groups, it will increase substantially for high-SES groups, leading to large increases in mortality inequality.

Using information on individuals' Primary Insurance Amount (PIA) and the mortality forecast, we simulate Social Security benefits from age 55 to death for each individual in our HRS sample. For simplicity, our models focus on benefits that individuals receive based on their own earnings histories, and ignore disability benefits, spouse benefits, and widow benefits. We define lifetime Social Security benefits as the sum of the inflation-adjusted benefit payments from age 55 to death. We find that lifetime Social Security benefits will increase over time, and the gap between richer and poorer individuals' lifetime benefits will grow substantially.

To investigate the effect of mortality inequality on Social Security benefits, we repeat the simulations using alternative assumptions about the future course of benefit levels and mortality. In the simplest model, we freeze both benefit levels and mortality over time. We then estimate models in which average mortality rates improve over time uniformly across SES groups, that is, with no change in mortality inequality. Finally, we allow SES-specific trends in mortality in our models, but we exclude the rich set of health predictor variables in our HRS analysis sample from the mortality forecast models. Overall, we find that the different assumptions about mortality have a large impact on lifetime Social Security benefit forecasts, and growing mortality inequalities increase average benefits.

We estimate models in which we assume that improvements in population longevity would decrease for younger cohorts. It is standard in the literature to assume a linear time trend in the mortality models (possibly interacted with some observable characteristics) and to extrapolate mortality from these past trends to predict the survival chances of a younger generation whose actual mortality is not yet observed. Members of the 1959 birth cohort, for example, were only 57 years old in 2016, the year of the last survey wave used in this study. Due to the increasing trends in some health problems, the linear trend assumption used in our preferred specification may not be appropriate. Although our preferred model permits a reduction in mortality improvements resulting from reductions in health, it may not capture the full extent of the reduction due to other unobserved trends. We investigate alternative assumptions and we find that slower growth in population longevity would have large impacts on lifetime Social Security benefits as well.

Several recent papers found that trends in mortality inequalities would have sizable effects on Social Security benefits (Bound et al. 2014; Goda et al. 2011; National Academies of Sciences, Engineering, and Medicine 2015; Waldron 2007). The main contribution of our paper to this literature is the inclusion of a large number of health predictor variables in the mortality models. Most papers in the literature use time trends and one or more SES indicators in the prediction models but no health measures. We simulate the effects of several mortality specifications on lifetime Social Security payouts.

Data

We use the HRS for our analysis. The HRS is a nationally representative, longitudinal survey of the U.S. population 51 or older. The survey started in 1992 and has interviewed respondents biennially since then. The HRS enrolls a new birth cohort of 51- to 56-year-old individuals every six years to maintain its age representation. The survey is conducted in English or Spanish. The HRS oversamples Blacks and Hispanics so that race- and ethnicity-specific statistics can be estimated with more precision. Survey weights are available to adjust the sample's demographic distribution to the American Community Survey.[1] When we report weighted statistics, we use weights defined as the person-specific mean of the survey waves in the baseline window. We use 13 waves of data from 1992 to 2016. Where available, we used RAND HRS variables. The RAND HRS Longitudinal File is a publicly available, cleaned version of the most commonly used HRS variables. The file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

As a multidisciplinary survey, the HRS covers a broad range of subjects including demographics, wealth, income, labor force history, and health. The survey is linked to several administrative datasets, including the Master Earnings File of the Social Security Administration (SSA) with high quality data about individuals' earnings histories. Compared to other large, general purpose surveys, the HRS has more detailed information on participants' health status, which allows researchers to study the relationship between mortality and mortality risk factors in greater detail. The survey asks about self-reported overall health status, the presence of various doctor-diagnosed health issues, limitations with activities of daily living (ADLs), exercise habits, drinking, smoking, body weight, depressive symptoms, and cognitive function. In this project, we

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

focus on health variables that have been consistently measured since the first wave of HRS and are strong predictors of mortality.[2]

The HRS also asks survey participants about their own survival expectations in a probabilistic format, using the question “What is the percent chance that you will live to be 75 or more?” These data were found to covary with mortality risk factors such as SES position (Delavande and Rohwedder 2011; Hudomiet and Willis 2013; Hurd and McGarry 2002) and to strongly predict future mortality in the panel (Gan et al. 2005; Hudomiet and Willis 2013; Hurd and McGarry 2002; Hurd, Rohwedder, and Winter 2005).

The HRS makes considerable effort to retain panel members until they die and to record the precise date of their death. The HRS seeks data on survival status and date of death for persons who drop from the sample: If their survival status is unknown, the HRS records in its Tracker File the last date the respondent was known to be alive. We model such observations as censored cases in survival models.

Our sample definitions and data cleaning methods closely follow those of our earlier paper (Hudomiet et al. 2019). 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 important variables, all measured at the baseline 54 to 60 age range. For individuals who appeared in the baseline age window multiple times, we took the average of their values, except for smoking status, the ever-

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

had medical conditions, and living with moderate to severe pain, for which we used the person-specific maximum (i.e., the worst outcome) in the 54 to 60 age window.

Table 1 shows that nearly half of the weighted sample is male, more than half of the sample has at least some college education, and more than three-fourths is non-Hispanic white. Relative to the weighted sample, the unweighted HRS sample is less educated, less white, and more likely to hold blue collar jobs, which is consistent with the oversampling of certain groups. The unweighted sample also has fewer men, which is the result of differential nonresponse and our sample selection. The sample varies widely in its baseline health status. On average, respondents reported a 63% chance of living to age 75, but the standard deviation of this average was 26%. On a 1 (excellent) to 5 (poor) scale, respondents rated their health at 2.7, or slightly better than “good” (which was a 3 on the scale). Class 2 obesity, defined as having a body mass index (BMI) exceeding 35, was present for 12% of the sample. The most common doctor-diagnosed conditions were arthritis and high blood pressure (49% each). Moderate to severe pain was reported by 36% of the sample. About a quarter of the sample were active smokers. White-collar, high-skill jobs, such as management or professional workers, were the most common current or most recent jobs; and blue-collar, low-skill jobs, were the least common. Nearly three in four respondents lived in metropolitan areas.

To index SES, we split individuals in the sample into five equal-sized quintiles based on their Social Security wealth. Social Security wealth has the advantage of reflecting lifetime success in the labor force and, further, 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 and is calculated by the HRS as described in Fang and Kapinos (2016).[3] The measure is based on individuals' lifetime earnings observed in the linked administrative SSA data and simple life-table probabilities of survival. In the case of couples, we assign to each spouse the maximum of the Social Security wealth of each. We define 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.

The first column of Table 1 shows the number of valid, nonmissing values in each variable. For job type and metropolitan status, the fraction of missing answers is shown in the last row of the relevant subpanel. Most variables have only a handful of missing entries, well below 0.5% of the sample. The only exceptions are 1) Social Security wealth (531 missing cases, 2.7%), 2) subjective survival probability (1,020, 5.2%), 3) BMI (137, 0.7%), and 4) last job type (572, 2.9%).

In order to keep the entire sample in our analysis, we imputed all missing predictor variables. In Hudomiet et al. (2019), we showed that the mortality predictions were robust to alternative ways of handling missing data. 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

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

indicator variables to flag the missing values in these variables. We imputed the three remaining variables — BMI, Social Security wealth, and subjective probabilities of living to age 75 — with regression-based models. Table A1 in the appendix shows the output of the imputation models. We estimated a linear regression of the logarithm of 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. As expected, the most important predictors of BMI were time (BMI increases over time), having diabetes or high blood pressure, and smoking. The most important predictors of Social Security wealth were time, occupation, earnings, and household income. The strongest predictors of subjective survival expectations were education, self-reported health, and a number of health conditions.

Results

We present our results in three steps. First, we document trends in selected health outcomes stratified by Social Security wealth quintile to demonstrate how health inequalities have changed over time.

Second, we present alternative forecasting models of mortality. We start with our preferred model that is based on a large number of predictor variables and flexible time trends. We then present simpler mortality models in which, for example, we keep mortality inequalities constant.

Third, we use our alternative mortality scenarios in microsimulation models to investigate how mortality patterns affect individuals' lifetime Social Security benefits. In particular, we show forecasted trends in lifetime Social Security benefits by Social Security wealth quintile using these alternative life expectancy scenarios.

Trends and inequalities in health

The six panels of Figure 1 show trends in selected health outcomes by Social Security wealth quintile and gender for birth cohorts from 1934 to 1959. In each panel, the birth cohort is shown on the X-axis, while the average value of the variable for each cohort is shown on the Y-axis. All graphs in the paper aggregate birth cohorts into six groups to increase the precision of the estimates. The youngest and oldest cohorts contain five-years (1934 to 1938 and 1955 to 1959); the four middle cohorts each have four years.

Figure 1 presents trends in three health outcomes:

- P75, which is individuals' subjective expectations of living to at least 75 years of age.
- Class 2 obesity, defined as having a BMI above 35. This level is also called "severe obesity" and is more strongly related to adverse health outcomes than regular obesity (which is defined as BMI > 30).
- Number of ADL functional limitations out of five (bathing, dressing, eating, getting out of bed, walking).

Figure 1 is based on Hudomiet et al. (2019), but unlike the similar figure in our earlier work, we show regression-adjusted trends in these outcomes. Each line on the figure is the fitted value of a simple regression of the health outcome on birth years. The regressions are separately estimated in the 10 quintile-gender groups. For example, the top left panel of Figure 1 shows trends in P75 for men by cohort and Social Security wealth quintile, with the light orange line showing trends for the highest quintile men and the black dashed line showing the overall average for men. The bottom right panel shows changes in the number of ADL limitations for women, with the dark brown line showing changes for women in the lowest quintile and the black dashed line showing the overall average.

The average of all three health outcomes worsened in both gender groups. Subjective probabilities of living to age 75 decreased from 62.6% to 59.4% among men and from 66.5% to 64.2% among women. The proportion of those with class 2 obesity increased from 4.5% to 13.4% among men and from 8.3% to 19.0% among women. Finally, the average number of ADL limitations increased from 0.32 to 0.38 among men and from 0.37 to 0.43 among women (of a maximum total of five).

These trends were generally worse for those in lower wealth quintiles. P75, for example, decreased from 67.5% to 66.4% among men in the highest wealth quintile, a drop of about 1 percentage point, but it decreased nearly 8 percentage points, from 57.9% to 50.2%, among men in the lowest quintile. Similarly, it decreased by nearly 2 percentage points, from 72.6% to 70.7%, for women in the top quintile but 8 percentage points, from 61.7% to 53.7%, among women in the bottom quintile.

Across all quintiles, the percentage of men with a BMI greater than 35 increased from an average of 4.5% to 13.4%, but the difference in this increase by quintile was minimal. Among women, we see a strong quintile-gradient in obesity, and similarly strong increases in inequalities over time. Among women in the top quintile, severe obesity increased by 7.6 percentage points, from 5.1% to 12.7%, while among those in the bottom quintile it increased by 14.6 percentage points, from 11.4% to 26.0%.

Inequalities in ADLs increased for both men and women. Among those in the top quintile, the number of ADL limitations decreased slightly among both men and women, indicating improved health in performing these activities. Among those in the bottom quintile, the number of ADL limitations increased from 0.77 to 0.84 for men and from 0.62 to 1.0 limitations for women.

Altogether, Figure 1 shows declining health and increasing inequalities for both men and women, with the increase in inequalities for women being sharper and stronger than for men.

Trends and inequalities in life expectancy

Increasing health inequalities can lead to increasing mortality inequalities among Social Security wealth groups. To discern how these may develop and their extent, we used HRS respondents' detailed health and demographic data to forecast their life expectancies.

For our forecasts, we fit Gompertz mortality models to individual data for respondents born from 1934 to 1959. In this model, the hazard of death at age *t* is

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

Because we measure age in months, the hazard can be interpreted as that of dying in a given month. In this equation

- λ_1 is the scale parameter of the survival function and is assumed to be a constant;

- λ_{0i} is the shape parameter and depends on predictor variables:

  $$\ln\left(\lambda_{0i}\right) = \beta' x_i \,. \tag{2}$$

Depending on the model, x_i may include health, SES indicators, demographics, birth-years, and interactions between these variables.

This Gompertz framework is widely used in demography and biology because the loglinear specification of the mortality hazard aligns closely with observed survival data of humans and many animal species (Vaupel 1997). The models are estimated by Maximum Likelihood. Observations with unknown death status, including HRS respondents who survived at least 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 as observed in the HRS Tracker file.

After estimating the model, we drew a random age of death for each sample member, using the estimated parameters of the model and a quasi-random variable. To reduce the influence of randomness on the means of the distributions, for each gender and Social Security wealth quintile we drew 10 vectors of uniformly distributed 0 to 1 random variables, with the size of each vector being equal to the number of individuals in each gender-quintile. Among the 10 vectors, we used the vector with a mean closest to 0.5 to assign a random value to each person in that quintile. We then used that random value and the Gompertz distribution to assign a date of death. We thus preserved the within-quintile variation in ages of death and, on average, the between-quintile differences in mean ages of death, while ensuring that the average between quintile-gender differences in mortality and lifetime benefits were not affected strongly by random noise. We only used such quasi-random variables in the mortality models; our other simulations were based on independent pure random variables.

We applied this procedure for every sample member, even those who were known by the HRS to be deceased. Instead of using observed death ages for such respondents, we used their simulated ages at death so that the procedure would be symmetric across birth cohorts.

Figure 2 shows predicted survival by quintile and gender based on our preferred mortality model. This model used the following predictor variables in the shape parameter of the Gompertz hazard:

- Demographic covariates (gender, race, marital status interacted with gender, last job type);
- SES measures (education quartiles, Social Security 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, Social Security wealth quintiles).

The output of the model can be found in Column 4 of Table A3 in the appendix.

Figure 2 shows our forecasts for years of survival from age 55 (top half) and years collecting Social Security (bottom half) for men (left half) and women (right half).

Our model predicts that life expectancy from age 55 will increase for both men and women. Among men, as the black dashed line in the top left panel shows, life expectancy from age 55 will increase from 26.0 years among those in the earliest cohort to 29.2 years in the latest cohort. Similarly, among women, life expectancy from age 55 will increase from 29.9 years to 32.6 years.

At the same time, mortality inequalities are also expected to increase. Among men in the lowest wealth quintile, life expectancies from age 55 will increase a bit more than one year, from 22.1 to 23.3 years, while among those in the top quintile it will increase more than seven years, from 29.3 to 36.5 years. Among women, life expectancy from age 55 would actually decrease, from 26.2 to 25.8 years, for those in the lowest quintile, while it would increase from 33.2 to 39.9 years for those in the top quintile.

Figure 2's bottom two panels of show the average number of years individuals would collect Social Security benefits. This variable is more closely related to individuals' lifetime benefits than their life expectancy. For HRS respondents who have not yet retired (n=6,971) or who had missing claiming ages for other reasons (n=1,470), we simulated Social Security claiming ages with a regression-based imputation model, which censored Social Security claiming ages to be between age 62 and 70. We ran separate imputation models for single individuals, married husbands, and married wives. For the model of married wives, we included husbands' claiming ages to allow for within-household correlations in claiming. The outcomes of the imputation models are in Table A2 in the appendix.

The average claiming age in the HRS is about 63 years, and so the number of years individuals collect benefits was expected to be about eight years less than life expectancy from age 55. Indeed, Figure 2's bottom two panels, which show the number of years collecting Social Security benefits by cohort for men and women, are similar to the top two panels showing years of survival from age 55, but with values about eight years less for each cohort over time. The model predicts that younger birth cohorts will collect benefits for a longer period of time, and that the quintile-specific inequalities would grow substantially as well. For example, the model finds that, for those in the top quintile, men in the youngest cohort will collect Social Security nearly seven years longer than those in the oldest cohort. Women in the top quintile of the youngest cohort will collect Social Security more than six years longer than women in the top quintile and the oldest cohort. Among those in the bottom quintile there is little change in the number of years that men or women will collect Social Security. As a result, the difference between the top and the bottom quintiles in years collecting Social Security will increase from about seven to 12 years for men and from about seven to 13 years for women. Figure A1 in the appendix compares the number of years individuals collect benefits in our preferred model to a simpler model in which everyone is assumed to retire at age 63. The two models are very similar.

Figure 3 shows the average years individuals collect Social Security benefits under alternative mortality scenarios. The figure has eight panels. Each row corresponds to a different mortality scenario, and the columns refer to gender.

The first row uses a model in which the shape parameter of the Gompertz model only depends on the Social Security wealth quintiles interacted with gender, but it does not depend on birth year, health status, or other demographic variables. That is, conditional on wealth quintile, this model has fixed mortality rates for men and for women. Consequently, the model predicts large differences by wealth quintile in the number of years that individuals collect Social Security benefits, but little change over time. This is because empirically the claiming age did not change much over time.[4]

The second row refers to models in which we added a linear trend in birth years, that is, in which we assume linear improvements in life expectancy for all persons regardless of Social Security wealth quintile. This trend variable was interacted with gender, but not with the Social Security quintiles. As longevity increased over time, the model now predicts an increase in the average number of years individuals collect Social Security. By design, we see no increase in inequalities over time.

The third row presents models in which the linear time trend is interacted with all five Social Security wealth quintiles, but the detailed health indicators are excluded. This model is most similar to recent papers studying mortality inequalities (e.g., Auerbach et al. 2017; National Academies of Sciences, Engineering, and Medicine 2015). The model predicts a strong increase in life expectancy and in mortality inequalities — even larger than that shown in our preferred model in the bottom half of Figure 2. For example, it predicts, on average, that average life expectancy would increase by 3.8 years among men and 3.9 years among women. Our preferred model predicted smaller increases of 3.2 years among men and 2.7 years among women, likely because it directly includes health measures in the mortality models, and those health measures did not improve or even worsened in younger birth cohorts. The exclusion of the health measures also affected predicted mortality inequalities. Our preferred model in the bottom half of

[4] The HRS data shows that the fraction of individuals who claim Social Security early (i.e. before age 62) somewhat increased over time mainly due to an increasing uptake of disability benefits. However, our simulation model restricted initial claiming ages to be between 62 and 70 years of age because we did not model disability.

Figure 2 shows an increase in the differences between the top and bottom quintiles of 6.7 years for men and 6.1 years for women. Excluding the health differences (Figure 3, third row) results in an increase in the differences between the top and bottom quintiles of 9.1 years for men and 9.0 years for women. The differences seem to accelerate in the youngest cohorts. Their mortality predictions are heavily based on extrapolations from older cohorts, however, and so they are less reliable. Because our preferred model includes a large set of covariates, including the health status of the youngest cohorts in their late 50s, we believe the results based on the preferred specification are more reliable.

The fourth row of Figure 3 is based on our preferred model, but here we assume a plateauing trend in mortality, that is, improvements in mortality diminish. This model shows a slight increase in the number of years collecting Social Security for the oldest cohorts, after which the patterns plateau and stabilize.

Lifetime Social Security benefits

Figure 4 shows forecasted lifetime Social Security benefits for each analysis cohort by Social Security wealth quintiles and gender. Our model here focuses on Social Security benefits individuals receive based on their own earnings histories. It does not include disability, spouse, or widow benefits that individuals may receive. As such, monthly Social Security benefits in this model only depend on individuals' PIA (which summarizes their earnings histories) and their claiming age.

The HRS data include the PIA and the claiming ages for most individuals in the survey. These variables had some missing values, and those missing cases were imputed as explained earlier. We used Social Security formulas to derive monthly Social

Security benefits in 2016 dollars for all individuals, conditional on their (observed or imputed) PIA values and claiming ages. We then multiplied this monthly benefit value by the number of months individuals collect benefits, as shown on the bottom panels of Figure 2. Our lifetime benefit measure assumes that monthly benefits would retain their real (2016 dollar) value in the future, which is a reasonable assumption given that benefits are inflation adjusted. Our measure also assumes a 0% (real) discount rate, which we think is easiest to interpret. Using positive discount rates would shrink all lifetime benefit values closer to zero, but the qualitative patterns would remain the same.

Figure 4 and Table 2 show the results. For men, average lifetime benefits would increase from about \$393,000 to \$446,000, or 14%. For women, average lifetime benefits would increase from \$282,000 to \$417,000, or 47%. The main reason the increase is sharper among women is because there was a significant increase in PIA across women birth cohorts because larger fractions of women in the younger cohorts have worked.

The table and the figure also show very sharp increases in inequalities. Among men, lifetime benefits would increase by 17% for those in the bottom quintile (from \$148,000 to \$174,000) and by 37% in the top quintile (from \$578,000 to \$792,000). Among women, lifetime benefits would increase by 15% for those in the bottom quintile (from \$129,000 to \$149,000) and by 74% for those in the top quintile (from \$433,000 to \$755,000). Among those in the top quintile, women's lifetime benefits would come to nearly match men's benefits, due to a larger increase in PIA among women, as well as longer lifespans and more years collecting Social Security benefits. Figure A2 in the appendix shows that predicted lifetime benefits are very similar when we use a simpler model that assumes everyone claims Social Security at age 63.

Next, we investigate how alternative mortality scenarios affect lifetime Social Security benefits. Figure 5's eight panels show simulated lifetime benefits using Figure 3's mortality scenarios. Tables A4 to A8 in the appendix show the corresponding numbers.

Figure 5's patterns largely follow the ones in Figure 3, but there are two notable exceptions. First, lifetime benefits among women would increase even if mortality rates were to remain unchanged. This is because of the strong increase in PIA among women, stemming from longer work histories among younger female cohorts.

Second, the model with quintile-specific trends in mortality (third row of figures) shows an enormous increase in lifetime benefits among women in the top quintile. For women in that quintile, lifetime benefits increase by 102% (from $413,000 to $834,000). This increase is significantly larger than the one in our preferred model (74%, from $433,000 to $755,000). The larger increase is likely the result of excluding heath indicators in the mortality model as discussed earlier. Our preferred model uses observable mortality risks in the prediction model and relies less on extrapolation from past mortality trends.

Figure 6 and Table 3 show how average lifetime Social Security benefits would change under alternative mortality and benefit scenarios. We consider the same five scenarios as above — our preferred model plus four alternatives: (i) fixed mortality, (ii) aggregate trends in mortality, (iii) quintile-specific trends in mortality, and (iv) a plateauing trend in mortality. As a baseline to show what would happen over time if neither longevity nor PIA levels were to change we added a sixth scenario: constant mortality and unchanging mean level of PIA within quintile-gender groups.

As expected, the model with no change in mortality and PIA, as shown by Figure 6's solid blue line, predicts no change in average lifetime benefits over the study period. The small fluctuations are due to the changing fraction of workers in the different gender and wealth quintile groups over time and because of variation in the claiming ages in the sample.

In the model when we fix mortality but allow changes in PIA levels, we see an increase in lifetime benefit levels by 11%, as shown by Figure 6's dotted orange line and from $324,000 to $361,000, as shown in Table 3. The increase is mainly due to the rising PIA and benefit levels of women.

When we allow a general (aggregate) trend for mortality (but not quintile-specific), lifetime benefits are predicted to increase by 26%, as shown by the solid gray line in Figure 6 (and from $323,000 to $407,000, as shown in Table 3). The increase from the 11% gain (dotted orange line) reflects the predicted increase in life expectancies over these birth cohorts.

The model that allows increases in mortality inequality but does not include health predictors predicts a 38% increase in lifetime benefits, as shown in the dashed yellow line in Figure 6 (and from $318,000 to $440,000, as shown in Table 3). This large increase is driven by very sharp longevity increases of the highest quintile women in the youngest birth cohorts. As we discussed earlier in connection with the results on life expectancy, mortality outcomes for these younger cohorts have only been observed for a few years, so the estimated increases in longevity are mainly due to extrapolating older cohorts' experiences.

Our preferred model shows a less sharp increase in lifetime benefits. We predict an increase of 28%, as shown by the dashed green line in Figure 6, and from $334,000 to $429,000, as shown in Table 3. This is only slightly above the model that used a constant increase in mortality over time.

When we assume that the general improvements in mortality would plateau for cohorts born after 1947, we find benefits would increase 18% (from $334,000 to $393,000).

Figure A3 in the appendix compares these outcomes to a simpler model in which everyone claims Social Security benefits at age 63. The results are similar.

Overall, lifetime payouts will increase because of increases in PIA. But the future course of mortality will have an additional strong influence on the future course of Social Security benefits, and consequently on the position of Social Security. Our results show that the predicted course of mortality depends importantly on how it is modeled.

Discussion and conclusion

Life expectancies have substantially increased in the past few centuries. In recent decades, however, there has been evidence of some health outcomes deteriorating, possibly because of changing dietary habits and physical activities in the population. There is also evidence that inequalities have grown both in health and in life expectancies. While life expectancies have stagnated among those of low SES (measured by education, income, or wealth), they have substantially increased among those of high SES.

Growing mortality inequalities have implications for Social Security. High SES individuals receive higher levels of benefits than low SES individuals. If the gap in life expectancy between these groups of individuals grows, then then the gap in average Social Security benefit levels for them would also grow, even if the overall average life expectancy for the population were to remain unchanged. It is therefore critical for Social Security to understand SES-specific trends in health and mortality.

This paper investigated the implications of growing health and mortality inequalities for expected future Social Security payments using a simple microsimulation framework. We simulated lifetime Social Security benefits for HRS respondents born between 1934 and 1959. Using our preferred specification, we found that lifetime benefits would increase over time partly due to increasing PIA among women, but mostly due to continuing increases in life expectancy.

We also found the gap between the lifetime Social Security benefits of richer and poorer individuals would increase substantially over time. Among men, we estimated a 17% increase in benefits for those in the bottom Social Security wealth quintile, and a 37% increase for those in the top quintile. Among women, we estimated a 15% increase for those in the bottom quintile. For those in the top quintile, we estimated a 74% increase due to both a larger increase in PIA and longer lifespans.

To investigate mortality inequality’s effects on Social Security benefits, we repeated our analyses using alternative assumptions about the future course of benefit levels and mortality. We found that if mortality were to remain constant, lifetime Social Security benefits would increase by 11% due to rising benefit levels, especially among younger women with longer work histories. When we allowed for a general trend in mortality, with no change in the differences by wealth quintile, we found lifetime benefits would likely increase 26% resulting from the general improvements in longevity.

When we allowed mortality to have quintile-specific trends, with those in the top wealth quintile having greater increases in life expectancy than those in the bottom quintile, we found aggregate lifetime benefits would increase 38%. The difference between the 26%, which incorporates a general improvement in longevity, and the 38%, which incorporates quintile-specific improvements in mortality, is substantial. The difference comes from two sources: (i) the positive correlation between benefit levels and longevity; and (2) differences in predicted average life expectancies in the two models.

Our preferred model predicts a more modest 28% increase in lifetime benefits. The difference between this model and the others is our preferred model's use of a far larger set of predictors, including detailed health status of individuals in their late 50s. Forecasting the longevity of the youngest cohorts inevitably relies on extrapolations from past mortality trends. For example, individuals in the youngest 1959 birth cohorts were only 57 years old when they were last observed in our sample in 2016. While the simpler mortality models rely entirely on extrapolations in mortality trends, our preferred model uses detailed information about the health of these individuals in their 50s. We believe such detailed information makes our preferred model more reliable. Hence, we believe the 28% increase in lifetime benefits, predicted by our preferred model, is more likely than the 26% or the 38% increase predicted by the simpler models that assume general or quintile-specific increases in longevity but rely more on extrapolation for predicted mortality of younger cohorts.

We estimated how lifetime benefits would be affected should improvements in life expectancy diminish. We did so because the recent deterioration observed in some health indicators may limit future increases in life expectancy. We found that if average gains in life expectancy were to plateau for cohorts born after 1947 then lifetime benefits would increase 18% rather than by 28% as in our full model.

Overall, we find that assumptions about mortality greatly affect the likely course of Social Security benefits and hence the position of Social Security. Therefore, tracking trends and inequalities in health and mortality status adds an important tool to informing the future course of Social Security finances.

This study has some limitations. Most importantly, for simplicity, we only modeled individuals' Social Security benefits based on their own earnings histories. We ignored disability, spousal, and widow benefits that individuals might receive. This assumption simplified the interpretation of the results and made it easier to understand the contribution of mortality inequalities to Social Security payments.

Future research could model these additional benefit categories as well. Even though disability payments account for a small fraction of lifetime benefits for most recipients, it is possible that increasing health inequalities will contribute to an increase in disability inequalities as well.

Spouse and widow benefits would also be important to investigate. Women's PIAs strongly increased over time. This likely implies that, relative to those in older cohorts, women in younger cohorts are relying less on spouse and widow benefits and more on benefits based on their own earnings. It would be interesting to know how much this may affect individuals’ total lifetime Social Security benefits. Decreasing marriage rates may also influence the extent of spouse and widow benefits.

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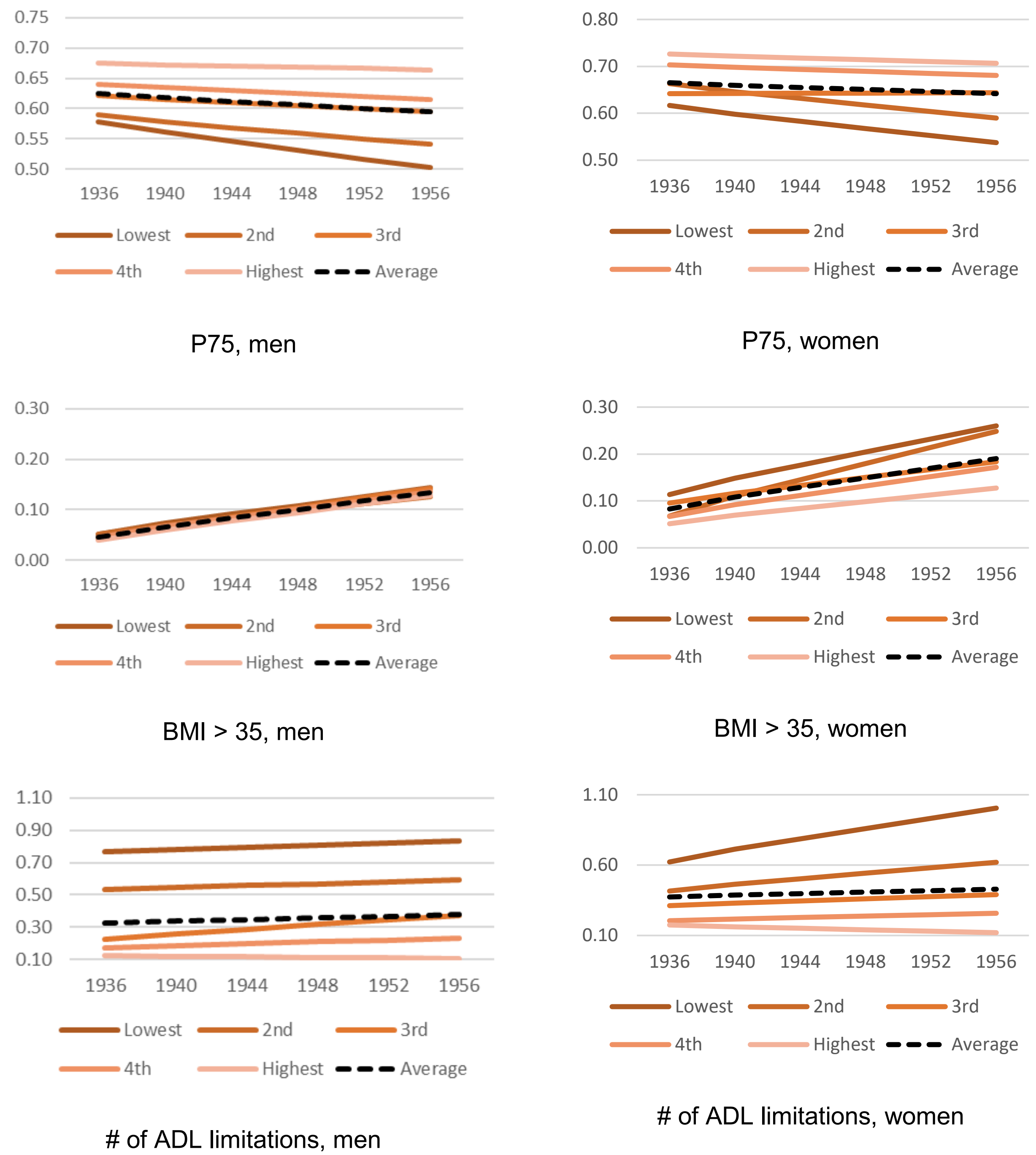
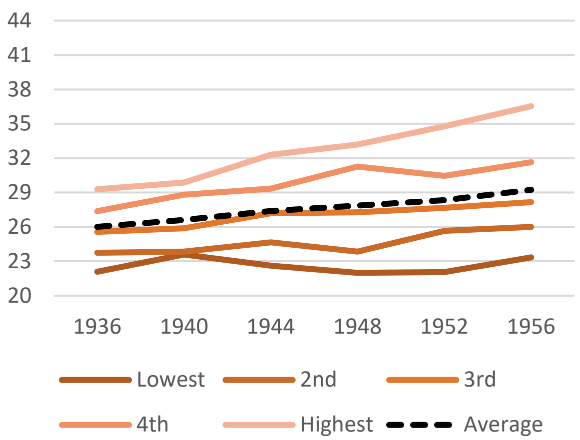
Figures and tables

Figure 1: Selected health outcomes by Social Security wealth quintiles and birth cohorts

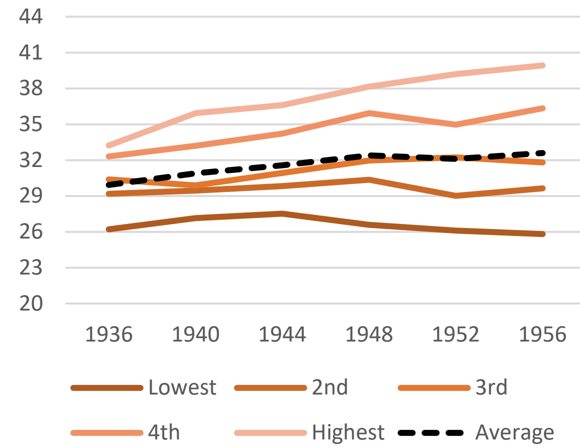


Notes: HRS, 1992 to 2016, ages 54 to 60. The figures show the fitted values of simple regression models of the health outcomes on birth-years. The models are estimated separately within SS wealth quantiles and gender groups. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife). Weighted statistics.

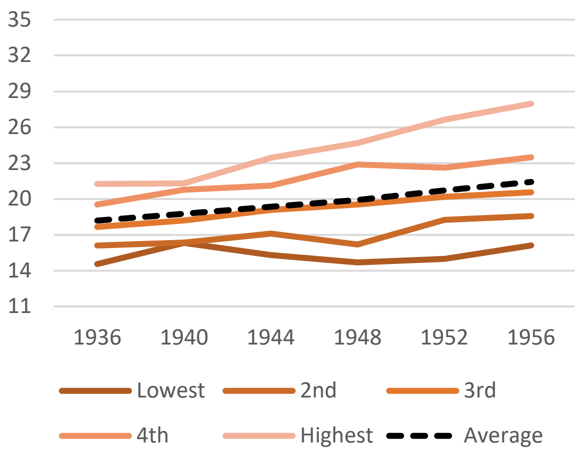
Figure 2: Average years of survival from age 55 and years collecting Social Security by gender, birth year, and Social Security wealth quintiles, preferred mortality model



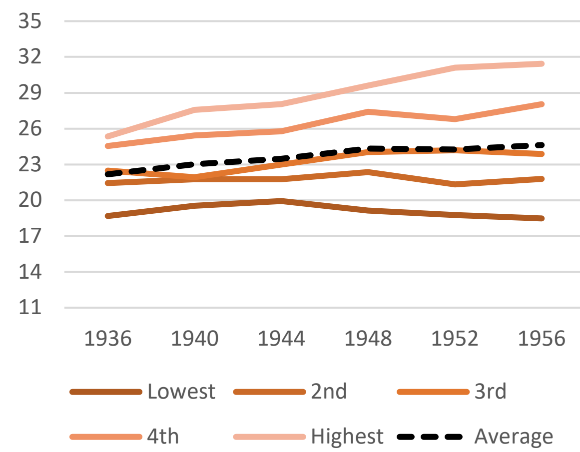
Years of survival from age 55, men



Years of survival from age 55, women



Years collecting Social Security, men



Years collecting Social Security, women

Notes: HRS, 1992 to 2016, ages 54 to 60. The figures show average simulated years of survival and average simulated years workers collect Social Security benefits based on their own earnings. The survival predictions are based on our preferred model using quintile-specific mortality trends and a large number of health predictor variables. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

Figure 3: Average years collecting Social Security, alternative mortality forecasting models

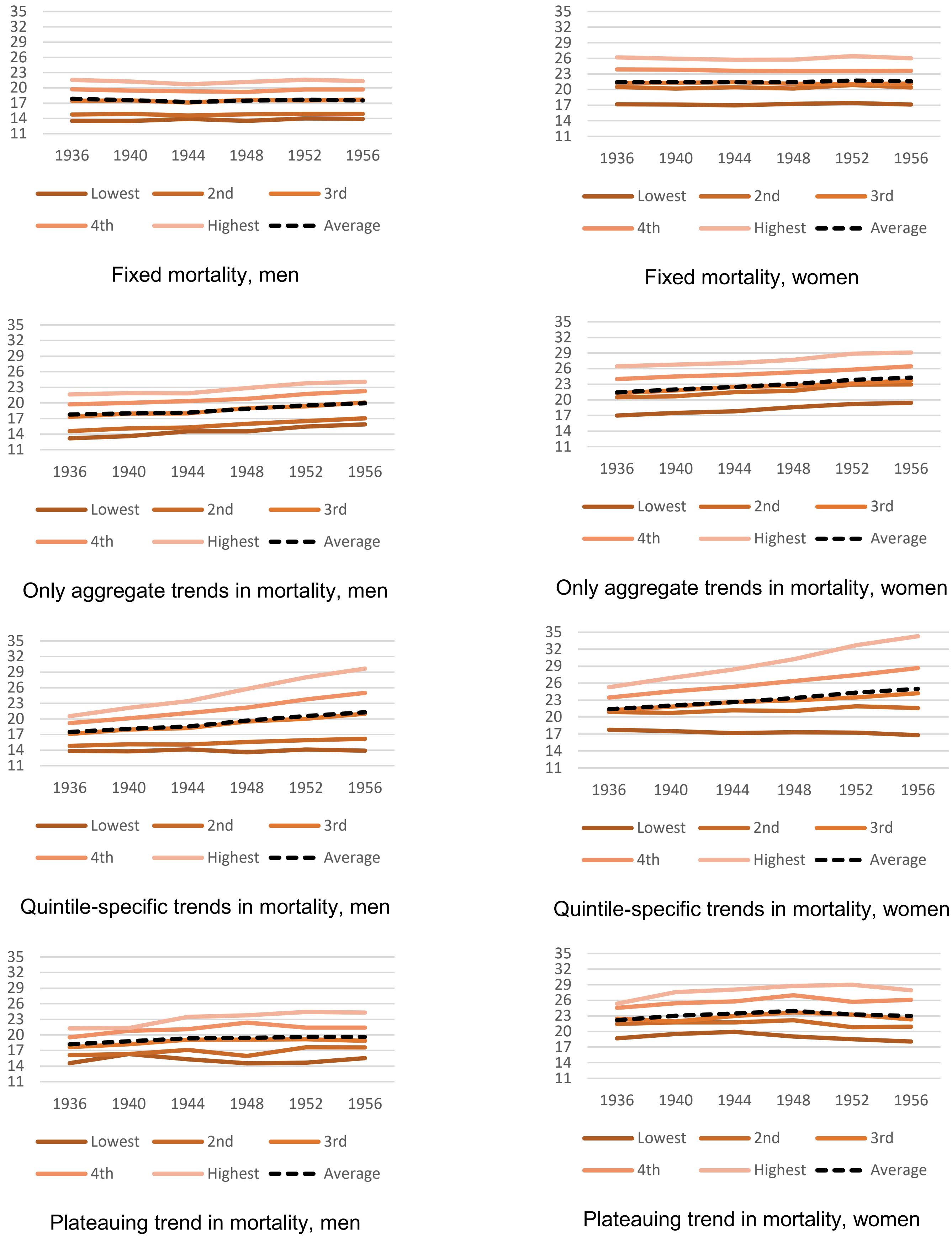
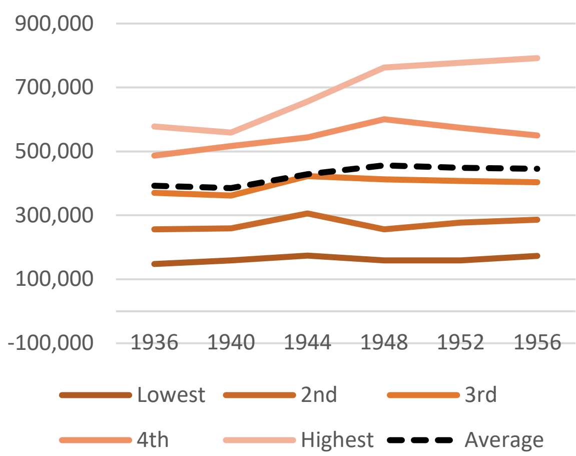
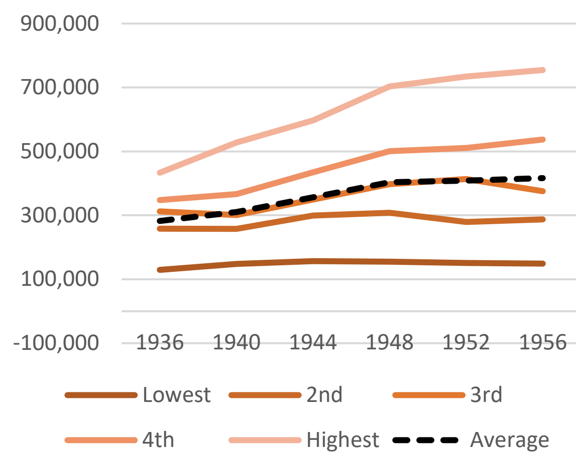


Figure 4: Lifetime Social Security benefits by gender, birth year, and Social Security wealth quintiles, preferred mortality model



Men



Women

Notes: HRS, 1992 to 2016, ages 54 to 60. The figures show lifetime simulated Social Security benefits of workers based on their own earnings histories. The benefits exclude disability, spouse, and widow benefits. The survival predictions are based on our preferred model using quintile-specific mortality trends and a large number of health predictor variables. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

Figure 5: Lifetime Social Security benefits, alternative mortality forecasting models

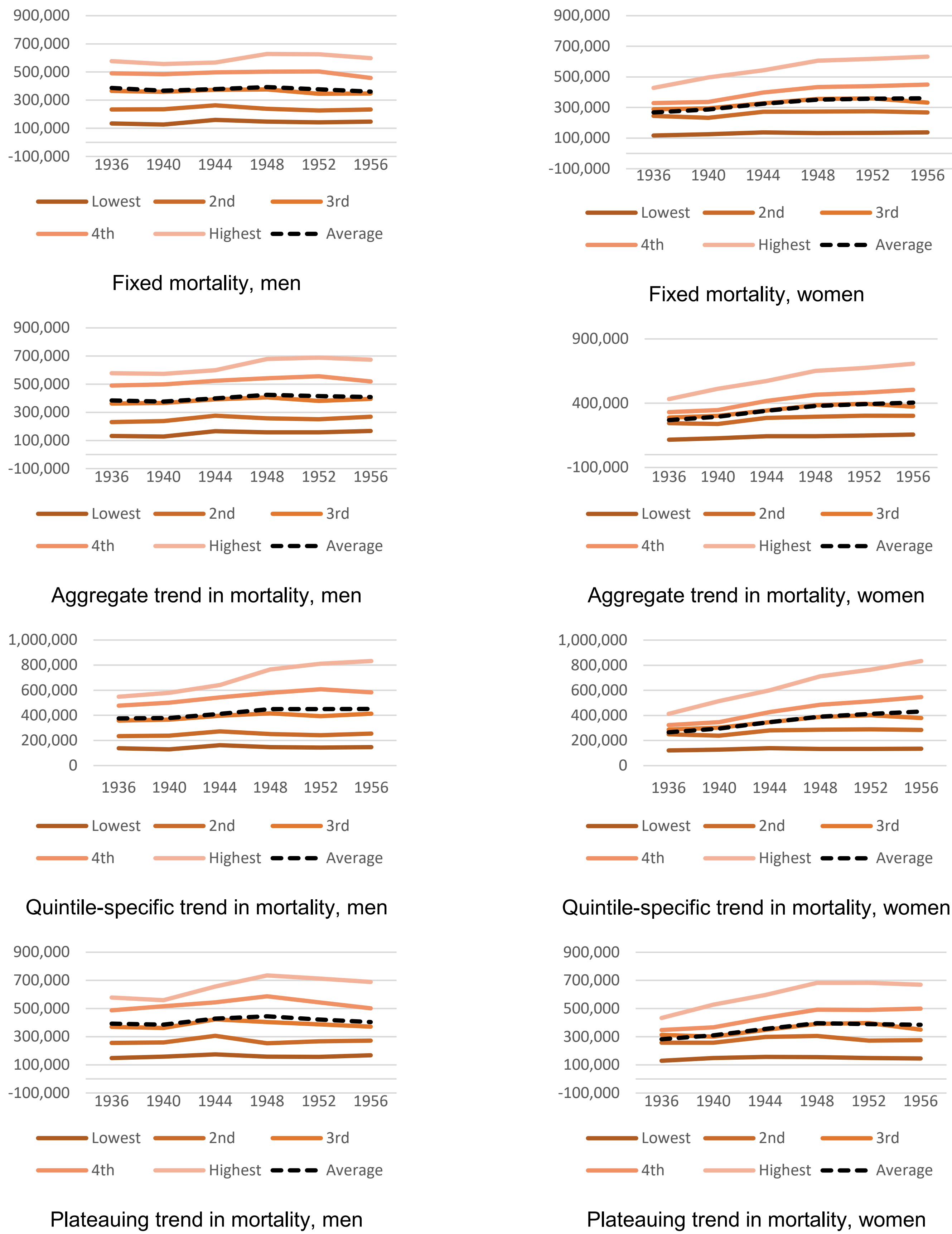
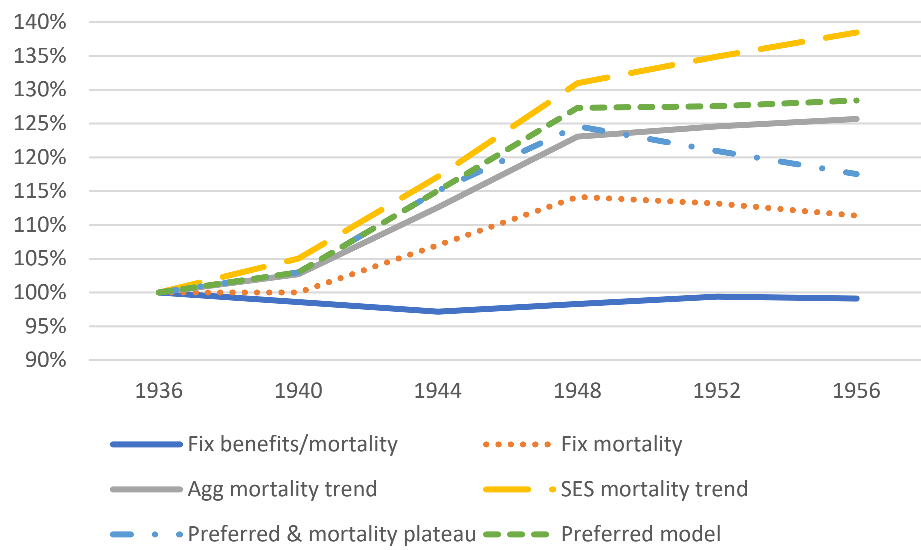


Figure 6: Trends in average lifetime Social Security benefits, comparison of various mortality and benefit level scenarios



Notes: HRS, 1992 to 2016, ages 54 to 60. The figure shows forecasted trends in average lifetime Social Security benefits of workers based on their own earnings histories under alternative benefit and mortality scenarios. The benefits exclude disability, spouse, and widow benefits. "Fix benefit" and "fix mortality" mean that average Social Security benefits or mortality rates are assumed to remain the same over time within gender and Social Security wealth quintile groups. "Agg mortality" means that the mortality model includes an aggregate trend, but the trend variable is not interacted with Social Security wealth quintiles or any other variables. "SES mortality trend" model also includes interaction terms between the trend and Social Security wealth quintiles. The "preferred model" also includes a large number of health predictor variables. The "preferred & mortality plateau" model assumes that aggregate mortality stops improving after the 1947 birth cohorts. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

Table 1: Baseline characteristics in the sample

		Weighted		Unweighted	
	N	Mean	SD	Mean	SD
Men	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, ages 54 to 60.

Table 2. Lifetime Social Security benefits by gender, birth year, and Social Security wealth quintiles, preferred mortality model

	Men					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	147,840	256,281	370,140	486,936	577,803	392,574
1939-1942	158,729	259,473	361,947	516,772	558,969	385,267
1943-1946	174,090	305,938	422,737	544,359	656,145	428,682
1947-1950	159,276	256,608	412,921	600,598	762,240	456,330
1951-1954	159,087	277,193	407,996	573,673	777,315	448,226
1955-1959	173,513	286,492	403,411	550,316	791,824	445,762
	Women					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	129,483	257,981	312,825	347,763	433,324	282,454
1939-1942	148,197	257,717	300,949	366,280	527,907	310,520
1943-1946	156,827	299,131	349,835	434,452	596,935	356,168
1947-1950	155,429	308,095	398,002	500,755	702,927	403,518
1951-1954	150,845	279,339	413,581	511,184	734,001	408,912
1955-1959	148,646	287,710	375,895	537,159	754,512	416,540
	All					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	135,234	257,192	341,833	423,649	509,458	334,436
1939-1942	151,964	258,555	328,460	438,186	543,637	344,433
1943-1946	162,377	301,777	382,405	478,359	621,905	384,845
1947-1950	156,787	285,909	404,352	544,199	730,803	425,876
1951-1954	153,882	278,366	410,746	541,421	753,079	426,608
1955-1959	159,093	287,173	388,136	543,150	771,382	429,476

Notes: HRS, 1992 to 2016, ages 54 to 60. The table shows lifetime simulated Social Security benefits of workers based on their own earnings histories. The benefits exclude disability, spouse, and widow benefits. The survival predictions are based on our preferred model using Social Security wealth quintile-specific mortality trends and a large number of health predictor variables. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

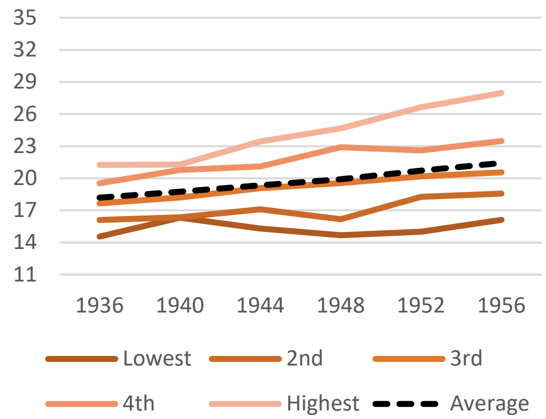
Table 3: Trends in average lifetime Social Security benefits, comparison of various mortality and benefit level scenarios

	Alternative mortality and benefit models					
Birth cohort	Fix benefits & mortality	Fix mortality	Aggregate mortality trend	Quintile-specific mortality trend	Preferred & mortality plateau	Preferred model
1934-1938	367,958	323,724	323,482	317,748	334,436	334,436
1939-1942	362,779	323,768	332,203	333,674	344,433	344,433
1943-1946	357,520	346,407	364,294	372,282	384,845	384,845
1947-1950	361,773	369,525	398,134	416,152	416,722	425,876
1951-1954	365,742	366,431	403,028	428,681	404,420	426,608
1955-1959	364,724	360,602	406,567	440,059	393,052	429,476

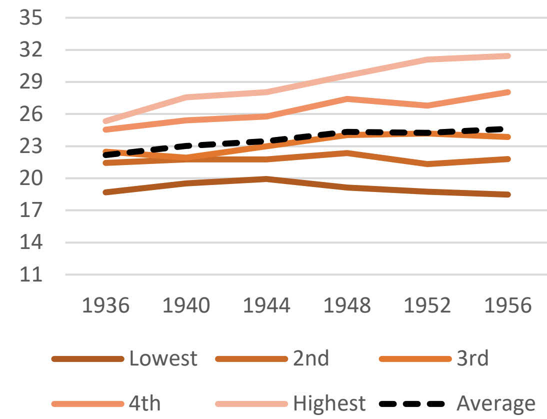
Notes: HRS, 1992 to 2016, ages 54 to 60. The table shows forecasted trends in average lifetime Social Security benefits of workers based on their own earnings histories under alternative benefit and mortality scenarios. The benefits exclude disability, spouse, and widow benefits. “Fix benefits” and “fix mortality” mean that average Social Security benefits or mortality rates are assumed to remain the same over time within gender and quintile groups. “Aggregate mortality trend” means that the mortality model includes an aggregate trend, but the trend variable is not interacted with Social Security wealth quintiles or any other variables. “SES-specific mortality trend” model also includes interaction terms between the trend and Social Security wealth quintiles. The “preferred model” also includes a large number of health predictor variables. The “preferred & mortality plateau” model assumes that aggregate mortality stops improving after the 1947 birth cohorts. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

Appendix figures and tables

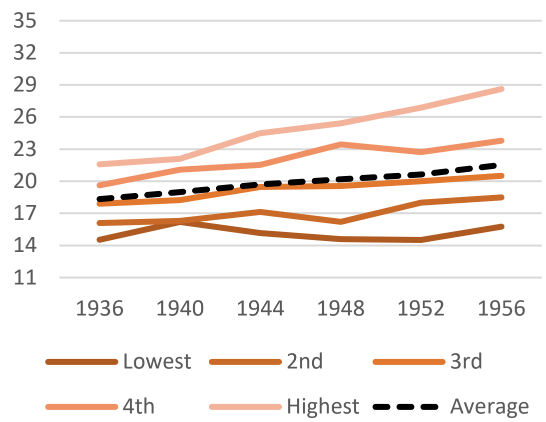
Figure A1: Average years in retirement by gender, birth year, and Social Security wealth quintiles, preferred specification of mortality, comparing alternative retirement models



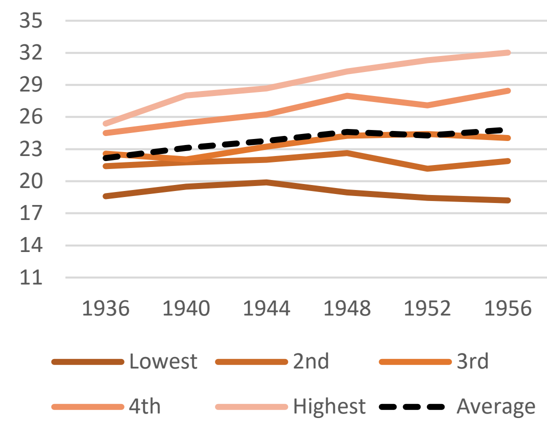
Preferred retirement model, men



Preferred retirement model, women



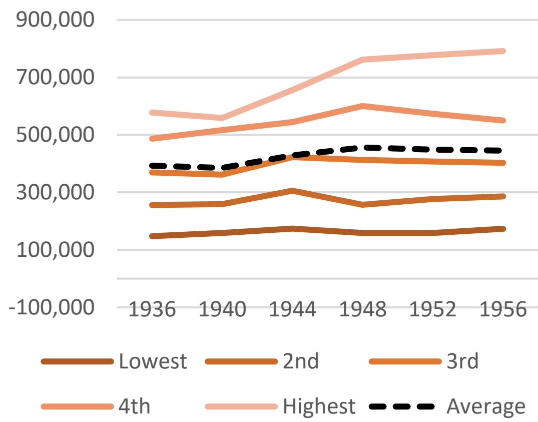
Assuming retirement at age 63, men



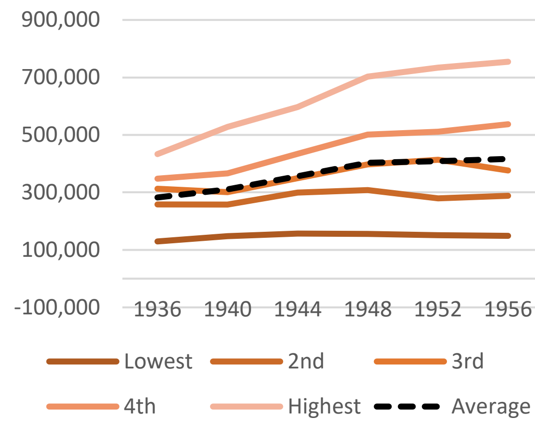
Assuming retirement at age 63, women

Notes: HRS, 1992 to 2016, age 54 to 60. The figures show average simulated years of survival and average simulated years workers collect Social Security benefits based on their own earnings. The survival predictions are based on our preferred model using quintile-specific mortality trends and a large number of health predictor variables. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

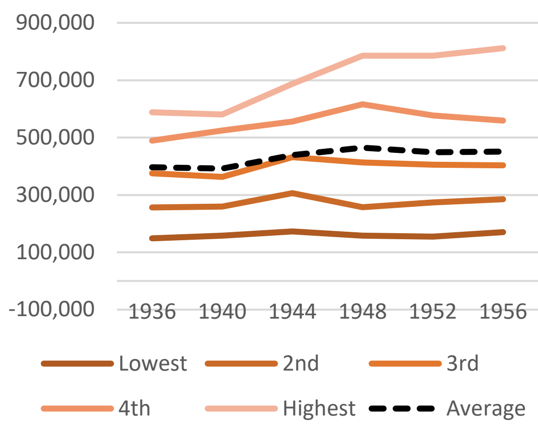
Figure A2: Lifetime Social Security benefits by gender, birth year, and Social Security wealth quintiles, preferred specification of mortality, comparing alternative retirement models



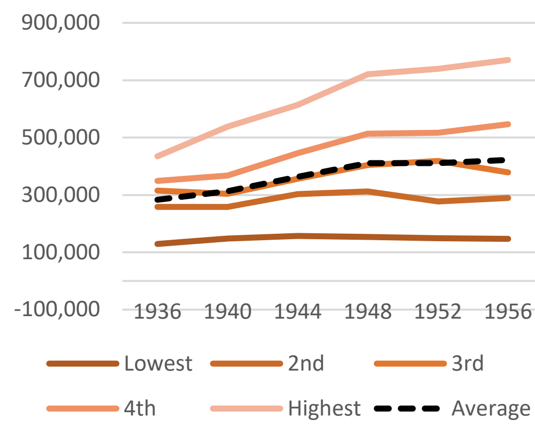
Preferred retirement model, men



Preferred retirement model, women



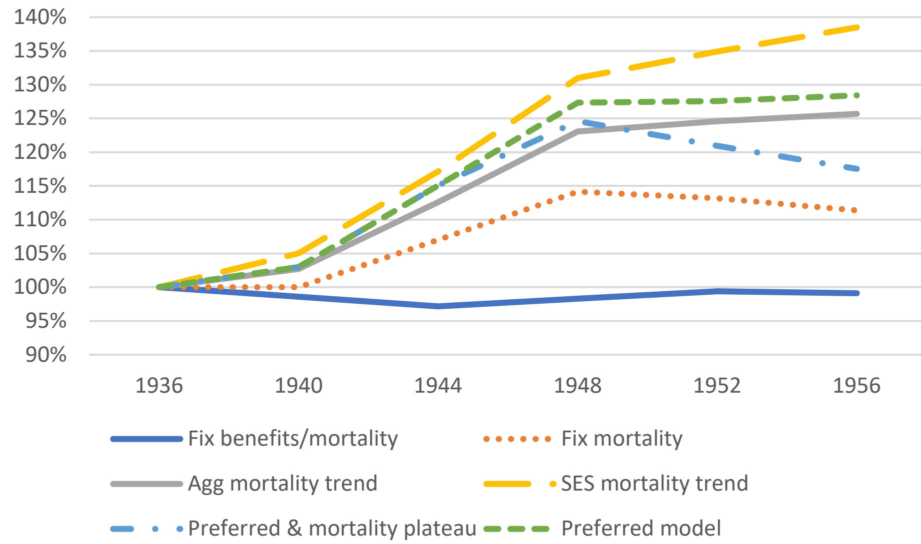
Assuming retirement at age 63, men



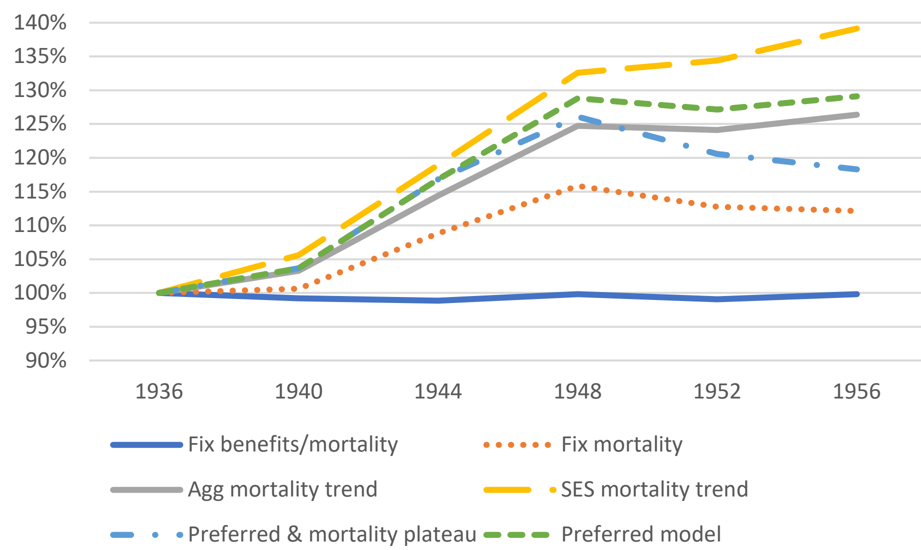
Assuming retirement at age 63, women

Notes: HRS, 1992 to 2016, ages 54 to 60. The figures show average simulated lifetime Social Security benefits based on workers own earnings. The survival predictions are based on our preferred model using quintile-specific mortality trends and a large number of health predictor variables. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

Figure A3: The effect of alternative mortality model assumptions on trends in average lifetime Social Security benefits, comparing alternative retirement models



Preferred retirement model



Assuming retirement at age 63

Notes: HRS, 1992 to 2016, ages 54 to 60. The figures show aggregate trends in lifetime Social Security benefits based on workers own earnings under alternative mortality scenarios and assumptions about claiming ages. Social Security wealth quintiles are cohort-specific quintiles of household Social Security wealth (maximum of husband and wife).

Table A1: Imputation models of missing predictor variables: 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]
Men	-0.001	0.003	10496***	996	-3.76***	0.45
Married	-0.004	0.004	-6496***	1207	-2.65***	0.54
Born 1934-1935	ref.	ref.	ref.	ref.	ref.	ref.
1936-1937	-0.003	0.006	4498*	1983	-0.01	0.88
1938-1940	0.014*	0.006	-7157***	1958	0.36	0.88
1940-1941	0.020***	0.006	6295**	1969	0.78	0.88
1942-1943	0.027***	0.007	5183*	2218	0.37	1.00
1944-1945	0.030***	0.007	3647	2360	0.16	1.07
1946-1947	0.033***	0.007	8609***	2308	0.97	1.04
1948-1949	0.040***	0.007	16806***	2210	0.31	1.00
1950-1951	0.053***	0.006	20167***	2110	0.12	0.95
1952-1953	0.054***	0.006	20239***	2089	-0.14	0.93
1954-1955	0.056***	0.006	28154***	2111	-0.34	0.93
1956-1957	0.069***	0.006	30912***	2111	-1.05	0.93
1958-1959	0.090***	0.006	27049***	2150	-2.17*	0.95
Education quartiles						
Lowest	0.006	0.004	-4827***	1347	-4.10***	0.60
2nd	0.005	0.004	-1914	1217	-2.07***	0.54
3rd	ref.	ref.	ref.	ref.	ref.	ref.
Highest	-0.016***	0.004	406	1267	0.42	0.57
Self-reported health	0.016***	0.002	1282*	598	-10.09***	0.27
Ever had high blood pressure	0.067***	0.003	471	926	-0.18	0.42
Ever had diabetes	0.082***	0.003	-2551*	1175	-1.44**	0.52
Ever had cancer	-0.017***	0.004	3386*	1491	-3.05***	0.66
Ever had lung disease	0.004	0.004	-2112	1523	-3.06***	0.67
Ever had heart problems	-0.001	0.004	-1110	1210	-2.90***	0.53
Ever had stroke	-0.028***	0.006	-1477	2053	-1.14	0.90
Ever had psychiatric problems	-0.016***	0.003	-1893	1166	-1.42**	0.51
Ever had arthritis	0.030***	0.003	-1057	961	1.29**	0.43
# of ADLs	0.011***	0.002	652	559	-1.08***	0.24
Urban county	ref.	ref.	ref.	ref.	ref.	ref.
Suburban	0.002	0.003	-3096**	1091	-2.87***	0.49
Rural	-0.004	0.003	-6864***	1099	-4.68***	0.49
Missing metro	-0.021	0.019	9669	7147	0.18	3.19
White collar, high skill	-0.006	0.004	12451***	1407	1.31*	0.63
White collar, low skill	-0.008*	0.004	3266*	1378	0.64	0.62
Blue collar, high skill	ref.	ref.	ref.	ref.	ref.	ref.
Blue collar, low skill	-0.006	0.004	-7147***	1356	-0.07	0.61
Never worked	-0.004	0.008	-9315**	2903	-2.51*	1.17

Missing	-0.002	0.008	-7782**	2966	1.03	1.23
Lives northeast U.S.	0.005	0.004	7756***	1263	0.01	0.57
Midwest	0.018***	0.003	4629***	1126	-0.82	0.50
South	ref.	ref.	ref.	ref.	ref.	ref.
West	-0.012**	0.004	-1400	1196	0.01	0.53
Other	-0.124**	0.048	16926	14632	-6.02	7.13
Number of years worked	0.001***	0.000	1319***	45	-0.02	0.02
Earnings lowest quintile	-0.006	0.005	-22205***	1622	-0.56	0.73
2nd	-0.008	0.004	-19149***	1480	-0.65	0.67
3rd	ref.	ref.	ref.	ref.	ref.	ref.
4th	0.010*	0.004	17502***	1374	-0.39	0.63
Highest	0.023***	0.005	37967***	1585	-1.10	0.73
HH income lowest quintile	-0.002	0.005	-13837***	1701	-2.01**	0.77
2nd	0.001	0.004	-4626***	1392	-0.45	0.63
3rd	ref.	ref.	ref.	ref.	ref.	ref.
4th	-0.013**	0.004	-281	1376	0.88	0.62
Highest	-0.031***	0.005	876	1536	1.53*	0.70
U.S. born	0.032***	0.004	10609***	1363	6.74***	0.61
Currently works	0.009	0.005	1225	1528	-1.13	0.69
Has back pain	-0.001	0.003	-566	961	0.24	0.43
No pain	ref.	ref.	ref.	ref.	ref.	ref.
Mild pain	0.013**	0.004	-1618	1433	-1.00	0.64
Moderate pain	0.020***	0.004	-410	1225	0.77	0.55
Severe pain	0.014**	0.005	-7600***	1740	2.34**	0.77
Currently smokes	-0.084***	0.003	-5478***	1154	-4.81***	0.52
Ever smoked	0.007*	0.003	2191*	1013	0.97*	0.45
Ever drinks	-0.014***	0.003	5555***	970	0.89*	0.43
Number of children	0.004***	0.001	-902***	215	0.46***	0.10
BMI			59	81	0.08*	0.04
SS wealth lowest quintile					1.88**	0.67
2nd					0.90	0.61
3rd					0.00	.
4th					0.44	0.60
Highest					-0.48	0.64
Constant	3.157***	0.011	97227***	4237	90.72***	1.92
sigma			56835***	298	25.31***	0.14
(Pseudo) R-squared	0.205		0.0176		0.0290	
N	19410		18274		18527	

Notes: HRS, 1992 to 2016, ages 54 to 60. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. 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 A2: Imputation models of claiming age

	Single individuals [1]	Married husbands [2]	Married wives [3]
PIA	0.001	0.000	0.000
	[0.000]***	[0.000]***	[0.000]***
Spouse PIA		0.000	0.000
		[0.000]	[0.000]
Husband claiming age			0.122
			[0.015]***
Female	0.287		
	[0.282]		
Female × PIA	0.000		
	[0.000]		
White collar, high skill	ref.	ref.	ref.
White collar, low skill	-0.314	-0.211	-0.144
	[0.135]**	[0.103]**	[0.088]
Blue collar, high skill	-0.789	-0.624	-0.447
	[0.154]***	[0.086]***	[0.138]***
Blue collar, low skill	-0.639	-0.606	-0.483
	[0.144]***	[0.096]***	[0.106]***
Never worked	-1.906	-1.661	-0.214
	[0.306]***	[0.431]***	[0.178]
Missing	-1.896	-1.216	-0.264
	[0.358]***	[0.296]***	[0.166]
No ADL limitations	ref.	ref.	ref.
1 ADL	-1.029	-0.756	-0.113
	[0.215]***	[0.173]***	[0.164]
2 ADL	-1.024	-1.326	-0.311
	[0.313]***	[0.285]***	[0.245]
3 ADL	-1.631	-1.514	-0.820
	[0.452]***	[0.425]***	[0.351]**
4 ADL	-0.859	-1.379	-0.461
	[0.432]**	[0.519]***	[0.488]
5 ADL	-0.377	-9.201	-2.385
	[0.629]	[306.347]	[1.002]**
Excellent health	0.495	0.242	0.385
	[0.152]***	[0.097]**	[0.103]***
Very good health	0.275	0.155	0.159
	[0.131]**	[0.084]*	[0.087]*
Good health	ref.	ref.	ref.
Fair health	-0.509	-0.465	-0.573
	[0.147]***	[0.112]***	[0.113]***
Poor health	-0.835	-1.115	-1.054
	[0.222]***	[0.182]***	[0.188]***
Non-Hispanic white	ref.	ref.	ref.
Non-Hispanic black	-0.182	-0.045	-0.181

	[0.115]	[0.102]	[0.108]*
Non-Hispanic other race	-0.343	0.177	0.068
	[0.300]	[0.201]	[0.265]
Hispanic	0.311	0.292	0.071
	[0.169]*	[0.114]**	[0.120]
Ever had high blood pressure	-0.319	-0.182	0.115
	[0.107]***	[0.072]**	[0.075]
Ever had diabetes	-0.295	-0.518	-0.043
	[0.160]*	[0.114]***	[0.125]
Ever had cancer	-0.412	-0.387	-0.144
	[0.214]*	[0.199]*	[0.134]
Ever had lung disease	-0.692	-0.358	-0.369
	[0.235]***	[0.193]*	[0.189]*
Ever had heart problems	-0.372	-0.438	-0.127
	[0.180]**	[0.107]***	[0.137]
Ever had stroke	-0.904	-0.839	-0.235
	[0.318]***	[0.222]***	[0.248]
Ever had psychiatric problems	-0.919	-0.403	-0.707
	[0.151]***	[0.149]***	[0.118]***
Ever had arthritis	-0.124	-0.169	-0.209
	[0.105]	[0.076]**	[0.072]***
Ever smoked	-0.035	-0.141	-0.138
	[0.119]	[0.076]*	[0.077]*
Currently smokes	-0.193	-0.396	-0.149
	[0.122]	[0.083]***	[0.098]
Ever drinks	0.225	0.126	0.079
	[0.102]**	[0.070]*	[0.070]
BMI above 35	-0.384	-0.202	-0.262
	[0.153]**	[0.129]	[0.115]**
Constant	62.064	62.969	54.967
	[0.318]***	[0.175]***	[0.973]***
Variance of residual	4.971	3.534	3.544
	[0.202]***	[0.100]***	[0.108]***
ll	-3945.2	-6418.2	-5947.8
N	3131	3993	3842

Notes: *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table A3: Output of the preferred mortality model

	No trend [1]	Agg-trend [2]	SES-trend [3]	Preferred [4]
Coefficients in the log shape parameter				
Female	-0.387	-0.392	-0.41	-0.598
	[0.065]***	[0.065]***	[0.092]***	[0.094]***
Birthyear (minus 1930)		-0.012	0.002	-0.008
		[0.003]***	[0.006]	[0.007]
Female × birthyear			0.003	0.002
			[0.006]	[0.006]
SS wealth lowest quintile	ref.	ref.	ref.	ref.
2nd quintile	-0.144	-0.149	-0.051	0.041
	[0.068]**	[0.068]**	[0.110]	[0.098]
3rd quintile	-0.429	-0.433	-0.225	0.092
	[0.071]***	[0.071]***	[0.114]**	[0.104]
4th quintile	-0.686	-0.693	-0.398	-0.028
	[0.074]***	[0.074]***	[0.119]***	[0.112]
Highest quintile	-0.886	-0.891	-0.453	0.062
	[0.077]***	[0.077]***	[0.127]***	[0.123]
2nd quintile × birthyear			-0.008	-0.005
			[0.008]	[0.008]
3rd quintile × birthyear			-0.019	-0.011
			[0.008]**	[0.008]
4th quintile × birthyear			-0.028	-0.013
			[0.009]***	[0.009]
Highest quintile × birthyear			-0.043	-0.027
			[0.010]***	[0.011]***
Female × 2nd quintile	-0.213	-0.206	-0.217	
	[0.095]**	[0.095]**	[0.095]**	
Female × 3rd quintile	-0.016	-0.008	-0.017	
	[0.099]	[0.099]	[0.099]	
Female × 4th quintile	-0.008	0.004	0.005	
	[0.105]	[0.105]	[0.106]	
Female × highest quintile	-0.04	-0.03	-0.026	
	[0.112]	[0.112]	[0.112]	
Non-Hispanic white				ref.
Non-Hispanic black				-0.002
				[0.044]
Non-Hispanic other race				-0.298
				[0.113]***
Hispanic				-0.509
				[0.064]***
Married				-0.249
				[0.059]***
Married X Female				0.164

	[0.077]**
White collar, high skill	ref.
White collar, low skill	0.113
	[0.056]**
Blue collar, high skill	0.1
	[0.059]*
Blue collar, low skill	0.135
	[0.056]**
Never worked	0.397
	[0.088]***
Missing	0.346
	[0.084]***
Lowest education quartile	ref.
2nd quartile	-0.018
	[0.093]
3rd quartile	0.083
	[0.096]
Highest quartile	-0.007
	[0.114]
2nd quartile × birthyear	0.007
	[0.007]
3rd quartile × birthyear	0.001
	[0.008]
4th quartile × birthyear	-0.003
	[0.009]
Ever had diabetes	0.384
	[0.054]***
Diabetes × female	0.163
	[0.074]**
Ever had high blood pressure	0.075
	[0.036]**
Ever had cancer	0.599
	[0.048]***
Ever had lung disease	0.168
	[0.047]***
Ever had heart problems	0.22
	[0.040]***
Ever had stroke	0.315
	[0.059]***
Ever had psychiatric problems	-0.126
	[0.043]***
Ever had arthritis	-0.258
	[0.038]***
# of ADLs	0.059
	[0.017]***
BMI above 35	0.142
	[0.053]***
Self-reported health	0.446

				[0.023]***
Ever smoked				0.276
				[0.046]***
Currently smokes				0.581
				[0.040]***
Ever drinks				-0.1
				[0.036]***
Moderate or severe pain				-0.16
				[0.042]***
Constant	-11.42	-10.916	-11.058	-13.948
	[0.169]***	[0.219]***	[0.227]***	[0.254]***
Other parameters of the model				
Scale parameter	0.0068	0.0064	0.0063	0.0076
	[0.0002]***	[0.0002]***	[0.0002]***	[0.0002]***
Log likelihood	-27297.4	-27291.2	-27278.8	-26072.8
N	19547	19547	19547	19547

Notes: HRS, 1992 to 2016, ages 54 to 60. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table A4: Lifetime Social Security benefits by gender, birth year, and Social Security wealth quintiles, assuming fix benefits and mortality

	Men					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	140,665	228,501	349,046	493,388	622,900	393,250
1939-1942	129,985	225,967	347,632	489,326	614,277	377,847
1943-1946	140,559	227,736	338,399	485,229	590,950	362,760
1947-1950	140,570	220,214	351,598	475,829	610,894	373,780
1951-1954	142,432	227,065	343,315	500,168	618,491	374,186
1955-1959	142,512	230,190	353,463	485,577	611,969	368,609
	Women					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	143,314	268,888	360,891	436,685	615,313	345,345
1939-1942	138,356	253,085	367,720	433,219	619,486	350,264
1943-1946	144,499	263,288	368,764	443,786	612,511	354,091
1947-1950	143,891	259,850	368,837	423,331	609,660	352,959
1951-1954	143,225	274,364	364,654	430,976	617,962	358,830
1955-1959	144,720	262,610	359,084	438,411	619,179	361,637
	All					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	142,484	250,126	354,896	467,603	619,311	367,958
1939-1942	135,362	240,151	358,660	460,027	616,848	362,779
1943-1946	143,232	249,467	355,198	460,342	603,418	357,520
1947-1950	142,718	242,771	361,500	446,174	610,240	361,773
1951-1954	142,933	252,913	353,823	464,456	618,195	365,742
1955-1959	143,793	248,311	356,584	459,889	615,919	364,724

Table A5: Lifetime Social Security benefits by gender, birth year, and Social Security wealth quintiles, assuming fix mortality

	Men					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	134,425	233,813	365,291	490,584	576,493	385,929
1939-1942	126,766	234,720	358,343	485,089	556,769	367,301
1943-1946	159,883	263,247	374,157	497,267	566,868	378,991
1947-1950	146,794	239,139	376,047	501,684	628,371	392,898
1951-1954	143,054	226,486	345,456	503,694	625,554	376,788
1955-1959	146,659	234,421	348,062	457,783	597,980	360,626
	Women					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	117,191	245,509	288,692	329,073	428,306	268,106
1939-1942	125,111	232,986	294,479	336,158	496,382	287,614
1943-1946	137,534	272,022	327,129	397,451	543,949	325,093
1947-1950	133,023	273,822	356,640	433,278	606,368	352,366
1951-1954	134,809	275,735	359,879	440,240	617,464	357,953
1955-1959	137,763	268,174	331,709	450,047	632,317	360,582
	All					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	122,590	240,075	327,460	417,139	506,394	323,724
1939-1942	125,703	233,813	323,282	407,319	526,962	323,768
1943-1946	144,719	268,611	348,139	437,327	553,614	346,407
1947-1950	137,885	258,878	364,900	463,043	616,709	369,525
1951-1954	137,847	253,400	352,559	470,943	621,027	366,431
1955-1959	141,501	253,287	338,983	453,570	616,792	360,602

Table A6: Lifetime Social Security benefits by gender, birth year, and Social Security wealth quintiles, assuming an aggregate trend in mortality

	Men					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	131,243	230,713	362,584	490,287	578,113	384,618
1939-1942	128,022	238,513	366,444	498,286	573,184	376,369
1943-1946	166,695	275,974	392,802	524,115	598,366	398,664
1947-1950	158,096	257,984	406,006	542,584	678,423	424,289
1951-1954	157,852	250,950	381,053	556,166	688,553	415,688
1955-1959	167,580	268,015	394,993	518,589	674,657	408,869
	Women					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	116,122	245,561	288,605	330,718	432,235	268,821
1939-1942	127,680	238,513	302,052	345,703	512,315	295,522
1943-1946	144,282	285,524	343,809	417,972	572,945	341,811
1947-1950	143,080	294,641	383,902	465,782	651,642	378,933
1951-1954	148,921	302,770	395,744	482,641	675,300	392,665
1955-1959	156,124	302,144	372,937	504,445	707,098	404,738
	All					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	120,859	238,663	326,047	417,725	509,106	323,482
1939-1942	127,802	238,513	331,093	418,609	543,139	332,203
1943-1946	151,488	281,811	365,697	460,375	583,666	364,294
1947-1950	148,382	278,846	393,310	499,201	664,228	398,134
1951-1954	152,211	279,269	388,287	518,217	681,137	403,028
1955-1959	160,937	287,091	382,749	510,886	692,430	406,567

Table A7: Lifetime Social Security benefits by gender, birth year, and Social Security wealth quintiles, assuming SES-specific trends mortality

	Men					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	137,962	234,395	358,186	477,146	548,366	375,550
1939-1942	129,241	238,833	366,681	501,361	579,155	378,673
1943-1946	162,339	272,549	397,888	543,715	641,035	410,903
1947-1950	147,891	251,471	416,105	579,176	766,343	450,434
1951-1954	143,985	241,688	394,135	607,860	811,756	449,682
1955-1959	146,696	254,462	413,154	582,471	832,820	451,222
	Women					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	121,294	250,444	287,247	323,132	412,760	266,066
1939-1942	127,946	238,954	302,323	346,058	515,095	296,302
1943-1946	139,344	281,541	345,800	426,924	600,836	347,017
1947-1950	133,313	285,732	387,913	485,977	712,428	390,985
1951-1954	133,496	289,364	401,676	512,879	765,508	411,490
1955-1959	135,072	283,924	380,165	546,354	833,819	431,192
	All					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	126,516	242,988	323,151	407,109	484,218	317,748
1939-1942	128,409	238,896	331,349	420,264	547,535	333,674
1943-1946	146,737	278,045	369,071	473,581	617,788	372,282
1947-1950	138,460	270,969	399,912	526,530	737,767	416,152
1951-1954	137,360	267,743	397,848	558,838	785,878	428,681
1955-1959	139,956	270,929	394,840	562,800	833,367	440,059

Table A8. Lifetime Social Security benefits by gender, birth year, and Social Security wealth quintiles, assuming a plateauing in aggregate mortality

	Men					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	147,840	256,281	370,140	486,936	577,803	392,574
1939-1942	158,729	259,473	361,947	516,772	558,969	385,267
1943-1946	174,090	305,938	422,737	544,359	656,145	428,682
1947-1950	157,846	252,999	403,511	586,697	734,954	444,518
1951-1954	155,745	267,441	387,996	543,301	712,526	422,066
1955-1959	167,572	271,084	370,684	501,316	687,876	403,699
	Women					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	129,483	257,981	312,825	347,763	433,324	282,454
1939-1942	148,197	257,717	300,949	366,280	527,907	310,520
1943-1946	156,827	299,131	349,835	434,452	596,935	356,168
1947-1950	154,707	305,550	391,905	492,324	683,044	396,316
1951-1954	149,020	272,789	397,350	489,888	683,101	389,975
1955-1959	145,426	276,483	351,193	499,851	668,928	384,596
	All					
	Lowest quintile	2nd	3rd	4th	Highest quintile	Average
1934-1938	135,234	257,192	341,833	423,649	509,458	334,436
1939-1942	151,964	258,555	328,460	438,186	543,637	344,433
1943-1946	162,377	301,777	382,405	478,359	621,905	384,845
1947-1950	155,815	282,906	396,845	533,389	707,441	416,722
1951-1954	151,498	270,363	392,602	515,733	696,062	404,420
1955-1959	154,730	274,102	359,864	500,518	677,496	393,052