NBER WORKING PAPER SERIES

THE PERSISTENCE AND HETEROGENEITY OF HEALTH AMONG OLDER AMERICANS

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Working Paper 20306
http://www.nber.org/papers/w20306

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
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July 2014

Funding for this project was provided by the National Institute on Aging grants P01-AG005842 and P30-AG012810 to the National Bureau of Economic Research. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Institute on Aging, the National Institutes of Health, or the National Bureau of Economic Research. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. I10,I19,J14

ABSTRACT

We consider how age-health profiles differ by demographic characteristics such as education, race, and ethnicity. A key feature of the analysis is the joint estimation of health and mortality to correct for the effect of mortality selection on observed age-health profiles. The model also allows for heterogeneity in individual health at a point in time and the persistence of the unobserved component of health over time. The observed component of health is based on a multidimensional index based on 27 indicators of health. Most of the key results are shown by simulations that illustrate the range of issues that can be addressed using the model. Differences in health by education and racial-ethnic group at age 50 persist throughout the remainder of life. Based on observed profiles, the health of whites is about 8 percentile points greater than the health of blacks at age 50 but by age 90 the gap is only 5 percentile points. However, when corrected for mortality selection, the health of blacks is actually declining more rapidly with age than the health of whites; the true gap widens with age. We also find that much of the difference in age-health profiles by racial-ethnic group is accounted for by differences in the levels of education between race-ethnic groups--from two-thirds to 85 percent for men and about half for women. We also simulate differences in survival probabilities by level of education and health and use these probabilities to calculate the expected present discounted value (EPDV) of an immediate annuity with first payout at age 66 for persons by gender, level of education, and health decile. The range of EPDVs is over two-fold for both men and women suggesting enormous potential for adverse selection.

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Section 1 Introduction

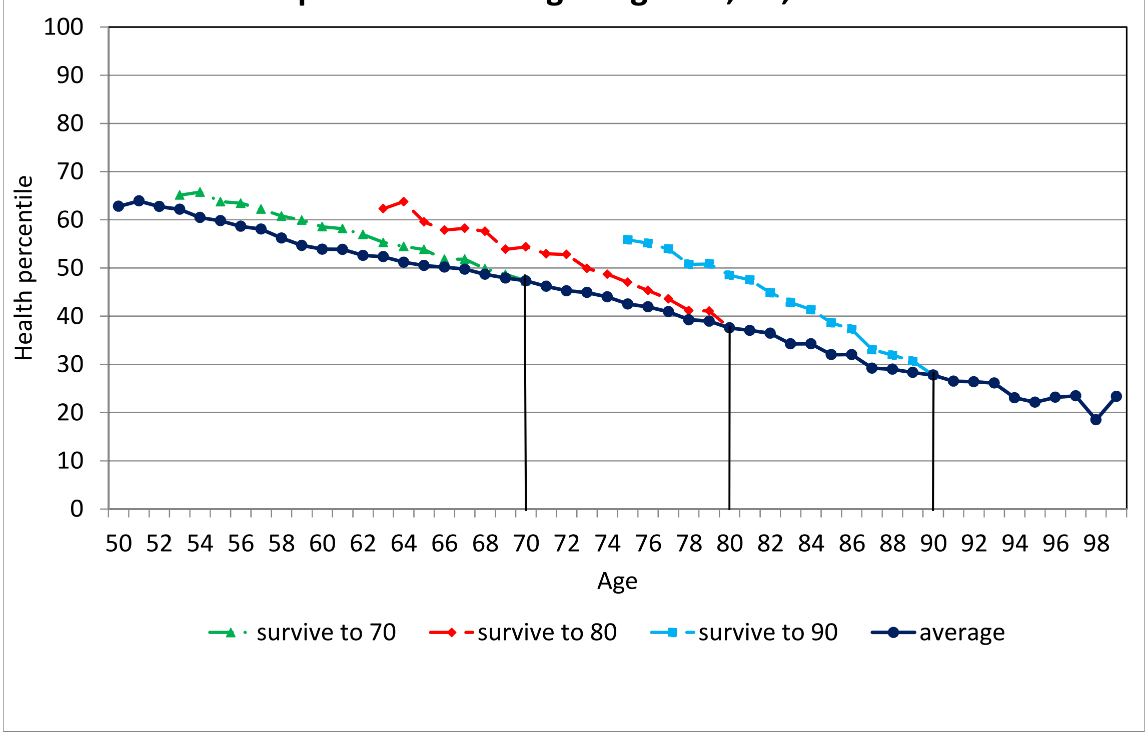
Health is one of the most important determinants of the quality-of-life of the elderly. Health has direct effects on well-being and life satisfaction and is a factor in many important decisions that the elderly face, including work, retirement, housing, living arrangements, and consumption choices more generally. A better understanding of how health evolves is critical to understanding the vast differences in health across levels of education, racial-ethnic groups, and other subgroups of the population. It is difficult however to infer how health evolves from existing data on health. One problem is that "true" health is unobserved and inferences are typically based on self-reported measures that are known to be very imperfect indicators of true health (Kerkhofs and Lindeboom (1995), Crossley and Kennedy (2002), Lindeboom and Doorslaer (2004), Baker, Stabile and Deri (2004)). In addition, how the dynamic properties of health are modeled can have important implications for estimating the true persistence of health from one age to the next. A further complication is that the observed relationship between age and health (however measured) is confounded by mortality selection (or survivorship bias) which can yield substantial underestimation of the decline of health with age.

Our goal is to estimate how health evolves after retirement, accounting explicitly for each of these issues. Health at retirement varies greatly across individuals and this variation persists into older ages. Some persons experience persistently good health and others experience persistently poor health. To investigate the source of this variation we pay particular attention to how individual demographic characteristics such as education and racial-ethnic group affect health-age profiles. We begin by describing a health index previously developed in Poterba, Venti and Wise (2013) that uses substantially more information than simple self-reported health measures. The index is based on a wide range of questions concerning functional limitations, health conditions, and medical care obtained in the Health and Retirement Study (HRS). We also carefully model the dynamics of the unobserved component of health that may be due to unreported prior health conditions, health behaviors, or malnutrition that may have long-lasting effects on health. We allow an inter-temporal correlation structure that is flexible enough to accommodate any degree of persistence of health over time. Finally, we account for mortality selection. Mortality selection arises because persons in poor health are more likely to die and leave the sample.

We use an econometric model that jointly estimates health and mortality. We then use the model to simulate the relationship between health at retirement and subsequent health-age profiles and to explore how the profiles depend on health at retirement, education, and other demographic characteristics. One advantage of the model-based approach is that it allows us to explore relationships that would otherwise be difficult to describe because of the small number of observations for specific groups of interest (identified by gender, race, ethnicity or level of education for example) in surveys such as the HRS. Another advantage is that it allows credible out-of-sample simulation of health-age profiles. For example, if we consider persons who survive to age 90, it is impossible in a short panel to "look back" far enough to see what their health was in earlier years. However, our model-based approach allows us to simulate health back to age 50.

A consequence of mortality selection is that the average health-age profile calculated for all persons can be a very misleading indicator of how health evolves for a particular person. The average level of health at each age averages the health of persons who might live one more year, two more years, etc. Figure 1-1 helps to motivate our analytical approach. The figure distinguishes the average health of all persons alive at each age (the observed health-age profile) from the average health of persons identified by age of survival. The heavy blue line with round markers shows the average health percentile (explained below) of all HRS respondents alive at each age. This average health trajectory reflects the offsetting effects of two forces. First, average health declines as people age. Most survey respondents report more health problems and more functional limitations at older ages. Second, there is a selection effect in the opposite direction—persons in better health are more likely to survive from one age to the next. This selection effect is illustrated by the other curves in Figure 1-1, that show the average health at prior ages of those who survived until at least age 70, age 80, and age 90. At any given age those who will survive longer are in better health. Those who survived until age 90 had much better health at age 75 than those who survived until age 80. Those who survived until age 80 had much better average health at age 62 than those who survived until age 70. Thus the average age-health profile shown by the heavy blue line with round markers is quite different from the health-age profile of persons who survive to a particular age. Moreover, the average profile is not typical of persons who survive to any age. To obtain correct estimates of how health evolves after retirement, we must account for mortality selection.

Figure 1-1. Average health percentile for all persons and for persons surviving to ages 70, 80, and 90



Several previous studies have addressed various aspects of the dynamics of health after retirement. Most of these studies are based on self-assessed health (SAH) which is typically reported on a five point ordinal scale ranging from poor to excellent. The two studies most closely related to the present study are Heiss, Boersch-Supan, Hurd, and Wise (2008) and Heiss (2011). The dynamic model of health and mortality we use is a close variant of the model developed in these papers. Like the present study, those analyses are based on data from the HRS, but use SAH instead of the health index we use. The focus on Heiss (2011) is on the dynamics of SAH and underlying true (or latent) health and he experiments with a variety of different error structures that can accommodate state dependence and unobserved heterogeneity. The particular model that succeeds best in simulations—one that allows for a non-constant autocorrelated latent health component—is adopted in the present study. Several other studies—Contoyannis et al. (2004), Hernandez-Quevedo et. al. (2008) and ,Halliday (2008)—document the observed persistence of health and focus on the decomposition of health into components attributable to first-order state dependence (the direct effect of last period's health on this period's health) and individual heterogeneity (unobserved factors that affect health in all periods). These studies, all of which use SAH, find that both sources play important roles. The present study uses a related error structure that also allows for unobserved heterogeneity and a latent health component that persists over time.

Two other studies of health dynamics—both using SAH—have also addressed mortality selection. Contoyannis et al. (2004) and Jones et al. (2006) account for attrition from the sample (for which mortality selection is only partly responsible) by using an inverse probability weighted (IPW) estimator that assumes that attrition is independent of unobserved factors that may affect both health and mortality. Both studies find that accounting for mortality selection using the IPW estimator has little effect on the coefficients on various measures of socioeconomic status in an ordered probit model of SAH.

The only study of health dynamics that does not rely exclusively on SAH as an indicator of health is Lange and McKee (2011). They emphasize the importance of using multiple measures of health to construct a single index. We also use a health index based on a large number of health measures available in the HRS, although the measures we use differ from the subset that Lange and McKee use. We use the first principle component based on 27 health measures and they use a factor analysis approach using a single health factor. They also allow endogenous mortality and adopt an error structure for the unobserved component of health that is similar to ours. They find a high degree of persistence in health, as we do, although they observe that some of the persistence in health is attributable to the persistence of measurement error rather than persistence in true health. Unlike our analysis however, they do not investigate the role of demographic characteristics (other than age and gender) on the evolution of health. We emphasize the role of education and racial-ethnic group.

The remainder of the paper is in six sections. In section 2 we describe the data used in the analysis and the health index that we use to measure health. We also describe the distribution of health at retirement ages. In section 3 we explain the model we use for estimation and in particular the way that mortality selection is addressed. Model estimates are presented in section 4. Section 5 presents simulations to illustrate several important implications of the model. We first assess the model fit and then show how accounting for mortality selection affects the estimated age profile of health. We then simulate educational and racial differences in health "corrected" for mortality selection. The effect of mortality selection is shown to be quite large. We then simulate the effect of health shocks at age 50 on health and mortality age profiles. In section 6 we simulate the evolution of health by education and racial-ethnic group. We emphasize that much of the difference in health across racial-ethnic groups is accounted for by differences in education, especially for men. In section 7 we simulate differences in survival probabilities by health and the level of education and use these estimates to show how the present discounted value (EDPV) of the payout from a fair annuity varies by gender, health, and level of education. Section 8 is a summary of our findings.

Section 2 Data and Descriptive Statistics

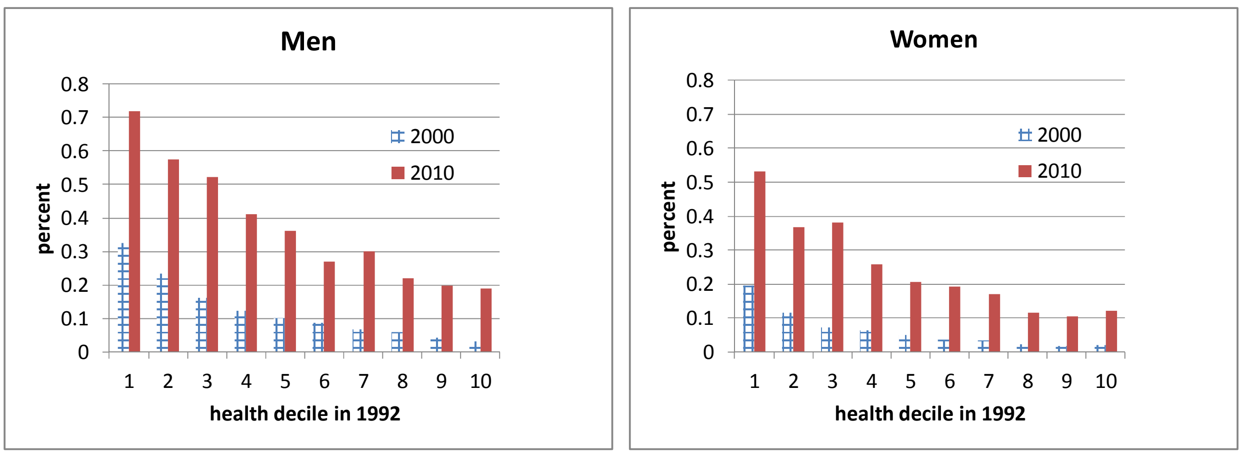
We first discuss the data used in the analysis and then describe the health index that is a key component of the analysis. We then show data on the variation in health at retirement ages by education and racial-ethnic groups and then discuss in some detail the evolution of health by level of education. Finally, we use the evolution of health for single and married persons to provide an alternative description of mortality selection and to highlight its quantitative importance.

The analysis uses data from the Health and Retirement Study (HRS). The HRS is a longitudinal survey that resurveys respondents every two years. The current HRS is comprised of five entry cohorts. The original HRS cohort surveyed respondents age 51 to 61 in 1992 and the Asset and Health Dynamics of the Older Old (AHEAD) cohort surveyed respondents age 70 and older in beginning in 1993. Subsequent cohorts include the War Babies (WB) cohort first surveyed at ages 51 to 56 in 1998, the Children of Depression (CODA) cohort first surveyed at age 68 to 74 in 1998, and the Early Baby Boomers (EBB) first surveyed at ages 51 to 56 in 2004. Respondents are resurveyed every two years.

The HRS sampling methods can yield some non-representative demographic subsamples in the early years of the HRS. For example, the HRS cohort includes households with at least one person (the "age-eligible" person) born between 1931 and 1941 and their spouses. These age-eligible persons were age 51 to 61 when first surveyed in 1992. If an age-eligible person has a spouse, the spouse is automatically selected even if he or she is not age-eligible. In married households the women is, on average, younger than the man. As a result, there are more women at younger ages, for example ages 51 to 55, in the first few waves of the HRS than in the population. This is because women who were under the age of 51 in 1992 but were married to age-eligible spouses will "age" into the sample in subsequent years. Thus in the second wave of the HRS there are few men less than age 53, but a substantial number of women. Moreover, none of these women are single (unless they were divorced, widowed, or separated since the previous wave) so the sample of women is highly unrepresentative of the general population. This aspect of the data is important to understanding some features of the model fit discussed in section 4.

The health index: One advantage of the HRS is the detailed information it provides on health conditions. We construct a health index based on the responses to 27 health-related questions concerning self-reported functional limitations, health conditions, and medical care usage. The index is the first principal component of these 27 indicators. The full set of questions was not asked of all respondents in the HRS cohort in 1992 and the AHEAD cohort in 1993, however. Thus we have dropped all data for the first wave of the HRS and AHEAD cohorts. A more detailed description of the index and a list of included variables are contained in Poterba, Venti and Wise (2013). We note several important features of the index used in this paper. First, the index used in Poterba, Venti and Wise (2013) only included data through 2008. The index used in the present paper includes data through 2010. Second, the index used here is based on a pooled sample that includes all respondents from all HRS cohorts in all years. The decision to pool was based on earlier experimentation with the index that showed little difference between estimates for men and women and little difference across years. The principal component loadings on the health variables were used to predict a raw health score for each respondent. This score was converted to a percentile index with values from 1 to 100. A person's percentile index value shows the person's position relative to the health of all persons in all HRS cohorts in all years.

Figure 2-1. Percentage deceased in 2000 and 2010 by health decile in 1994, persons age 53 to 63 in 1994



The index has several important properties for our analysis. First, it is strongly related to mortality. Figure 2-1 illustrates this for men and women using data from the earliest of the five HRS cohorts. These persons were age 51 to 61 in 1992 when first surveyed and age 53 to 63 in 1994. The figures show the percent of persons in each health decile in 1994 that were deceased by the year 2000 and the percent that were deceased by the year 2010. The figures show that the index strongly predicts mortality. For example, over 71.6 percent of men (58.1 percent of women) in the poorest health decile in 1994 were deceased by 2010 but only 19.7 percent of men (10.3 percent of women) in the top health decile were deceased by 2010. Second, the index is strongly predictive of future morbidity as well. Figure 2-2 shows the percent of persons (of both genders) who report future health events such a stroke, the onset of diabetes, lung disease, and other health conditions. Persons in the poorest health decile in 1994 report higher incidence of each condition (with the exception of cancer) by 2010.

Figure 2-2. Probability of health events by 2010 by health quintile in 1994, all persons age 53 to 63 in 1994

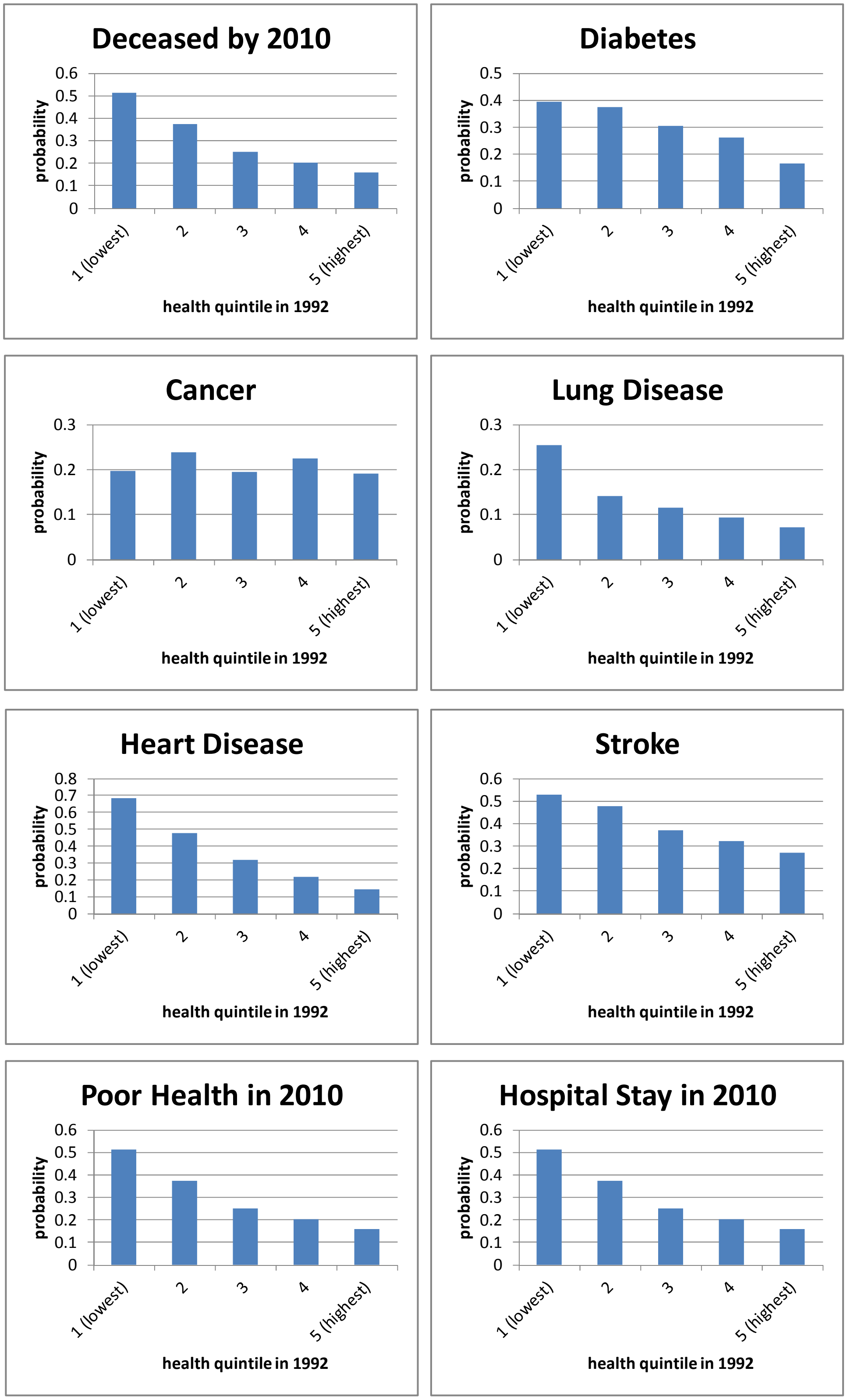
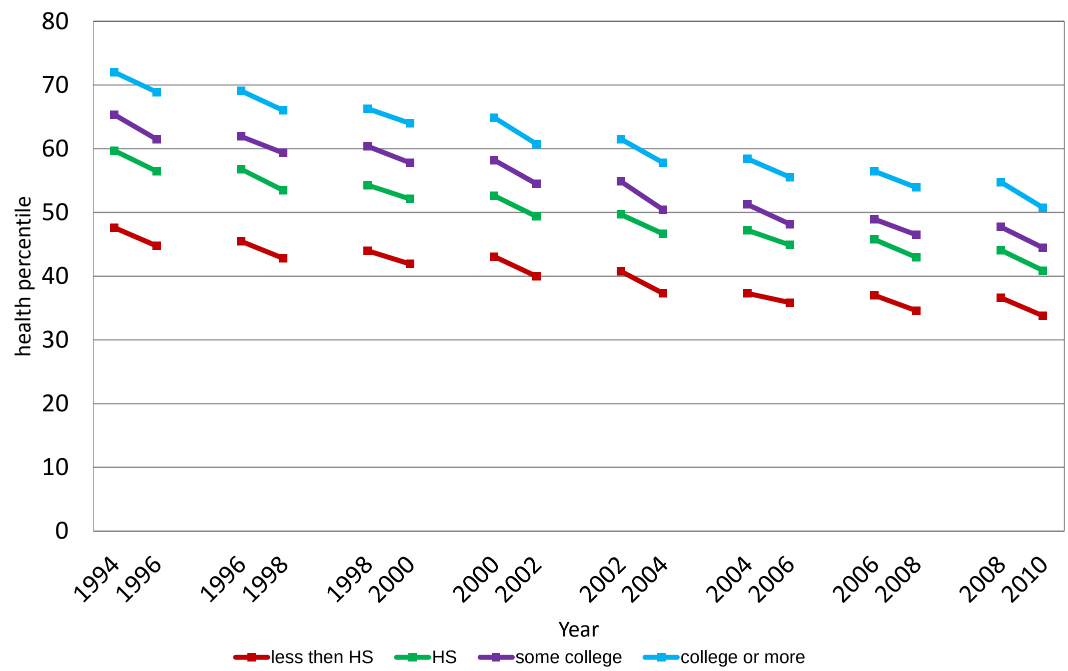


Figure 2-3. Mean health trajectories by level of education for persons age 53 to 63 in 1994



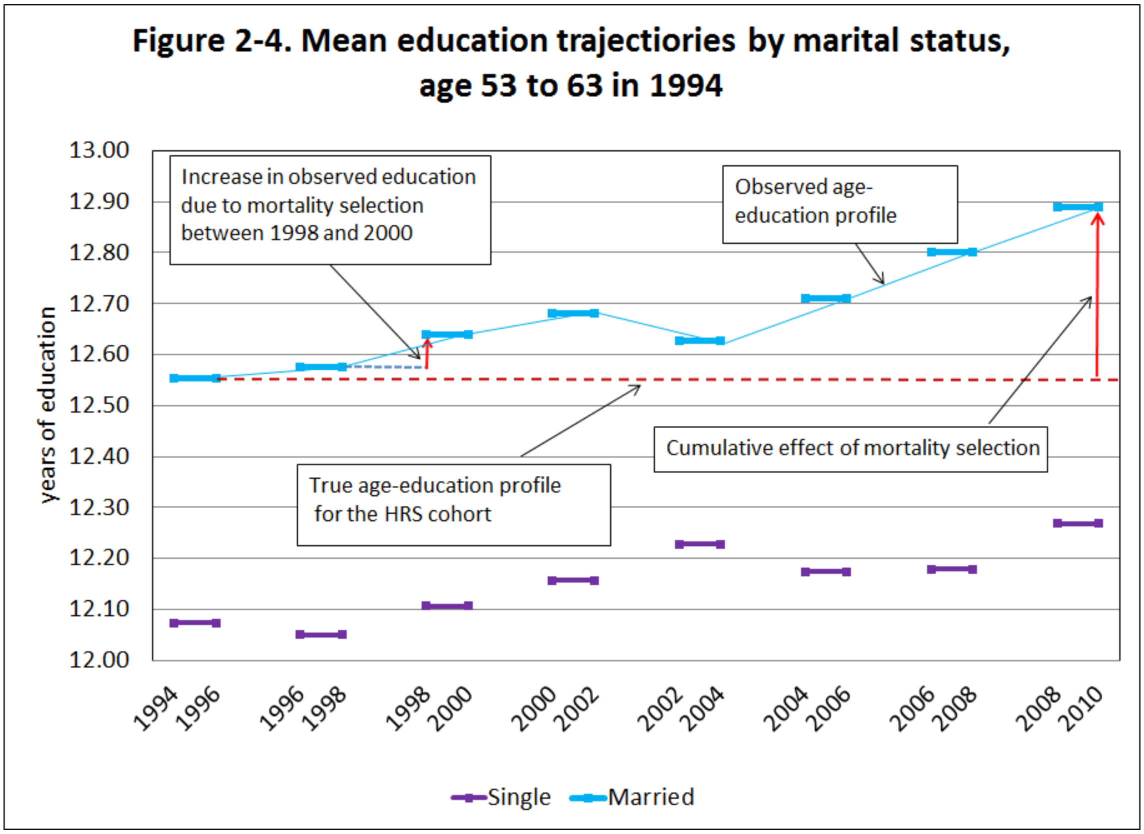
Variation in health after retirement: The index can also be used to show the variation in the health of persons near the age of retirement. Figure 2-3 shows how health varies by level of education for members of the original HRS cohort between 1994 and 2010. This figure is similar to Figure 2-1 in Poterba, Venti and Wise (2013) where details about how the figure was constructed are presented. The figure shows that large differences in health by level of education persist over time even as health declines for persons in all education groups. The slope of each line segment shows the health trajectory for persons alive at the beginning and end of each two-year interval. The "gaps" between line segments are an indicator of mortality selection. These gaps are discussed below. When first observed at ages 53 to 63 in 1994, the differences in health by education group are very large. The mean health percentile in 1994 is 72.0 for persons with a college degree and 47.6 for persons with less than a high school degree. The key feature of the figures is that the level of health in subsequent years is largely determined by the level of health when first observed in 1994. Over time, health declines by approximately the same amount (in percentiles) for persons at all levels of education. This suggests that there is little effect of education on the *change* in health after 1994, the first year members of this cohort were observed. Poterba, Venti and Wise (2013) show similar figures for the AHEAD and the CODA cohorts of the HRS and for all persons age 65+ in 1998. Although there are some differences across the groups, the basic pattern is the same for the cohorts.

Mortality selection: The observed age-health profile is the mean health in each year (or at each age) for all persons who survive to each year (age). Because of mortality selection, however, observed age-health profiles are an inaccurate representation of how the health of persons evolves over time. Here we show how the age-health profile is distorted by selection. In the next section we describe a model to formally estimate and correct for mortality selection.

As noted above, there are two distinct processes that determine observed age-health profiles. The first is that persons become less healthy as they age. The second—the selection effect—is that the least healthy are more likely to die and leave the sample. To isolate the role of selection we begin with a simple example where the first process is inoperative. Education (unlike health) does not change over time for persons in the HRS cohort. For any individual the age profile of education is flat (horizontal). However, the empirical age-education profile rises because of mortality selection—persons with lower education are more likely to die. Thus, for example, if we track married persons in the HRS cohort (age 53 to 63 in 1994) from 1994 to 2010 we find that mean years of education is 12.55 in 1994 and 12.89 in 2010. The difference of 0.34 years is purely the result of (cumulative) mortality selection.

We can also measure the extent of selection bias associated with each wave-to-wave transition in the HRS. Figure 2-4 shows average years of education of persons alive in consecutive waves in the HRS cohort between 1994 and 2010. Separate profiles are shown for single and for married persons. Each line segment in the figure shows the change in the education of persons alive in both the beginning year and the end year of the interval. Each of these segments is flat because the level of education of each person does not change over time. In this figure the observed age-education profile is the solid line connecting the end-points of each of the line segments for married persons. For example, the slope of the observed education profile between 1998 and 2000 is the difference between the mean education of all persons alive in

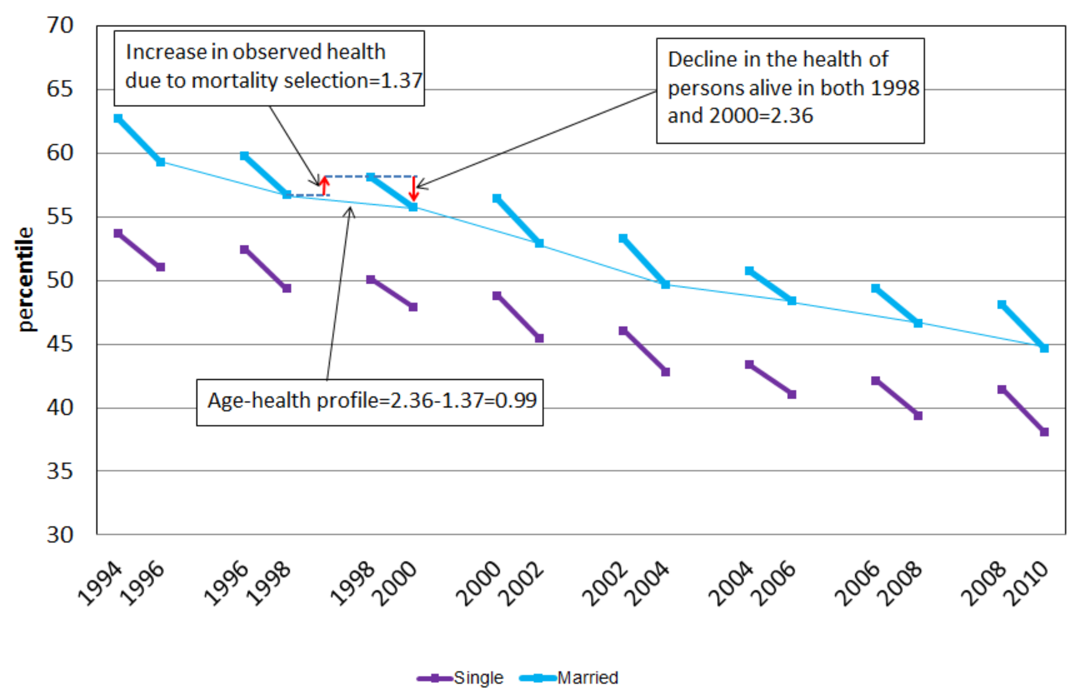
1998 (the last point of the 1996 to 1998 segment) and the mean education of all persons alive in 2000 (the last point of the 1998 to 2000 segment).



Some persons alive in 1998 did not survive to 2000. These persons are included in the 1996 to 1998 segment, but not in the 1998 to 2000 segment. Thus the education in 1998 of those who survived until 2000 is greater than the education of all persons who were alive in 1998, including those who did not survive until 2000. The difference is the mortality selection effect and it is identified in the figure as the vertical height of the gap between the end of the 1996 to 1998 segment and the beginning of the 1998 to 2000 segment. These gaps, of course, account for the upward slope of the observed age-education profile since the true age-education profile for individuals is flat. The sum of these gaps is the 0.34 years of education—the same selection effect reported above.

Health, unlike education, changes over time. Figure 2-5 shows a figure using health rather than education as the outcome variable. The height of the gaps is still a measure of the extent of mortality selection. However, if health is the outcome variable the segments are not flat—this reflects the decline of true health over time. For the period 1994 to 2010 the observed change in health—reflecting mortality selection and the true change in health—is -15.6 percentile points (from the end year point of the 1994 to 1996 segment to the end year point of the 2008 to 2010 segment) for married persons. This can be decomposed into a "true" decline in health of -23.1 percentile points (the sum of the changes in slope segments) and a mortality effect of +7.5 percentile points (the sum of the gaps). The decomposition for single persons is quite similar. Over the 16 year period the observed decline in health is -18.0 percentile points. This is comprised of a "true" decline of -24.5 percentile points for survivors and a selection effect of 6.4 percentile points. These results pertain to persons in the original HRS cohort who were age 53 to 63 in 1994 and age 69 to 79 when last observed in 2010. Similar calculations made for persons surviving to other ages show that selection effects are larger for persons at older ages. The average wave-to-wave selection effect is 0.93 for married persons, but this ranges from about 0.7 percentile points for the 1994 to 1996 interval to about 3.0 percentile points over the last two-year interval ending in 2010. Thus mortality selection is substantial at all ages and can lead to very misleading inferences about how health evolves in old age.

Figure 2-5. Mean health trajectiories by marital status, age 53 to 63 in 1994: "true" vs observed health decline



Section 3 The Model

Health: We begin with a description of the evolution of health from wave to wave. In our framework h_{it} is the true (unobserved) health for person i in period t. We assume that true health is a function of observed individual characteristics X_{it} and an individual random term R_{it} that captures the unobserved components of health and their evolution over time:

(3-1) $$h_{it} = X_{it}\beta_H + R_{it}\gamma_H$$

The random component R_{it} allows for heterogeneity in health across persons as well as for persistence in health over time for the same person. It is specified to follow an AR(1) process with

(3-2) $$R_{it} = \rho R_{it-1} + u_{it}$$

where R_{it} is normalized to have mean zero and unit variance. The parameter ρ captures the persistence of the unobserved component of health over time. In the special case that ρ=1 the error structure is equivalent to a random effects model and the unobserved health component is constant over time. Noting that $R_{it} - \rho R_{it-1} = u_{it}$ and assuming that the process is stationary, then $u_{it} \sim N(0,(1-\rho^2))$. We then interpret the error term u_{it} as capturing health shocks. Heiss (2011) weighs the relative merits of alternative error structures that can be used to accommodate persistence. We assume that the observed health index H_{it} is equal to true health measured with error:

(3-3) $$H_{it} = h_{it} + e_{it} = X_{it}\beta_H + R_{it}\gamma_H + e_{it}$$

We treat the random term e_{it} as measurement error with zero mean and variance σ_e^2— $e_{it} \sim N(0,\sigma_e^2)$. The total variance of H, given observed covariates X, is given by $V(H_{it} \mid X_{it}) = Var(R_{it})\gamma_H^2 + Var(e_{it}) = \gamma_H^2 + \sigma_e^2$.

Mortality: Mortality between period $t-1$ and period t is a function of individual characteristics in the prior period X_{it-1} and true health in the prior period h_{it-1}. (Neither X nor h are defined for deceased persons in the present period). We assume that mortality (the likelihood of death) can be described by latent continuous variable m_{it}, with

(3-4) $m_{it} = X_{it-1}\tilde{\beta}_M + h_{it-1}\tilde{\gamma}_M + \upsilon_{it}$

where v_{it} is an error term with zero mean and unit variance and is uncorrelated with e_{it} and u_{it}, the error terms in the health equation. Substituting health h_{it-1} from equation (3-1), into 3-3 yields:

$$\begin{aligned} m_{it} &= X_{it-1}\tilde{\beta}_M + \left(X_{it-1}\beta_H + R_{it-1}\gamma_H\right)\tilde{\gamma}_M + \upsilon_{it} \\ &= X_{it-1}\left(\tilde{\beta}_M + \beta_H\tilde{\gamma}_M\right) + R_{it-1}\gamma_H\tilde{\gamma}_M + \upsilon_{it} \\ &= X_{it-1}\beta_M + R_{it-1}\gamma_M + \upsilon_{it} \end{aligned} \tag{3-4}$$

where $\beta_M = \tilde{\beta}_M + \beta_H\tilde{\gamma}_M$ and $\gamma_M = \gamma_H\tilde{\gamma}_M$.

Note that the total (reduced form) effect of X_{it-1} on mortality is given by β_M which can be decomposed into a "direct" effect $\tilde{\beta}_M$ and an "indirect" effect through health $(\beta_H\tilde{\gamma}_M)$. In summary: the health equation yields estimates of β_H and γ_H. The mortality equation yields estimates of β_M and γ_M. Given estimates of β_H, β_M, γ_H, and γ_M we can recover $\tilde{\gamma}_M = \gamma_M / \gamma_H$ and $\tilde{\beta}_M = \beta_M - \beta_H(\gamma_M / \gamma_H)$.

Mortality selection occurs through both X_{it} and R_{it}. Let M_{it} be a mortality indicator that that takes on the value one if a person dies between periods $t-1$ and t, and zero otherwise. Following the conventional probit specification, we assume that M_{it} tales a value of one if latent mortality m_{it} crosses a threshold (normalized to be zero), so $M_{it} = 1$ if $m_{it} > 0$ or v_{it}> -($X_{it-1}\beta_M$+$R_{it-1}\gamma_M$). The probability that person i dies between $t-1$ and t is then given by:

(3-6) $\Pr[M_{it} = 1 | X_{it-1}, R_{it-1}] = \Phi\left[X_{it-1}\beta_M + R_{it-1}\gamma_M\right]$

where $\Phi[\ ]$ is the standard normal cumulative distribution function.

Conditional on the sequence $\left\{R_{i1},...,R_{iT}\right\}$, health and mortality are assumed to be independent over time, so if latent health were observed, the likelihood contribution of individual i would simply be

(3-7) $\mathrm{P}_i\left(R_{i1},...,R_{iT}\right) = \prod_t \mathrm{f}(H_{it} | X_{it}, R_{it}) \cdot \Pr[M_{it} | X_{it-1}, R_{it-1}],$

where $\mathrm{f}(H_{it} \mid X_{it-1}, R_{it})$ denotes the conditional density of observed health. The fact that respondents in the HRS are obviously alive when they enter the sample, has to be taken into account when integrating out the latent health process since mortality has created a more or less selected sample with respect to R_{it}, depending on the age and other covariates. We follow Heiss (2011) and explicitly derive the distribution of R_{it} conditional on survival to the first wave (S_{i1}) when we do our likelihood calculations. The likelihood contribution then becomes

(3-8) $L_i = \int \cdots \int \mathrm{P}_i\left(R_{i1},...,R_{iT}\right) f\left(R_{i1},...,R_{iT} \left| S_{i1}\right.\right) dR_{i1} \cdots dR_{iT}$

This integral could simply be approximated using Monte-Carlo simulation methods or multivariate numeric integration (Heiss and Winschel 2008). We use the sequential deterministic integration algorithm of Heiss (2008) since it is more accurate and less computational costly for this model class.

Mortality selection occurs because the unobserved components of the health and mortality equations are correlated. If the correlation is zero then there is no selection bias. If the correlation is negative then persons with higher health (given X_{it}) will have lower mortality and will be less likely to leave the sample via death. The covariance between unobserved components of the health and mortality equations (3-3 and 3-5) is:

$$Cov\left[R_{it-1}\gamma_H + e_{it-1}, R_{it-1}\gamma_M + v_{it}\right] = \sigma_R^2 \gamma_H \gamma_M \ ,$$

The correlation between the unobserved components is:

$$\frac{\sigma_R^2 \gamma_H \gamma_M}{\sqrt{\left(\sigma_R^2\gamma_H^2 + \sigma_e^2\right)}\sqrt{\sigma_R^2\gamma_M^2 + \sigma_v^2}} = \frac{\gamma_H \gamma_M}{\sqrt{\left(\gamma_H^2 + \sigma_e^2\right)}\sqrt{\gamma_M^2 + \sigma_v^2}}$$

Section 4. Results

Joint Estimation Results: Results from the joint estimation of equations 3-3 and 3-6 are shown in Table 4-1a for women and Table 4-1b for men. Both equations include the same set of X_{it} covariates: 1) an age spline with breakpoints at ages 60, 70, 80 and 90, 2) a set of race-ethnicity indicators (the omitted group is white-non-Hispanic), 3) indicator variables for the level of education attained (the omitted category is less than a high school degree), and a variable indicating whether the respondent's longest tenure job was blue collar.

Each table shows the estimated coefficients on covariates X_{it} in the health and the mortality equations. The estimates for the mortality equation are the total effects (β_M) described above. (The total effect is decomposed into direct and indirect effects in Tables 4-3a and 4-3b below.) The probit estimates have been converted to marginal effects to make them easier to interpret. For each X_{it} variable we calculate $\frac{\partial P_i}{\partial X_{ij}} = \frac{\partial \Phi(X_i \beta)}{\partial X_{ij}} = \beta_j \phi(X_i \beta)$ and then average over all observations (by gender). The exception to this rule is that we calculate marginal effects of the age spline variables by averaging over observations in the relevant age interval. The probit estimate of γ_M has also been converted to a marginal effect in Table 4-1.

Table 4-1. Joint estimates of health and mortality (marginal effects) for women and for men

Variable	Women				Men			
	Health effects (β_H)		Mortality effects (β_M)		Health effects (β_H)		Mortality effects (β_M)	
	Coeffi-cient	z	Coeffi-cient	z	Coeffi-cient	z	Coeffi-cient	z
Age								
50-59	-1.269	-34.2	0.001	3.5	-1.455	-28.2	0.007	1.9
60-69	-0.986	-31.5	0.002	13.2	-1.121	-30.1	0.029	12.2
70-79	-1.417	-38.3	0.005	18.0	-1.634	-36.0	0.007	16.9
80-89	-2.004	-39.0	0.014	24.2	-2.066	-30.4	0.017	19.4
90+	-1.784	-13.1	0.023	13.9	-2.243	-12.4	0.020	7.3
White Hispanic	-0.533	-0.7	-0.022	-3.7	1.060	1.1	-0.019	-3.2
Non-white non-Hispanic	-6.467	-12.3	0.024	6.7	-3.237	-5.1	0.018	4.8
Non-white Hispanic	-5.674	-4.6	-0.009	-0.9	-0.323	-0.2	-0.015	-1.5
Education								
HS	9.006	16.9	-0.039	-11.5	5.321	8.5	-0.023	-6.4
Some college	11.958	19.3	-0.050	-12.1	7.378	10.2	-0.031	-7.4
college or more	18.206	25.0	-0.073	-14.7	16.545	20.4	-0.065	-14.1
Blue collar	-2.503	-5.2	-0.004	-1.2	-1.785	-3.4	-0.015	-4.8
Intercept	55.769	91.6			65.356	80.1		
σ_e	9.403	205.6			9.442	154.9		
γ_H	25.526	137.4			25.863	117.5		
γ_M	-0.086	-49.2			0.000	-41.6		
ρ	0.941	766.2	N	88,326	0.931	543.9	N	64,812

The estimated marginal effect of the unobserved individual random term R_{it} in the health and mortality equations, γ_H and γ_M respectively, are shown at the bottom of the tables. The effect of the unobserved health component is positive and statistically significant in the health equation (γ_H) and is negative and statistically significant in the mortality equation (γ_M).[1] The estimated autocorrelation parameter (ρ) is greater than 0.93 for both men and women and suggests strong persistence in the unobserved component of health over time. The standard deviation of the measurement error in the health equation (σ_e) is about 9.4 percentile points for both men and women. The correlations between the unobserved components of the health and mortality equation are -0.48 for women and -0.41 for men, verifying the strong mortality selection effect.

Health equation estimates: The effect of age on health is roughly similar for men and women. The estimates imply that health declines between one and 2 percentile points with each year of age. Health declines more rapidly at older ages than at younger ages and the estimated decline is more pronounced for men than for women. The one unexpected pattern is that the estimate for ages 60-69 is slightly lower than the estimate for ages 50-59 for both men and women. The race-ethnicity estimates for women suggest that African-American health is 5.7 percentile points lower than the health of whites (among non-Hispanics). The Hispanic effect is quite small, about ½ of a percentile point less among whites and about one percent less among non-whites. The race-ethnicity effects for men are smaller and less consistent. The non-white effect is -3.2 percentile points for non-Hispanics, but is negligible for Hispanics. The

[1] To understand the estimate of γ_H, recall that $V(H_{it} \mid X_{it}) = Var(R_{it})\gamma_H^2 + Var(e_{it}) = \gamma_H^2 + \sigma_e^2$. The measurement error has mean zero and the estimated standard deviation is 9.40 for women and 9.44 for men. The estimate of λ_H is 25.53 for women and 25.86 for men. The standard error of σ_e is approximately 9.4, so a one standard deviation change in e_{it} will change H by 9.4. The unobserved random term R is distributed N(0,1). Thus a one standard deviation change in R (a one unit change) will change H by $R_{it}\gamma_H$ and is approximately 25. Then $V(H_{it} \mid X_{it}) = \gamma_H^2 + \sigma_e^2$=625 + 88.36 = 713.36. Thus 87.6% of the unobserved variation in health given the covariates X is explained by unobserved health R and 12.4% by measurement error e.

education-health gradient is large and statistically significant for both men and women. For women, the health percentile of persons with a college degree or more is 18.2 points higher than the health percentile of persons with less than a high school degree (the omitted category). The difference for men is 16.5 percentile points. Primary employment on blue collar jobs is associated with lower health for both men and women. Although statistically significant, the estimates are much smaller than the estimated effects of education. Controlling for other covariates, the estimates for a blue collar job are -2.5 and -1.8 percentage points for women and men respectively.

Mortality equation estimates: The columns on the right side of Tables 4-1a and 4-1b show the marginal effect of each X variable on the probability that a respondent dies between the waves. These are the total (reduced form) effects from Equation 3-4. For women, mortality increases sharply with age—by one-tenth of one percent for each year of age between 50 and 59 and by about 2.3 percent for each year of age above 90. The probability of death for men is greater than for women between ages 50 and 59 but lower than the probability for women at older ages. The one anomaly for which we have no explanation is the high (2.9 percent) estimate for men in the 60 to 69 age interval. For both men and women, non-whites have higher mortality than whites and Hispanics have lower mortality than whites. That Hispanics have lower income and education than whites but live longer is known as the “Hispanic paradox” in the demographic literature (Scommegna 2013).

While primary employment on blue collar jobs is associated with lower health for both men and women, the relationship to mortality is different for men and women. Controlling for education and other covariates, blue collar employment has little effect on mortality for women. However, a blue collar job is associated with a 1.5 percent *decline* in the probability of dying for men. As with health, however, the effect of education on mortality is much greater than the effect of a blue collar job on mortality for both men and women. The difference in mortality of persons with less than a high school degree and those with a college degree or more is -7.3 percent for women and -6.5 percent for men; the effect of a blue collar job is -0.4 percent for women (and not statistically significant) and -1.5 percent for men.

Joint Versus Single Equation Estimates of the Health Equation: The joint estimates of health and mortality shown above "correct' the parameter estimates in the health equation for mortality selection. Table 4-2 below reproduces these estimates and also shows single-equation estimates of the health equation. The key comparison is the estimated effect of age on health. For both men and women the estimated decline in health with age is greater in the two-equation model than in the single-equation counterpart. This is consistent with mortality selection leading to an empirical health-age profile of survivors that declines less rapidly than the true decline in health with age. The joint estimates are slightly lower than the single equation estimates for most of the other covariates.

Table 4-2. Comparison of joint and single-equation estimates of parameters of the health equation

	women				men			
	joint estimates		single equation estimates		joint estimates		single equation estimates	
variable	coef-ficient	z	coef-ficient	z	coef-ficient	z	coef-ficient	z
Age								
50-59	-1.269	-34.2	-0.982	-20.3	-1.455	-28.2	-1.002	-15.8
60-69	-0.986	-31.5	-0.657	-19.1	-1.121	-30.1	-0.757	-19.4
70-79	-1.417	-38.3	-0.791	-20.1	-1.634	-36.0	-0.961	-21.2
80-89	-2.004	-39.0	-1.262	-22.8	-2.066	-30.4	-0.925	-12.5
90+	-1.784	-13.1	-0.476	-3.6	-2.243	-12.4	-0.666	-2.9
White Hispanic	-0.533	-0.7	-1.470	-3.9	1.060	1.1	0.726	1.7
Non-white non-Hispanic	-6.467	-12.3	-5.689	-23.7	-3.237	-5.1	-1.737	-5.8
Non-white Hispanic	-5.674	-4.6	-5.848	-9.8	-0.323	-0.2	-0.107	-0.2
Education								
HS	9.006	16.9	7.778	32.9	5.321	8.5	4.826	17.1
Some college	11.958	19.3	10.730	38.9	7.378	10.2	6.573	20.1
college or more	18.206	25.0	16.453	53.3	16.545	20.4	14.546	43.1
Blue collar	-2.503	-5.2	-2.398	-10.8	-1.785	-3.4	-2.213	-9.4
Intercept	55.769	91.6	54.162	124.9	65.356	80.1	63.129	107.8
σ_e	9.403	205.6			9.442	154.9		
γ_H	25.526	137.4			25.863	117.5		
γ_M	-0.573	-49.2			-0.486	-41.6		
ρ	0.941	766.2			0.931	543.9		
R^2			0.171				0.148	
N	88,326		88,326		64,812		64,812	

The Direct and Indirect Effect of Covariates and Unobserved Health on Mortality: The estimated coefficients in the mortality equation (β_M and γ_M) capture the "total" (reduced form) effect of the covariates X and unobserved health R on mortality. Recall that we can decompose the total effect of each of the X covariates into its direct effect on mortality ($\tilde{\beta}_M$) and the indirect effect through health ($\beta_H\tilde{\gamma}_M$). We can also estimate the direct and indirect effects of R on mortality ($\tilde{\gamma}_M$ and $\gamma_H\tilde{\gamma}_M$). The first column of Table 4-3a (for women) and Table 4-3b (for men) reproduces the total effects (probit estimates converted to marginal effects) of each X variable on mortality from Table 4-1.

The next two columns show the calculated direct effects and the indirect effects (through health) for each of the X variables.

Table 4-3a. Estimated effects of X variables on mortality for women - total, direct, and indirect (through health) effects

Variable	Total Effect (β_M)		Direct Effect ($\tilde{\beta}_M$)		Indirect Effect ($\beta_H \tilde{\gamma}_M$)	
	coeff-	z	coeffi-	z	coeffi-	z
Age						
50-59	0.001	3.5	-0.004	-0.1	0.004	28.4
60-69	0.002	13.2	-0.001	7.5	0.003	26.7
70-79	0.005	18.0	0.000	8.4	0.005	30.5
80-89	0.014	24.2	0.008	11.1	0.007	31.0
90+	0.023	13.9	0.017	7.0	0.006	12.7
White Hispanic	-0.022	-3.7	-0.024	-4.6	0.002	0.7
Non-white non-Hispanic	0.024	6.7	0.002	0.8	0.022	11.9
Non-white Hispanic	-0.009	-0.9	-0.028	-3.2	0.019	4.6
Education						
HS	-0.039	-11.5	-0.009	-3.2	-0.030	-15.9
Some college	-0.050	-12.1	-0.010	-2.8	-0.040	-18.0
college or more	-0.073	-14.7	-0.012	-2.9	-0.061	-22.3
Blue collar	-0.004	-1.2	-0.013	-4.1	0.008	5.2

Table 4-3b. Estimated effects of X variables on mortality for men - total, direct, and indirect (through health) effects

Variable	Total Effect (β_M)		Direct Effect ($\tilde{\beta}_M$)		Indirect Effect ($\beta_H \tilde{\gamma}_M$)	
	coeff-	z	coeffi-	z	coeffi-	z
Age						
50-59	0.007	1.9	0.003	-1.5	0.004	23.5
60-69	0.029	12.2	0.026	6.5	0.003	24.6
70-79	0.007	16.9	0.002	7.8	0.004	27.4
80-89	0.017	19.4	0.011	10.0	0.006	24.7
90+	0.020	7.3	0.014	2.3	0.006	12.0
White Hispanic	-0.019	-3.2	-0.016	-3.1	-0.003	-1.1
Non-white non-Hispanic	0.018	4.8	0.009	2.9	0.009	5.0
Non-white Hispanic	-0.015	-1.5	-0.016	-1.8	0.001	0.2
Education						
HS	-0.023	-6.4	-0.008	-2.8	-0.015	-8.3
Some college	-0.031	-7.4	-0.011	-3.1	-0.020	-9.8
college or more	-0.065	-14.1	-0.020	-5.1	-0.045	-18.1
Blue collar	-0.015	-4.8	-0.020	-7.6	0.005	3.4

For the most part each covariate has both direct and indirect effects on mortality. Perhaps the most striking result of the decomposition is for education. The total effect of education on mortality is quite substantial for both men and women, but the direct effect is small; most of the effect of education on mortality is indirect (through the effect of education on health). For women, between 77.3 and 84.4 percent of the total effect of education on mortality is through health; for men between 64.3 and 69.7 percent is through health. It is also striking that the lower mortality of Hispanics (the Hispanic paradox) is almost exclusively a direct effect. The indirect effect through health is small and not statistically significant for either men or women. As noted above, a surprising result is that controlling for education and other covariates, blue collar employment has little effect on mortality for women but is associated with a 1.5 percent *decline* in the probability of dying for men.

Section 5 Simulations: Model Fit, Mortality Selection and Health Dynamics

We use simulations to verify the model fit, to describe the measurement of mortality selection, and to demonstrate the dynamic properties of health.

The Model Fit: We perform several simulations to assess the fit of the model. Each simulation is based on 1,000 replications for each person in the original HRS data set. Health-age profiles for each replicated person are simulated from age 50 until death. The race/ethnicity, education and occupation variables remain constant over time. To simulate the unobserved components at age 50 we draw u_{it} from its estimated distribution with mean zero and variance $(1-\rho^2)$ and draw υ_{it} from its estimated distribution with mean zero and unit variance. As we simulate forward we make new draws of u_{it} and υ_{it} from their respective distributions to generate the latent process R_{it}. The simulation yields a value for H_{it} and a probability of death, $\Pr[M_{it}=1 \mid X_{it}, R_{it}]$, in each period. At each age persons are randomly dropped from the sample with probability $\Pr[M_{it}=1 \mid X_{it}, R_{it}]$.

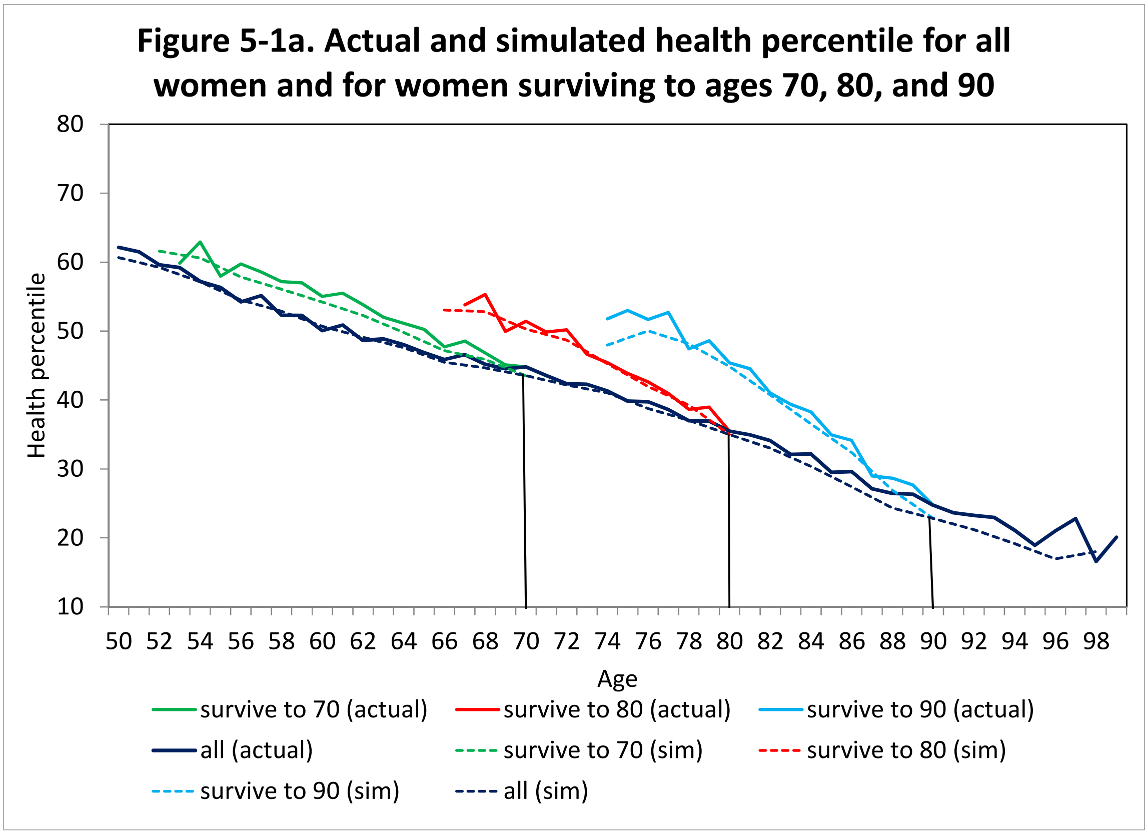


Figure 5-1a. Actual and simulated health percentile for all women and for women surviving to ages 70, 80, and 90
Health percentile
80
70
60
50
40
30
20
10
50 52 54 56 58 60 62 64 66 68 70 72 74 76 78 80 82 84 86 88 90 92 94 96 98
Age
survive to 70 (actual)
survive to 80 (actual)
survive to 90 (actual)
all (actual)
survive to 70 (sim)
survive to 80 (sim)
survive to 90 (sim)
all (sim)

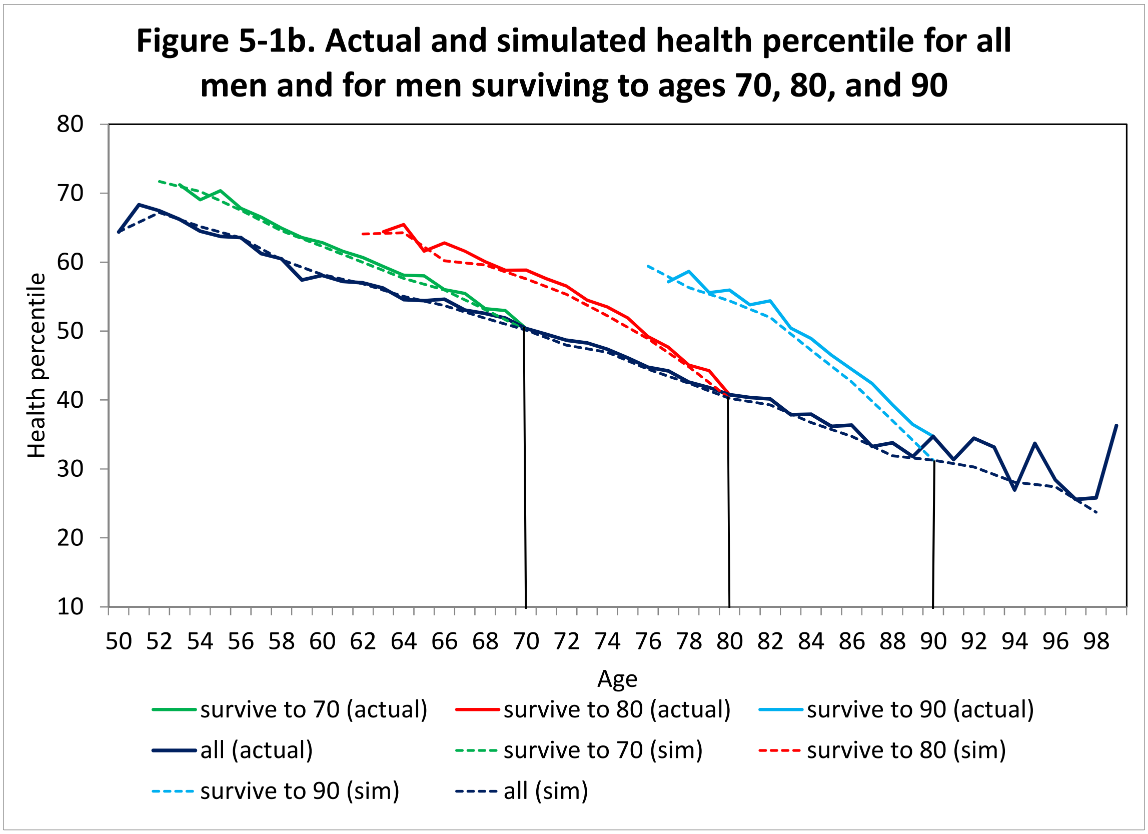


Figure 5-1b. Actual and simulated health percentile for all men and for men surviving to ages 70, 80, and 90
Health percentile
80
70
60
50
40
30
20
10
50 52 54 56 58 60 62 64 66 68 70 72 74 76 78 80 82 84 86 88 90 92 94 96 98
Age
survive to 70 (actual)
survive to 80 (actual)
survive to 90 (actual)
all (actual)
survive to 70 (sim)
survive to 80 (sim)
survive to 90 (sim)
all (sim)

Figure 5-2a. Actual and simulated mortality rate for women

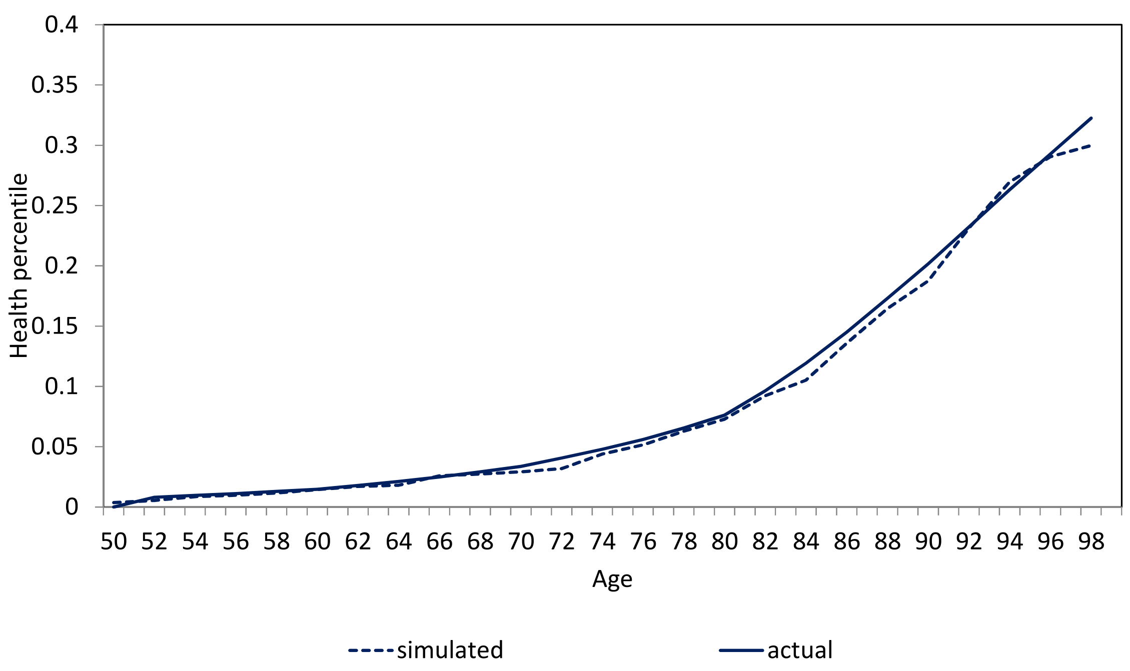
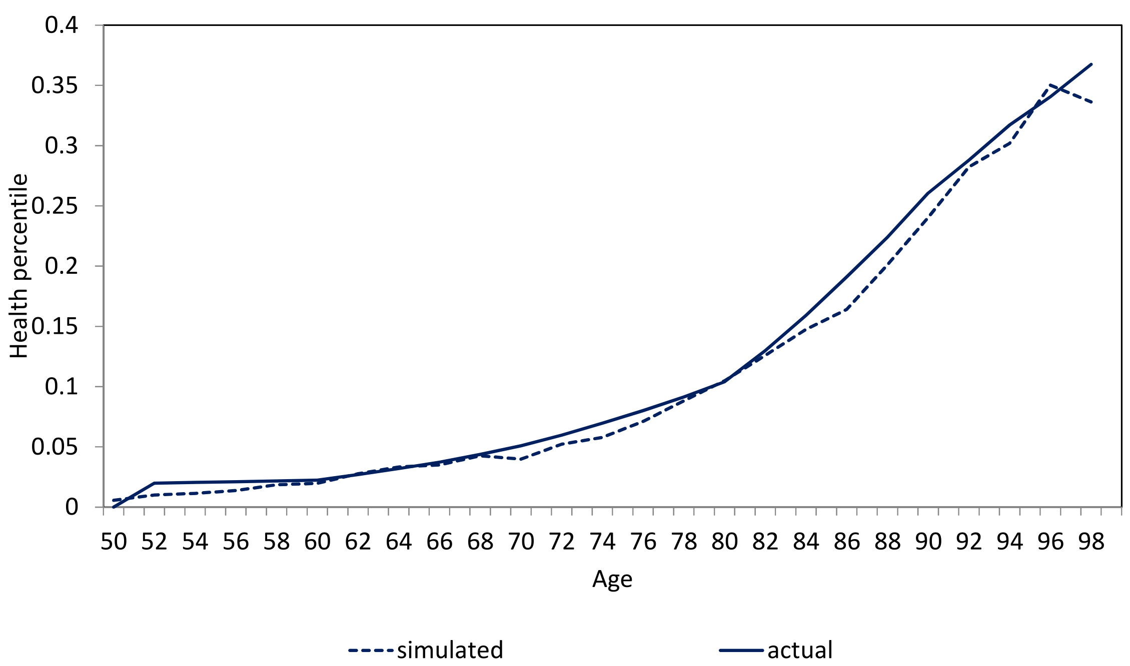


Figure 5-2b. Actual and simulated mortality rate for men



To show the model fit we have "reproduced" by simulation Figure 1-1 that shows the average health percentile at each age based on HRS data. Figures 5-1a and 5-1b below compare the observed health profile with the simulated profile for men and women respectively. The figures compare both the average age-health profile (labeled "all") as well as the prior health profiles of persons who survived to age 70, to age 80, and to age 90. The actual and the simulated profiles correspond very closely.

Figures 5-2a and 5-2b compare actual and simulated mortality rates by age for women and men respectively. The actual mortality rates come from the Social Security period life table for 2007. Again, the two profiles correspond quite closely.

Measuring Mortality Selection: We emphasized above the two distinct processes that determine observed age-health profiles—the first is that persons become less healthy as they age and the second, the selection effect, is that the least healthy are more likely to die and leave the sample. Simulations based on our model can help to understand the magnitude of the selection effect as well as other implications of mortality selection. The observed age-health profile of survivors is the sum of the effects of these two processes and is given by $H_{it} = X_{it}\beta_H + R_{it}\gamma_H + e_{it}$, where the measurement error e_{it} has mean zero at all ages. This profile is shown by the heavy solid line in Figure 5-3a (women) and Figure 5-3b (men). This is the simulated value of H_{it} for persons who have survived to each age and is the same profile shown earlier as the fitted lines in Figures 5-1a and 5-1b. The blue dashed profile in these figures is the average value of the unobserved component $R_{it}\gamma_H$ of the health of survivors and measures the extent of mortality selection. The first process—the decline in health with age—is shown by the dashed red line which is H_{it} minus the unobserved component R_{it} . This is the mortality corrected age-health profile. By age 80 the observed age-health profile understates the decline in health by about 8.8 percentile points for women and 10.7 percentile points for men.

Figure 5-3a. Simulated components of the observed health-age profile for women

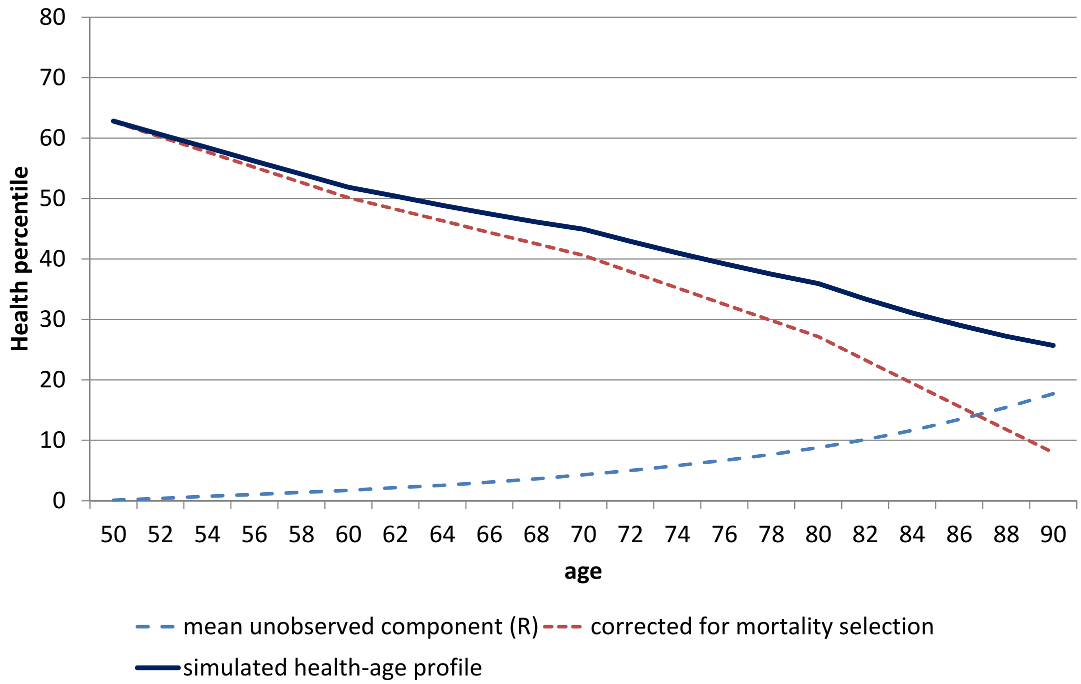
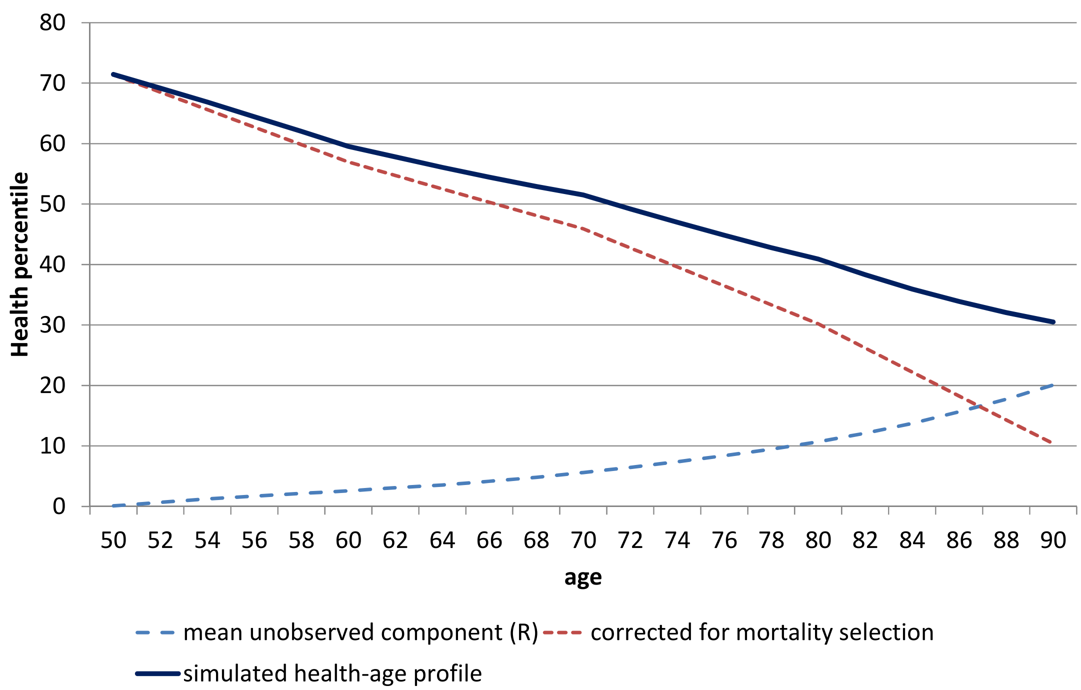


Figure 5-3b. Simulated components of the observed health-age profile for men



By assumption R_{it} has mean zero at age 50 (before mortality selection begins). This unobserved health component increases with age because persons with large negative values of R_{it} are more likely to die and leave the sample. The red dashed line shows the evolution of the observed component $X_{it}\beta_H$. Note that this description implies that the health-age profile is corrected for selection on the *unobserved* component of health, but not for selection on *observed* covariates X_{it}. We also correct for selection on observables by reweighting. Without reweighting, the simulated sample of survivors would include (for example) proportionately more highly educated persons at older ages because more highly educated persons are more likely to survive. To keep the composition of the sample constant over time—thus correcting for selection on observables—we do not update the weights during the simulation.[2] It turns out that almost all of the mortality correction is due to the unobserved component. The effect of selection on observables is negligible—less than one percentile point at age 80 for both men and women.

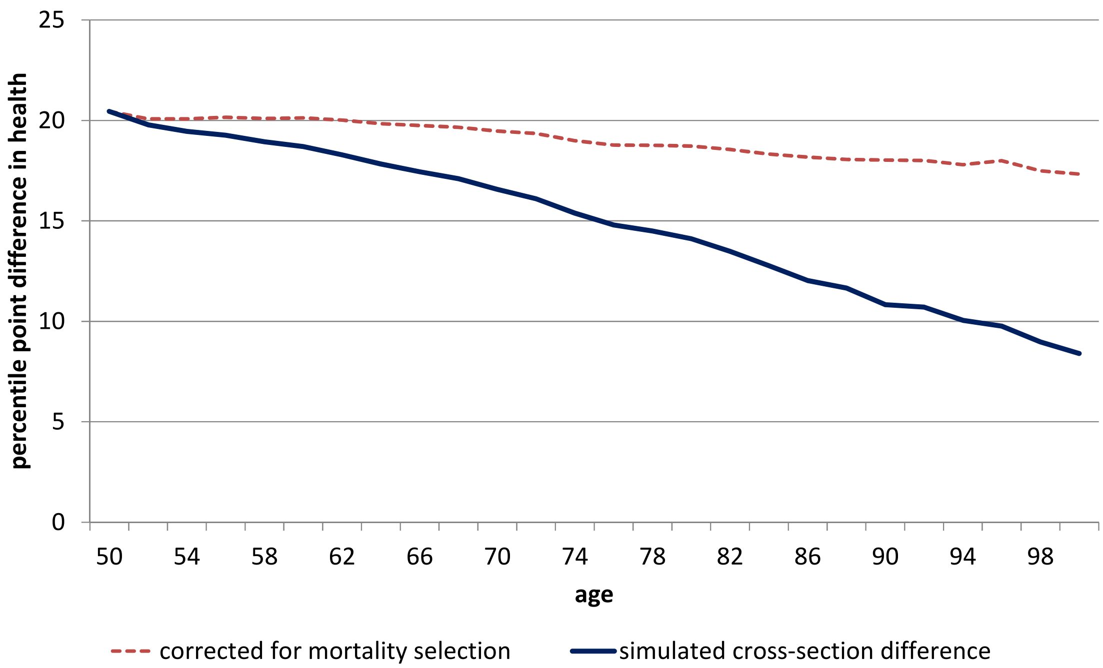
Mortality selection also distorts estimates of health differences by age. Consider observed health differences by level of education at each age. The solid blue line in Figure 5-4 shows the observed difference at each age between the health percentile of persons (averaged over gender and race) with a college degree and the health percentile of persons without a high school degree. The figure shows that at age 50 the average health of college graduates is over 20 percentile points higher than the average health of otherwise identical persons without a high school degree. This gap narrows to about 10 percent by age 90 -- suggesting that the health of less educated persons is declining more slowly than the health of more educated persons. However, much of the narrowing of the gap is the result of mortality selection, not changes in true health. The less educated are more likely to die, thus at each age the effect of mortality selection is

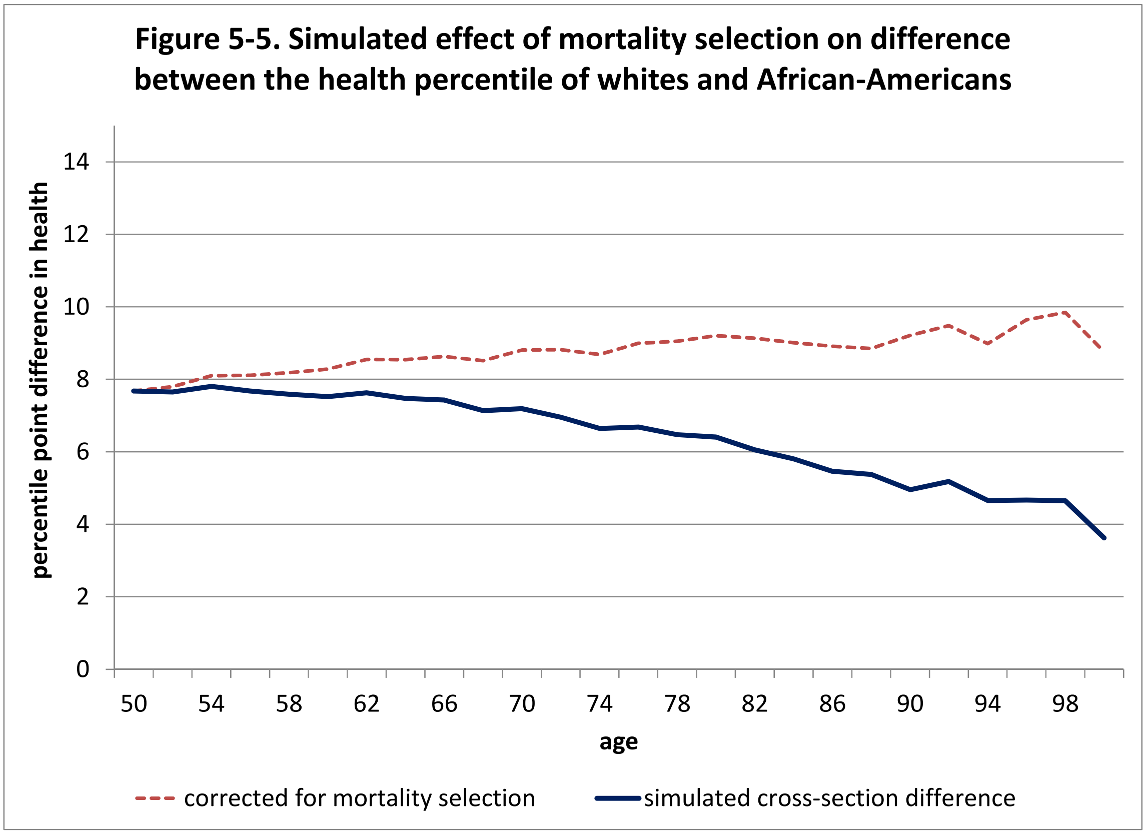
[2] We simulate health at each age for each of 64 groups defined by race, ethnicity, education and occupation, beginning at age 50. The simulated profiles in Figures 5-3a and 5-3b are weighted averages (for each of the three series shown) of the 64 groups at each age. Simulated profiles corrected for selection on unobservables can be obtained by using weights that update the initial (age 50) weights with simulated mortality risks. Simulated profiles corrected for observables and unobservables (shown in the figures) are obtained by using weights that are not updated.

greater for the less educated than for the more educated. The health difference corrected for mortality selection is shown by the dashed line in Figure 5-a. This difference declines modestly from 20 percent at age 50 to about 18 percent at age 90.

Figure 5-5 shows the age profile of the difference between the health percentile of whites and the health percentile of African-Americans, averaged over gender and education. Again, the solid line is the observed difference in health by age and the dashed line is the difference corrected for mortality selection. Based on the observed profile, the health of whites is about 8 percentile points greater than the health of blacks at age 50. By age 90 the gap is only 5 percentile points. This narrowing of the gap might be interpreted as evidence that black health is declining more slowly than the health of whites. However, as the dashed line indicates, when corrected for mortality selection, the health of blacks is declining more rapidly than health of whites. The true gap widens with age, but mortality selection is strong enough to give the appearance of a narrowing of the observed gap.

Figure 5-4. Simulated effect of mortality selection on difference between the health percentile of persons with a college degree or more and persons without a high school degree





Health dynamics: The unobserved component of health is specified as the sum of an AR(1) process and pure measurement error: $R_{it} = \rho R_{it-1} + u_{it}$ where u_{it} is an independent shock to health each period. The estimated values of ρ are 0.94 and 0.93 for women and men respectively and indicate substantial persistence in health. Figures 5-6a and 5-6b show how a health shock (u_{it}) that occurs in mid-life affects the level of health and the probability of survival at older ages. Consider a white man with a high school degree and a blue collar job. Profiles associated with three health shocks at age 50, corresponding to the 50th (solid line) and the 10th and 90th percentiles (dashed lines) of the distribution of u_{it} are shown. Figure 5-6a shows that a large negative health shock at age 50 can have long-lasting effects. A shock at the 10th percentile rather than the 90th percentile lowers health by almost 45 percentile points at age 60 and by over 16 percentile points at age 80. Figure 5-6b shows the effect of the same shocks on the probability of survival. A person receiving a 90th percentile shock at age 50 has an 82 percent probability of living to age 74 but an otherwise identical person receiving a 10th percentile shock at the same age has only a 45 percent probability of living to age 74.

Figure 5-6a. Simulated effect of health shocks at age 50 (10th, 50th and 90th percentile) at age 50 on the evolution of health

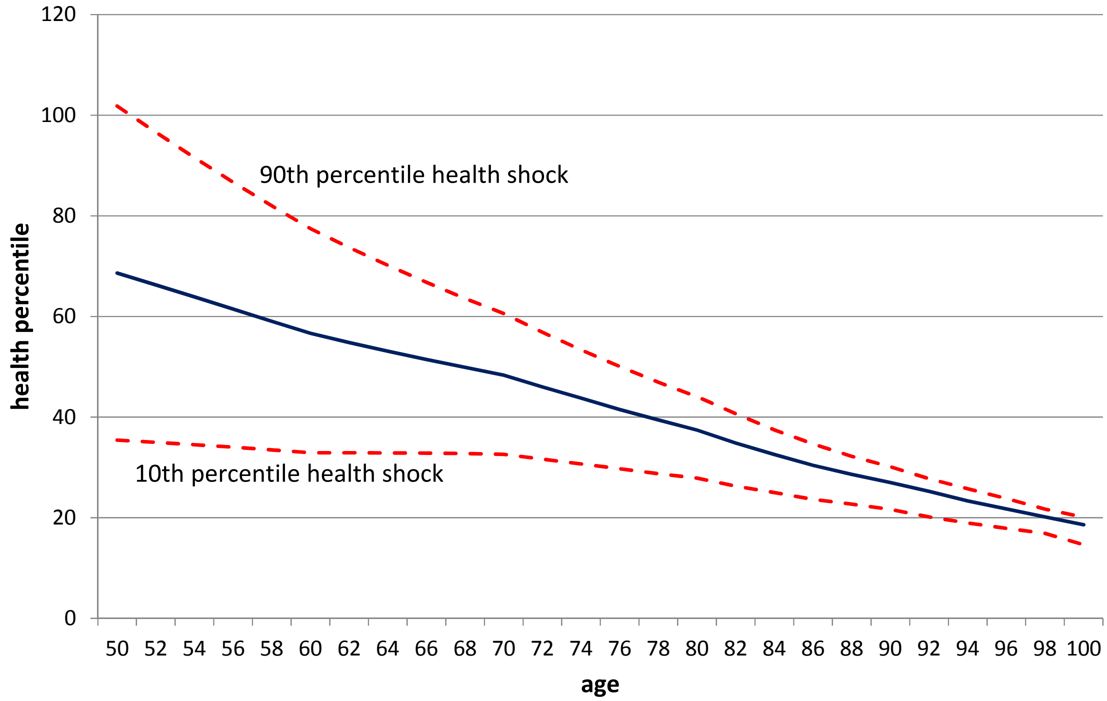
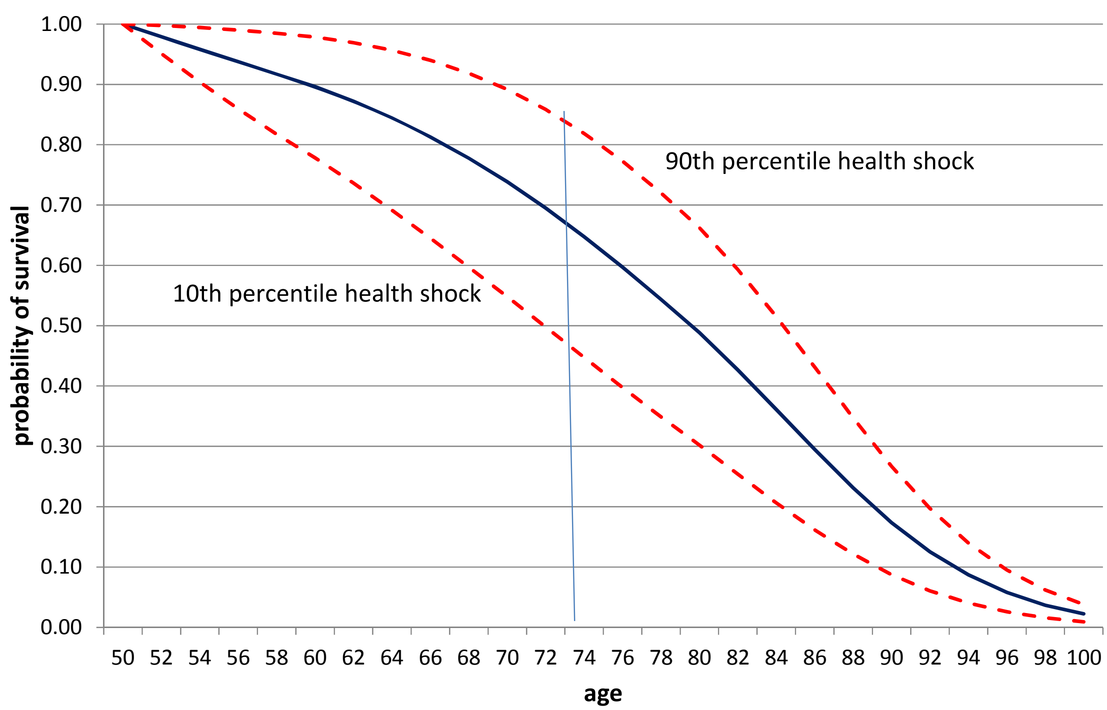


Figure 5-6b. Simulated effect of health shocks at age 50 (10th, 50th and 90th percentile) at age 50 on the probability of survival

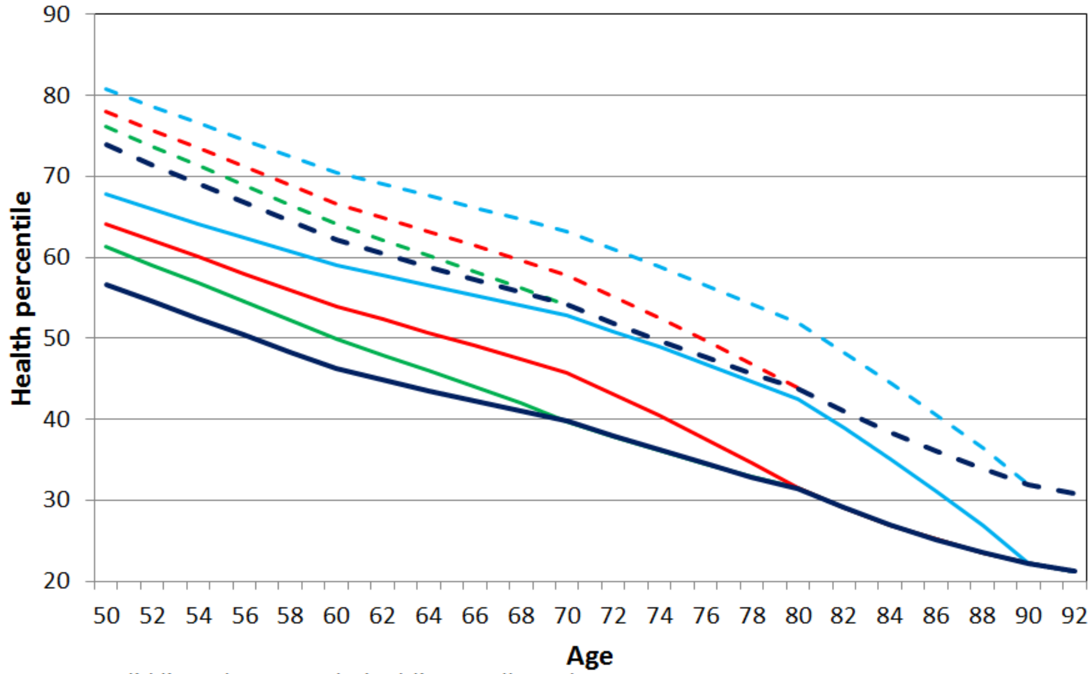


Section 6 Simulations: Level of Education, Racial and Ethnic Groups, and the Persistence of Health

We consider first how health differences at age 50 persist by level of education. We then consider the persistence of health among groups of persons classified by level of education and race-ethnicity. The comparisons are all based on age-health profiles by education level and by racial-ethnic group. Figures 5-1a and 5-1b above show the fit of the model to observed data and, in particular, to the observed data for persons surviving until age 70, age 80, and age 90. To obtain the age-health profiles for this section we use our model to back-cost survival profiles to age 50 for education and race-ethnic groups.

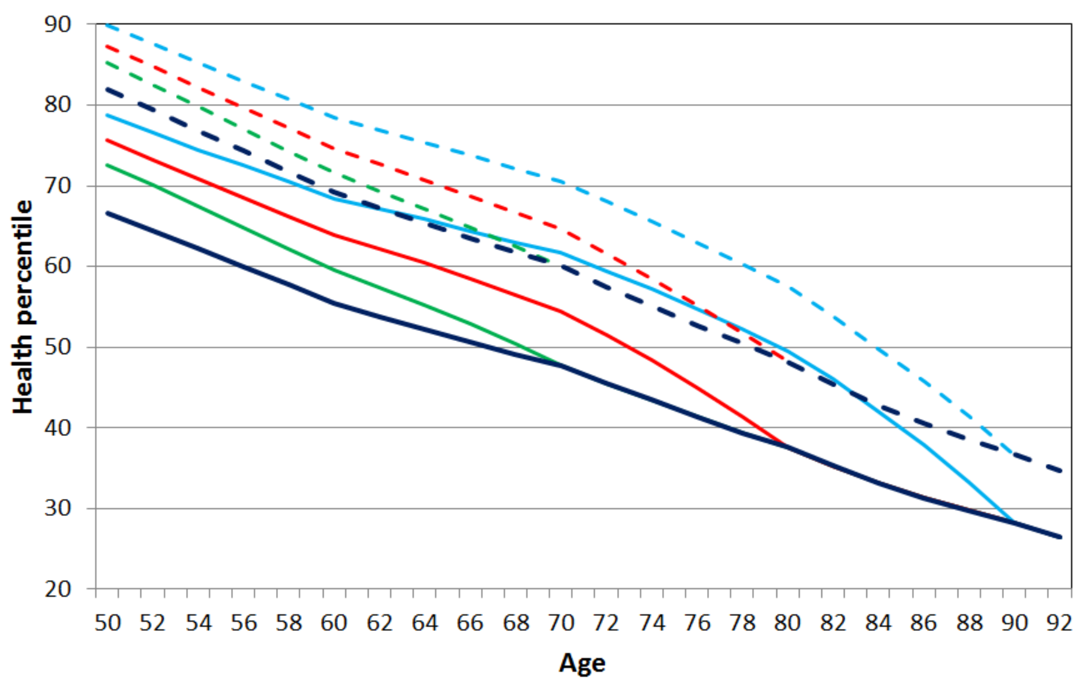
Education and Health: The simulated age-health profiles of men and women with less than a high school degree and those with a college degree or more are shown in Figures 6-1a and 6-1b for women and men respectively. These and subsequent figures in this section pertain to persons in white collar occupations. The health of persons who survive to age 50 is shown by the value at age 50 of the heavy solid line in each of the panels in the figures. Within each level of education the health differences that are evident at age 50 in the profiles for the groups that survive to 50, 70, 80, and 90 persist over the entire age range. In addition the initial health differences between the profiles of those with less than a high school degree and of those with a college degree or more persist throughout the age range. For example, the difference at age 50 between those with less than a high school degree who will survive until age 90 and those with a college degree who with survive until age 90 persists until age 90, although the gap narrows as persons in each group age. Within each level of education the figures also show a widening in the health gap between survival profiles with age. The widening is especially apparent for those with less than a high school degree where, for example, the difference between the health profiles of women who survive to age 80 and women who survive to age 90 doubles from 3.6 percentile points at age 50 to 7.2 percentile points at age 70. The health of those who live longer declines less rapidly with age.

Figure 6-1a. Simulated health percentile for all women and for women survivors to ages 70, 80 and 90 by level of education.



Solid lines--less <HS; dashed lines--college degree or more

Figure 6-1b. Simulated health percentile for all men and for men survivors to ages 70, 80 and 90 by level of education.



Solid lines-- <HS, dashed lines--college degree or more

Racial-Ethnic Group, Education, and Health: We next consider how health profiles differ by race and ethnicity and then turn to profiles by race-ethnicity and level of education. Figure 6-2a shows health profiles for women by racial-ethnic group. There are substantial differences in the profiles by racial-ethnic group at age 50 and these differences persist into old age. The highest profile is for white and non-Hispanic (with health at age 50 between the 69th and 77th percentile for the four survival groups) and the lowest is for non-white and Hispanic (with the profiles between the 56th and 66th percentiles). The profile for white and Hispanic and for non-white and non- Hispanic are quite similar and lie between the other two groups.

Figure 6-2a. Simulated health percentile for all women and for women survivors to ages 70, 80 and 90 by race/ethnicity

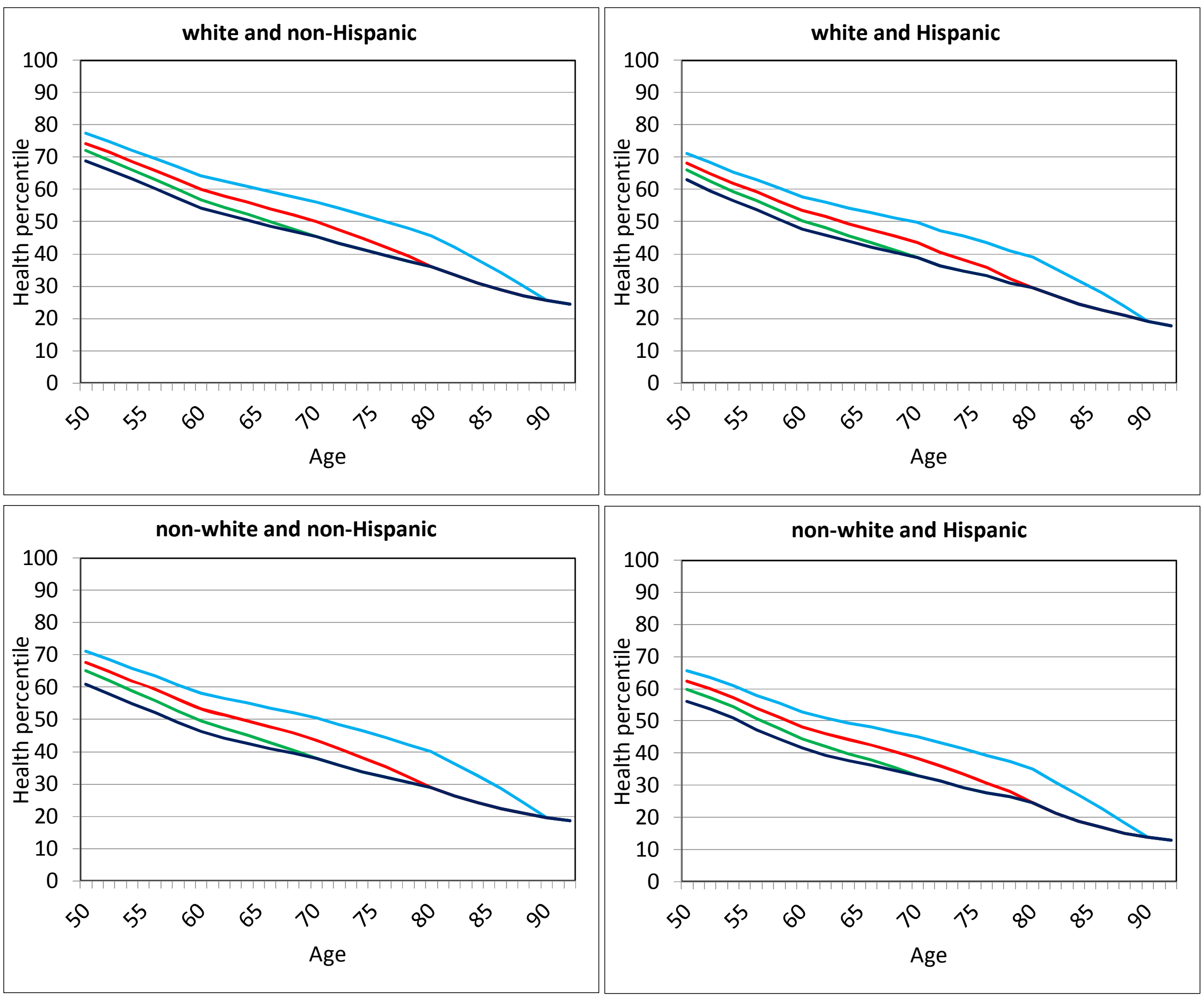


Figure 6-2b. Simulated health percentile for all women and for women survivors to ages 70, 80 and 90 by race/ethnicity and level of education

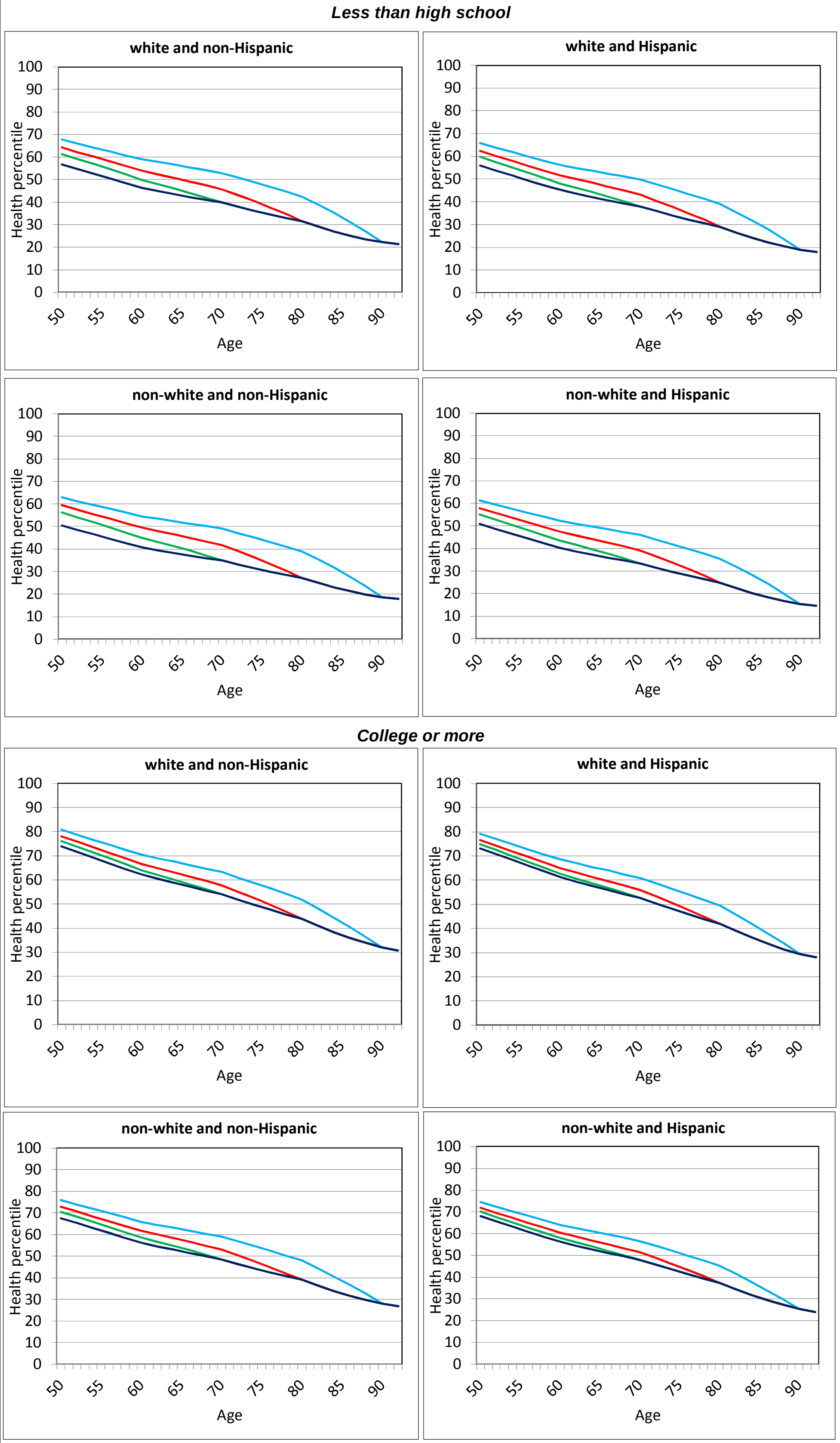
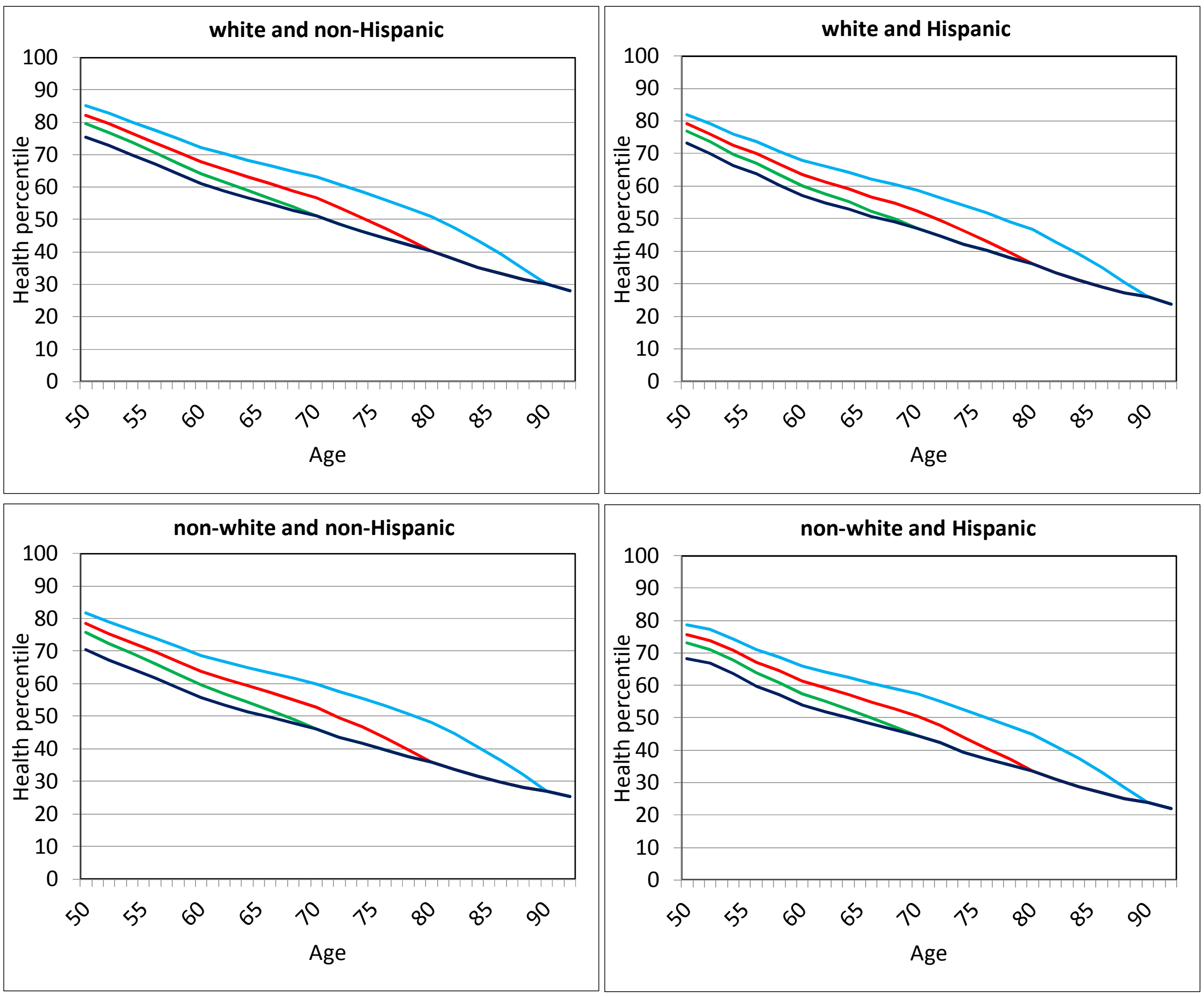


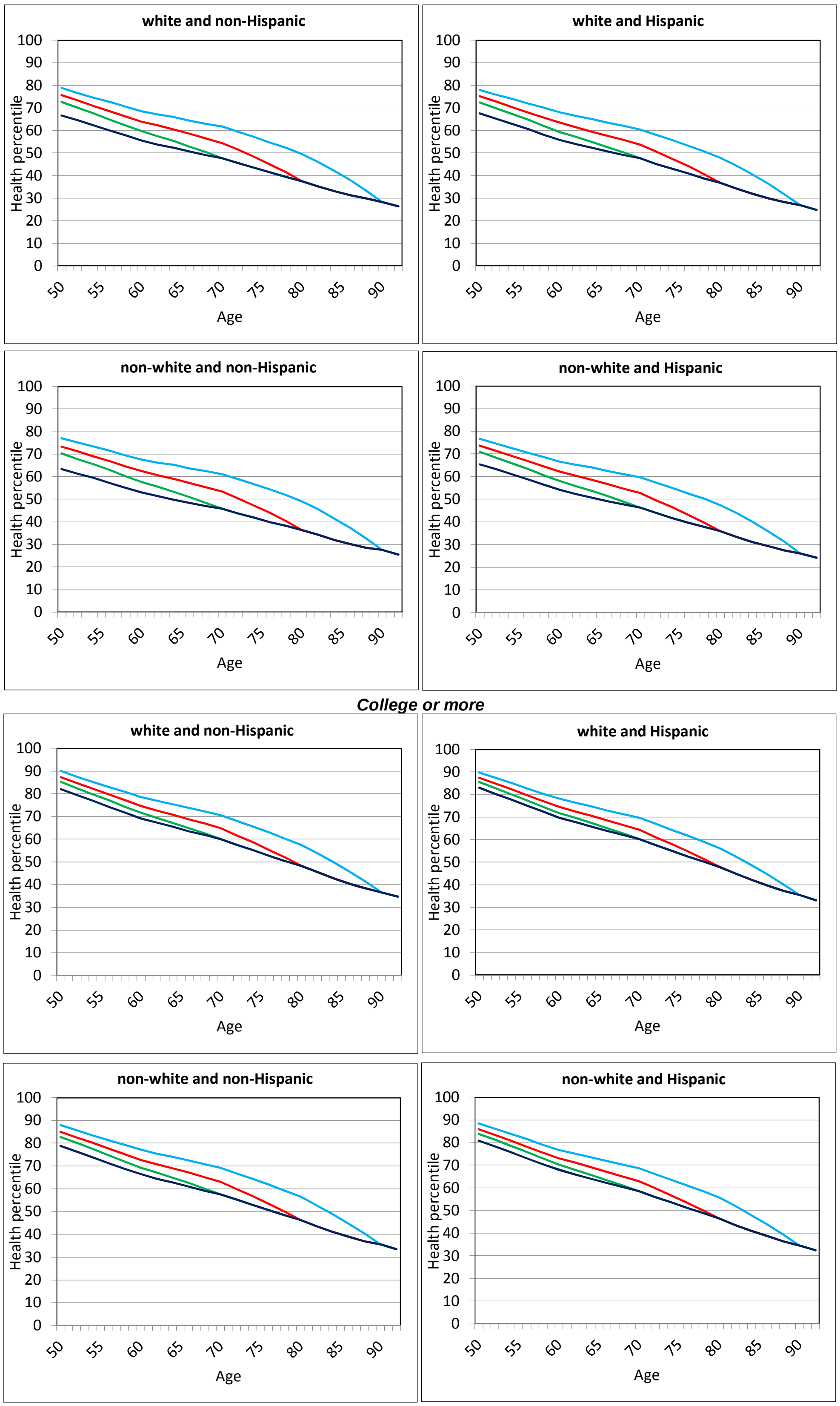
Figure 6-2b shows profiles for the same racial-ethnic groups for two of the levels of education. The top four panels show profiles for persons with less than a high school degree and the bottom four panels show profiles for persons with a college degree or more. Within each racial-ethnic group the profiles are substantially higher for those with a college degree or more than for those with less than a high school degree. If we look within each level of education, the profiles of the four racial-ethnic groups do not differ by much. This suggests that much of the difference between the health profiles of racial-ethnic groups is accounted for by differences in education between the racial-ethnic groups. Within each level of education some variation between racial-ethnic groups remains, due in large part to differences between the two white and the two non-white groups.

Figure 6-3a. Simulated health percentile for all men and for men survivors to ages 70, 80 and 90 by race/ethnicity



Analogous figures for men are shown in Figures 6-3a and 6-3b. When education is not controlled for (Figure 6-3a) the differences in health percentiles across the four survival groups for men at age 50 are very similar to the differences for women. When education is controlled for (Figure 6-3b), however, there is very little difference remaining in the health profiles for men. Thus for men, the differences among the

Figure 6-3b. Simulated health percentile for all men and for men survivors to ages 70, 80 and 90 by race/ethnicity and level of education



profiles for racial-ethnic group, when education is not controlled for, are also accounted for in large part by differences in education among racial-ethnic groups.

Table 6-1 summarizes some of the key results shown in Figures 6-2 and 6-3. The table shows the health percentile at age 50 for persons who survive to ages 50, age 70 and age 90. (The value for a person who survives to age 50 is the value at age 50 of the heavy solid line in each of the panels in the Figures above.) The table is divided into three panels. The left panel shows health percentiles for persons with less than a high school degree and the middle panel shows values for those with a college degree or more. The panel to the right shows health percentiles for the three survival groups for all levels of education. The bottom section of the table pertains to men and the top portion to women.

Table 6-1. Simulated health percentile at age 50 by gender, level of education and race-ethnic group for persons who survive to age 70 and for persons who survive to age 90

	Survival Age and Level of Education								
	Less than a HS Degree			**College Degree or More**			**All Levels of Education**		
Race and Ethnicity Group	Persons Surviving to Age 50	Persons Surviving to Age 70	Persons Surviving to Age 90	Persons Surviving to Age 50	Persons Surviving to Age 70	Persons Surviving to Age 90	Persons Surviving to Age 50	Persons Surviving to Age 70	Persons Surviving to Age 90
Women									
White and non-Hispanic	56.7	61.4	67.8	73.9	76.2	80.8	68.9	72.0	77.3
White and Hispanic	56.0	59.7	65.7	73.2	74.9	79.1	63.0	65.9	71.2
Non-White and non-Hispanic	50.4	56.1	62.8	67.6	70.5	76.0	60.8	65.0	71.0
Non-White and Hispanic	50.8	55.1	61.4	68.0	70.1	74.5	56.1	59.9	65.7
Men									
White and non-Hispanic	66.6	72.6	78.8	82.0	85.2	90.0	75.5	79.6	85.0
White and Hispanic	67.6	72.5	78.0	83.0	85.6	89.8	73.2	76.9	82.1
Non-White and non-Hispanic	63.4	70.2	77.1	78.8	82.8	88.0	70.4	75.7	81.7
Non-White and Hispanic	65.5	71.0	76.7	80.9	83.9	88.4	68.3	73.0	78.7

Consider first the far right panel for men. For all men who survive until age 50, the health percentile at age 50 ranges from a high of 75.5 for the white and non-Hispanic group to a low of 68.3 for the non-white and Hispanic group, a 7.2 percentile point difference. For those who survive until age 70, the difference is 6.6 percentile points and for those who survive to age 80 the difference is 6.3 percentile points. For men with less than a high school degree the health percentile difference between the white non-Hispanic and the non-white and Hispanics groups are 1.1, 1.6, and 2.1 percentile points respectively for those who survive to age 50, 70, and 90. For persons with a college degree or more, the differences are 1.1, 1.3, and 1.6 percentile points respectively for those who survive to 50, 70, and 90. Thus for each age of survival, the health gap between the highest and lowest racial-ethnic groups (shown in the right panel) is considerably reduced if education is controlled for. In other words, racial-ethnic differences in the level of education account for between 67 and 84 percent of the overall racial-ethnic health gap, depending on the level of education and the survival group. Note also that rank ordering of the four racial-ethnic groups in some cases differs when the level of education is controlled for, but for ease of exposition the percentage reductions calculated above use differences between the white and non-Hispanic and the non-white and Hispanic throughout.

Race and ethnic differences in health are substantially greater for women than for men as shown in the top right panel. The difference between the health percentiles of the white and non-Hispanic and the non-white and Hispanic groups is 12.9, 12.1, and 11.6 percentile points for the age 50, age 70, and age 90 survival groups respectively. If we control for education, then these ~~ranges~~ differences are reduced by 44 to 55 percent. Again, a large proportion of the racial-ethnic difference in health is accounted for by racial-ethnic differences in educational attainment.

Table 6-2 shows the health percentile at age 70 for persons who survive to ages 70 and 90. Like Table 6-1, the table is divided into three panels but with only two age survival groups in each pane.

Without controlling for the level of education, the range of health percentiles for women is 12.3 and 11.1 percentile points for the age 70 and age 90 survival groups respectively. For men the ranges are only 6.6 and 5.9 percentile points respectively. For women the health percentile ranges are reduced from 38 to 49 percent when education is controlled for. For men, controlling for education reduces the health percentile range across racial-ethnic groups from 66 to 77 percent.

Table 6-2. Simulated health percentile at age 70 by gender, level of education and race-ethnic group for persons who survive to age 70 and for persons who survive to age 90

	Survival Age and Level of Education					
	Less than a HS		College Degree or		All Levels of	
Race and Ethnicity Group	Persons Surviving to Age 70	Persons Surviving to Age 90	Persons Surviving to Age 70	Persons Surviving to Age 90	Persons Surviving to Age 70	Persons Surviving to Age 90
			Women			
White and non-Hispanic	39.8	52.8	54.1	63.3	45.3	56.1
White and Hispanic	38.0	49.8	52.7	60.9	39.9	49.7
Non-White and non-Hispanic	34.9	49.1	48.6	59.1	37.8	50.5
Non-White and Hispanic	33.5	46.0	47.9	56.7	33.0	45.1
			Men			
White and non-Hispanic	47.7	61.7	60.1	70.6	51.1	63.2
White and Hispanic	47.6	60.5	60.2	69.6	47.0	58.8
Non-White and non-Hispanic	45.8	61.2	57.6	69.3	46.2	60.0
Non-White and Hispanic	46.2	59.7	58.6	68.7	44.5	57.3

Section 7 Health, Education, Mortality and the EDPV from a Fair Annuity

A long-standing puzzle for economists is that very few people purchase private annuities; most individuals only receive annuity payments from the Social Security system or employer-provided defined benefit pension benefits. One explanation may be that the length of the payout stream from an annuity may depend heavily on health but the price of an annuity is independent of the potential annuitant's health; the annuity premium typically depends only on age and gender.[3] Thus for many the health risk of a short-lived annuity payout may offset the insurance against outliving assets that an annuity provides. This creates the problem of adverse selection in annuity markets. Persons with short life expectancy—and likely poor health—are unlikely to purchase annuities at a price that is actuarially fair for the *average* person of the same age and gender and will be even less likely to purchase annuities at prices that are even higher due to adverse selection and provider costs and profit.

We calculate the expected present discount value (EPDV) of a fair immediate life annuity by health and level of education for men and women. The EPDV is one of two components used in "money's worth" calculations for annuities. The other component is the premium paid which we do not observe. The money's worth calculation is discussed in Mitchell, Poterba, Warshawsky and Brown (1999). For each person we calculate the EPDV of a $1 annuity with the first payout at age 66, using simulated survival probabilities for men and for women by health decile at age 66 and by education level.[4] These survival probabilities for men and women for those with less than a high school education and for those with a college education or more are shown in Figures 7-1a and 7-1b for men and women respectively. Separate profiles are shown for each decile of health at age 66 (the bottom curve is the lowest health decile). Notice that given health,

[3] In life insurance markets providers go to great lengths to learn about the individual's health, often requiring medical histories, access to medical records, and exams. In annuity markets providers have no information on individual health. The price an individual faces for an annuity typically depends only on age, gender and state of residence.

[4] Given our fitted model, we simulate the evolution of health and mortality starting at age 50 for an artificial population of 100,000 individuals for each of the demographic cells. Those who survive to age 66 are divided into health deciles and followed through the rest of their lives. This allows us to calculate remaining life expectancies and the value of annuities conditional on demographic characteristics and initial health deciles.

survival probabilities vary a great deal by level of education. For example, the figure for men shows that a survival probability of forty percent for those in the lowest health decile occurs at about age 75 (marked by the dashed blue lines). For men with a college degree or more a forty percent survival probability occurs at about age 80. A survival probability of eighty percent for men in the top health decile and with less than a high school degree occurs at about age 80 (the solid blue lines). The same survival probability for men with a college education or more occurs at about age 84. A similar pattern is evident in Figure 7-1b for women.

Figure 7-1a. Survival probabilities for men with less than a high school degree and with a college degree or more by health decile at age 66

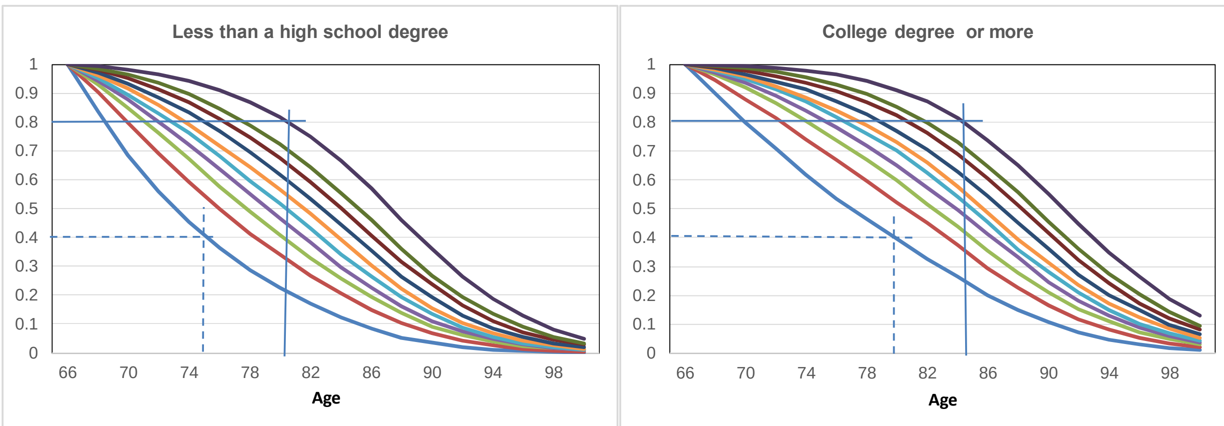
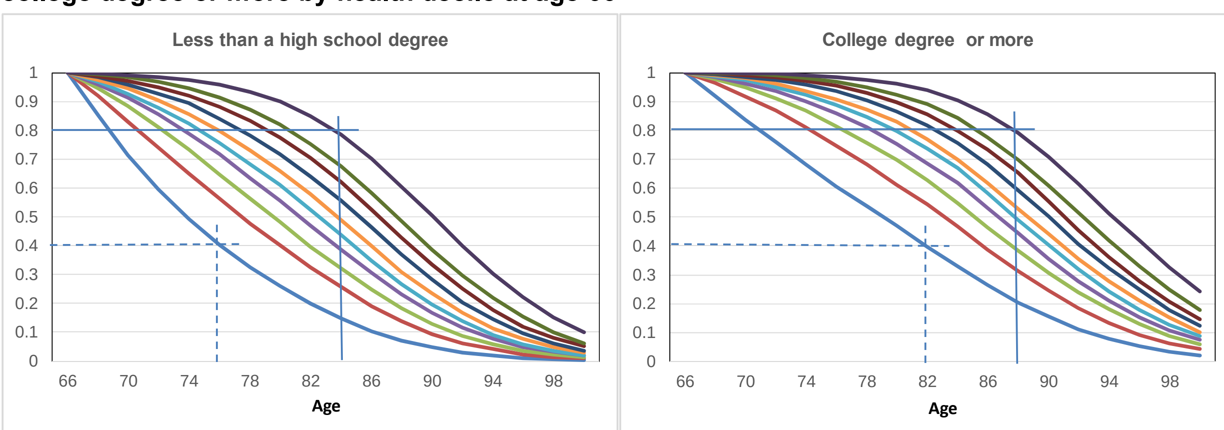


Figure 7-1b. Survival probabilities for women with less than a high school degree and with a college degree or more by health decile at age 66



The EPDV calculation uses survival probabilities like these for each of four education levels and assumes a 3 percent discount rate. Table 7-1 shows these EPDVs by gender, level of education and health decile at age 66. The EPDV ranges from $7.75 for men with less than a high school degree and in the lowest health decile to $17.54 for men with a college degree or more an in the top health decile, a difference of more than two-fold (2.26). For women the EPDV ranges from $8.26 to $18.97. This suggests that potential annuitants will have vastly different valuations of the same annuity simply based on health at age 66. Since all persons of the same age and gender will face the same annuity premium, the scope for adverse selection is enormous.

Table 7-1. Expected discounted present value of an annuity paying $1 each year beginning at age 66, by level of education, gender and health decile at age 66

Level of Education	Health Decile at Age 50									
	1	2	3	4	5	6	7	8	9	10
					Men					
Less than high school	7.75	9.45	10.46	11.14	11.74	12.33	13.03	13.77	14.40	15.64
High school degree	8.43	10.24	11.17	11.91	12.52	13.07	13.83	14.49	15.13	16.28
Some college	8.70	10.54	11.46	12.20	12.85	13.33	14.12	14.76	15.40	16.53
College or more	10.09	11.88	12.88	13.59	14.20	14.64	15.27	16.01	16.55	17.54
					Women					
Less than high school	8.26	10.29	11.40	12.32	12.95	13.62	14.40	15.19	15.86	17.13
High school degree	9.74	11.81	13.01	13.81	14.51	15.02	15.78	16.50	17.09	18.17
Some college	10.18	12.25	13.45	14.28	14.93	15.43	16.17	16.84	17.41	18.44
College or more	11.13	13.21	14.35	15.14	15.77	16.24	16.92	17.50	18.06	18.97

Section 8 Summary

Health at retirement varies enormously among individuals and this variation persists into older ages. Our goal is to understand the source and implications of the variation. To understand how health evolves we need to address two related issues. One is that “true” health is unobserved and is typically proxied by an empirical measure of health--most studies use self-assessed health status. We use a health index based on a broad range of health indicators. In either case empirical measures of health are imprecise proxies for “true” health. Thus given measured health, there remain unobserved differences in health. If this unobserved component of health is large, then understanding the dynamic properties of this component is crucial to the understanding of the evolution of “true” health. The second issue is the mortality selection that arises because healthier persons are more likely to survive to older ages. A well-known consequence of mortality selection is that health-age profiles (calculated from the average health of survivors at each age) do not indicate how the health of an individual (or a subset of individuals) evolves. In particular, observed health-age profiles of survivors substantially underestimate the true decline in health with age.

A central component of our analysis is the development and estimation of a model that addresses each of these issues. The key feature of the model is joint estimation of health and mortality. An important input to the model is the health index developed by Poterba, Venti, and Wise (2013) that uses substantially more information than a simple self-reported health measure. The index is based on a wide range of questions concerning functional limitations, health conditions, and medical care usage obtained in the Health and Retirement Study (HRS). The model assumes that "true" health is the sum of measured health (the index) and an unobserved health component that is allowed to persist over time. The model yields estimates of the relationship between a set of covariates (age, race, ethnic group, education, and blue collar employment) and health and mortality. Estimates are obtained separately for men and women.

A comparison between estimates from the joint health-mortality model and estimates from a conventional single equation health model shows that mortality selection is important. The estimated effect of most of the covariates on health is larger in the joint health-mortality model. In particular, the estimated effect of education is quite large. Controlling for other covariates, the estimated difference between the health percentile of persons with a college degree or more and those with less than a high school degree is 18.2 percentage points for women and 16.5 percentage points for men. Primary employment on blue collar jobs is associated with lower health for both men and women but the effects are much smaller than the education effects. The health percentile of whites is estimated to be 5 to 6 percentile points higher than that of non-whites. The Hispanic effect is small and not statistically significant.

Each covariate can affect mortality in two ways: either directly or indirectly through its effect on health. The total effect of each covariate is the sum of the direct and indirect effects. Again, the most striking result is the decomposition into direct and indirect effects for education. The total effect of education on mortality is substantial for both men and women, but most of the effect of education on mortality is through the effect of education on health (that is, education has a strong effect on health and health has a strong effect on mortality). For women, between 77.3 and 84.4 percent of the total effect of education on mortality is through health, depending on the education level; for men between 64.3 and 69.7 percent is through health. The estimated effect of blue collar employment on mortality is perhaps surprising. Controlling for education and other covariates, blue collar employment has little effect on mortality for women but is associated with a 1.5 percent *decline* in the probability of dying for men.

Most of the key results are shown by simulations that illustrate the range of issues that can be addressed using the model. The first simulations verify the model fit, describe the measurement of mortality selection, and demonstrate the dynamic properties of health. The model fits actual HRS health and actual mortality data (life tables) extremely well. Simulations are also used to demonstrate the magnitude of mortality selection. For example, based on observed profiles, the health of whites is about 8 percentile points greater than the health of blacks at age 50 but by age 90 the gap is only 5 percentile points. This narrowing of the gap might be interpreted as evidence that black health is declining more slowly with age than the health of whites. However, when corrected for mortality selection, the health of blacks is actually declining more rapidly with age than the health of whites; the true gap widens with age. Simulations also demonstrate how a health shock that occurs in mid-life affects the level of health and the probability of survival at older ages. To illustrate, we consider a white male with a high school degree and a blue collar job with health at the lowest 10^{th} health percentile at age 50 and a similar person at the 90^{th} health percentile at age 50. The person at the 90^{th} percentile of health at age 50 has a probability of survival to age 74 of almost 82 percent but an otherwise identical person at the 10^{th} percentile at age 50 has a 45 percent probability of living to age 74.

The second set of simulations show the interaction between education and racial-ethnic group on the one hand, and the evolution of health and survival probabilities on the other. We begin with simulations of the age-health profiles by level of education. These simulations emphasize the strong persistence in health differences by level of education over the entire age range between age 50 and age 90. We also consider age-health profiles by level of education within racial-ethnic groups. We find that much of the difference in age-health profiles by racial-ethnic group is accounted for by differences in the levels of education between racial-ethnic groups. This is especially true for men, with two-thirds to 85 percent of the difference accounted for by differences in education. For women approximately half is accounted for by differences in education.

Finally, we simulate the differences in survival probabilities by level of education and use these probabilities to illustrate the large variation in the expected present discounted value (EPDV) of a fair annuity. We calculate the EPDV of an immediate annuity with first payout at age 66 for persons by gender, level of education, and health decile at age 66. The range of EPDVs is striking for both men and women. The EPDV of an immediate annuity for persons in the top health decile with a college degree or more is more than double the EPDV for persons in the lowest health decile with less than a high school. Because all persons of the same age and gender face the same annuity premium, this suggests the scope for adverse selection is enormous.

This paper has developed a joint model of health and mortality to estimate how health evolves after retirement. One key feature is that the model captures the dynamic properties of the unobserved component of health. Another feature is that it allows us to “correct” observed age-health profiles for the effect of mortality selection. The methodology used here is also applicable to other economic outcomes where the age profile is affected by mortality selection. In future work we plan to extend the model to examine the role of mortality selection in age-wealth profiles.

References

Baker, Michael, Mark Stabile and Catherine Deri. 2004 "What Do Self-Reported, Objective, Measures Of Health Measure?," *Journal of Human Resources*, 39(4): 1067-1093.

Case Anne and Christina Paxson, “Sex Differences in Morbidity and Mortality,” *Demography* 2005; 42: 189-214.

Crimmins, Eileen, Jung Ki Kim and Aida Sole-Auro. 2010. “Gender Differences in Health: Results from SHARE, ELSA and HRS,” *European Journal of Public Health*, Vol. 21(1): 81–91

Cummings, Jason and Pamela Jackson. 2008. “Race, Gender, and SES Disparities in Self-Assessed Health, 1974-2004,” *Research on Aging*, 30(2):137-167.

Contoyannis, Paul, Andrew Jones, and Nigel Rice. 2004. The Dynamics of Health in the British Household Panel Survey,” *Journal of Applied Econometrics*, 19: 473-503.

Crossley, T. and S. Kennedy. 2002. “The Reliability of Self-Assessed Health Status,” *Journal of Health Economics*, 21(4):643-658.

Halliday, Timothy. 2008. “Heterogeniety, State-Dependence and Health,” *Econometrics Journal*, 11:499-516.

Hernandez-Quevedo, Cristina, Andrew Jones and Nigel Rice. 2008. “Persistence in Health limitations: A European Comparative Analysis,” *Journal of Health Economics*, 27:1472-1488.

Heiss, Florian. 2008. “Sequential Numerical Integration in Nonlinear State Space Models for Microeconometric Panel Data,” *Journal of Applied Econometrics*, 23:373-389.

Heiss, Florian. 2011. “Dynamics of Self-Rated Health and Selective Mortality,” *Empirical Economics*, 40(1): 119-140.

Heiss, Florian, Axel Boersch-Supan, Michael Hurd, and David Wise. 2008. “Pathways to Disability: Predicting Health Trajectories, in D. Cutler and D. Wise (ed.) *Health at Older Ages*, University of Chicago Press, 105-150.

Heiss, Florian and Viktor Winschel. 2008. ”Likelihood Approximation by Numerical Integration on Sparse Grids,” *Journal of Econometrics*, 144(1):62-80.

Jones AM, X. Koolman, and N. Rice. 2006. “Health-related Non-response in the British Household Panel Survey and European Community Household Panel: Using Inverse-Probability-Weighted Estimators in Non-Linear Models,” *J Royal Statistical Society A* 169(3):543–569

Kerkhofs, Marcel and Maarten Lindeboom. 1995. “Subjective Health Measures and State Dependent Reporting Errors,” *Health Economics*, 4:221-235.

Lange, Fabian and Douglas McKee. 2011 “The Evolution of Latent Health over the Life Course,” Yale University, December.

Lindeboom, Maarten and Peter Doorslaer. 2004. “Cut-Point Shift and Index Shift in Self-Reported Health,” *Journal of Health Economics*, 23:1083-1099.

Poterba, James, Steven Venti and David Wise. 2013. “Health, Education and the Post-Retirement Evolution of Household Wealth, *Journal of Human Capital*. 7(4):297-339.

Scommegna, Paola. 2013. “Exploring the Paradox of U.S. Hispanics’ Longer Life Expectancy,” Population Reference Bureau Bulletin.