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A forward looking age based on longevity expectations

Aktas, A. and Sanderson, W.C.

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International Institute for
Applied Systems Analysis
Schlossplatz 1
A-2361 Laxenburg, Austria

Tel: +43 2236 807 342
Fax: +43 2236 71313
E-mail: publications@iiasa.ac.at
Web: www.iiasa.ac.at

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A Forward Looking Age based on Longevity Expectations

Arda Aktaş (aktas.arda@stonybrook.edu)
Warren C. Sanderson (warren.sanderson@stonybrook.edu)

Approved by

Wolfgang Lutz (lutz@iiasa.ac.at)
Program Director, World Population Program

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Abstract

Many personal decisions are shaped by people's expectations of the future, but these expectations are rarely included in the study of those decisions. Often, studies that analyze these forward-looking decisions use chronological age, an inherently backward-looking measure, as a proxy for those expectations. In this paper, we use a two part methodology to compute a forward-looking age which is based on data of longevity expectations collected in the Health and Retirement Study (HRS). In the first part, we propose a method to translate those expectations into life tables. In the second part, those life tables are used to produce forward-looking ages that can be used in the study of forward-looking decisions. We find that education has a great effect on subjective life expectancy, therefore, on forward-looking age. Also, we observe that at any given education level, the forward-looking age of the younger cohort is always greater than or equal to the forward-looking age of the older cohort. Finally, the difference between forward-looking age and chronological age is increasing as individuals get older, but the speed of this change varies depending on education level, cohort and health-related conditions.

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About the Authors

Arda Aktaş is a Ph.D. candidate in Economics at Stony Brook University.

Warren C. Sanderson is Professor of Economics and Professor of History at Stony Brook University in New York. He is also an Institute Scholar with the World Population Program at the Wittgenstein Centre for Demography and Global Human Capital (IIASA, VID/ÖAW, WU), International Institute for Applied Systems Analysis.

A Forward Looking Age based on Longevity Expectations

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1 Introduction

Economics is one of those scientific fields where subjective expectations play a crucial role due to the intertemporal nature of the topics examined. Decisions regarding retirement age and savings for retirement are such topics. Therefore, quantifying these subjective expectations is important in order to examine their effects on individual behavior.

Nevertheless, a large fraction of the existing work in this discipline describes people's behavior in terms of 'chronological age' or 'calendar age', that is, the number of years a person has already lived. Implicit in this approach is the notion that all groups regardless of their characteristics move through life-course stages in a chronological lockstep. On the contrary, we may actually observe that different groups behave differently even though they are all members of the same birth cohort. There are many reasons for this heterogeneity, including the fact that perceptions of ageing may not be the same for all individuals, because they might have different characteristics. In other words, how individuals experience specific transitions in their life course can be influenced by their perception of ageing associated to their characteristics at that point of time. Thus, depending on which particular stage they are in at that point of time, their behaviors will be different compared to other members of the same cohort with different characteristics.

Even though using the heterogeneous perceptions of ageing in economic models might be very appealing and intuitive, this approach faces an important challenge given that these perceptions cannot be directly observed. One way to capture individual's perception of ageing can be done by linking it with subjective life expectancy, that is, how many years an individual thinks that she/he has to live. Indeed, people with different characteristics have different expectations of their own longevity and, moreover, these longevity expectations change as their characteristics evolve over time.

Subjective life expectancies are generally obtained from socio-economic surveys in the form of survival beliefs, that is the probability of surviving up to a specified target age which depends on the respondent's current age and is generally 11 to 15 years above it. Researchers have started to analyze subjective survival probabilities after the Health and Retirement Survey (HRS), which is one of the largest socio-economic surveys on the American elderly population, introduced two questions to assess people's expectations of their longevity in terms of survival probabilities. The results of this extensive literature show that subjective survival probabilities in HRS are consistent with the observed survival patterns at the mean and at individual level (e.g., Smith et al. 2001; Hurd and McGarry 2002; Siegel et al. 2003; Hurd 2009; Novak and Palloni 2013); they vary across individuals (Khwaja et al. 2007; Ludwig and Zimper 2013; Perozek 2008; Bissonnette et al. 2014;) and this variation is correlated with a number of known risk factors including smoking, health condition, parental longevity (Hurd and McGarry 1995; Hurd and McGarry 2002).

Moreover, individuals modify their survival probabilities in response to new information or health shocks, such as the onset of a new illness (Hurd and McGarry 1995; Hurd and McGarry 2002; Smith et al. 2001). Another branch of this literature assesses subjective survival probabilities within the context of economics of ageing and examines the effect of subjective survival probabilities on a number of economic decisions of elderly people such as retirement, consumption and saving decisions (e.g., Hurd et al. 1998, 2004; Bloom et al. 2007; Delavande et al. 2006; Khan et al. 2014; Bissonnette et al. 2014).

However, previous studies do not use these subjective survival probabilities to construct a new age measure which includes individuals' longevity expectations which, in turn, depend on the individuals' characteristics. Our aim is to capture this heterogeneity in people's expectations using subjective survival probabilities and transform it to an index measured in years in order to facilitate easier use in any analysis where people's expectations matter and make it comparable with the conventional age measure.

To do this, we combine insights from two streams of literature. The first one is concerned with eliciting information from subjective survival probabilities by addressing possible problems in the data, including measurement errors and rounding (e.g., Hurd et al. 1998; Gan et al. 2005; Kleinjans and Soest 2014) and constructing subjective survival curves (e.g., Bissonnette 2012; Bissonnette et al. 2014; Elder 2007; Gan et al. 2005; Khwaja et al. 2007; Perozek 2008). The second stream of literature is related to the 'Characteristics Approach' developed by Sanderson and Scherbov (2013) which provides a framework for measuring ageing based on the characteristics that change with chronological age, including life expectancy[1].

In this paper we propose a method to quantify people's longevity expectations, and in order to simplify their use in decision analysis we translate the subjective remaining life expectancies into ages using the technique of Sanderson and Scherbov (2013). We call this new approach of measuring age 'forward-looking age'. This alternative age measure can contribute to existing literature by providing new insights in the examination of individual decision making. Moreover, it can be even more predictive of an individual's actual behavior than their chronological age, as forward-looking age varies depending on individual characteristics in a dynamic setting.

We exemplify our method by using HRS data, but as we will show, it can be applied to any other dataset[2] that includes similar types of questions about life expectancy probabilities.

We find that there is substantial variation in forward-looking ages of individuals with different characteristics (such as gender, cohort, education, place of birth, adverse health conditions and smoking) and this variation tends to increase with chronological age. In particular, we observe that education matters for both genders, but the magnitude of its effect is larger for women. Also, the presence of any particular health condition or smoking increases the forward-looking age. Therefore, the effect of smoking or having any adverse health condition is larger at low educated groups compared to high educated groups. Finally, the effect of education is higher for women of the younger cohorts. For men, there is

[1] For more details, also look at some previous papers ,where the approach is used without being explicitly named: Sanderson and Scherbov (2005, 2007, 2008, 2010); Lutz et al. (2008)

[2] The following surveys also use very similar structures for the questions related to subjective survival probabilities: Asset and Health Dynamics among the Oldest Old (AHEAD), The Survey of Health, Ageing and Retirement in Europe (SHARE), Dutch Household Survey (DHS), English Longitudinal Study of Ageing (ELSA), Korean Longitudinal Study of Aging (KLOSA), Longitudinal Ageing Study in India (LASI), Chinese Health and Retirement Longitudinal Study (CHARLS).

no significant difference in terms of education between cohorts. Our findings on the effect of education and gender on subjective life expectancy are in line with the results of the literature on objective life expectancy in the US (Olshansky et al. 2012; Hendi 2015), but there is a disparity in cohort effects by level of education.

The structure of the paper is as follows. Next section introduces the data that we use and explains the sample selection procedure. Section 3 explains the three step methodology and provides a detailed example of the calculation of forward-looking ages from individual subjective life tables. Section 4 presents our results and Section 5 offers some concluding remarks.

2 Data

2.1 Subjective Survival Probabilities in HRS

The Health and Retirement Study (HRS) is a longitudinal panel survey of a representative sample of the American population 50 years old and above. The baseline (the 1992 - Wave 1) consists of the 1931-41 cohort and their spouses, if they are married. Follow up interviews have continued on a biennial basis through 2010. As the HRS matured, new cohorts have been added.

Starting from the first wave, HRS has asked about the subjective probability of surviving for 10 or 15 more years. Depending on the age of the respondent, the probability of survival has been asked for either one or two target ages. At the age interval 51-64 respondents have been asked about their survival probabilities for age 75 and 85, and older age groups about one value, where the target age of interest (80, 85, 90, 95, 100) exceeds the individual's age by at least 10 years. The probability scale attached to the event of surviving up to a specified target age is bounded to be between 0% and 100%, with 0 corresponding to 'no chance of survival' and 100% corresponding to 'completely sure survival'. The only exception is Wave 1 where respondents were asked to report their likelihood of survival up to a specified target age on a discrete scale from 0 to 10.

2.2 Sample Selection

For this study, we use the 1994-2010 waves of the HRS. We start our sample selection by dropping observations of Wave 1 from the full HRS sample to avoid inconsistencies that could arise from the difference in scale between year 1992 and the subsequent years.[3] After that, the sample is restricted to individuals aged 51 to 64 years, who were asked about their subjective survival probabilities for two different target ages (75 and 80 or 85), and has non-missing values for these subjective survival probabilities. Finally, we drop the internally inconsistent subjective survival probabilities, that is, when the probability of living up to age 80 or 85 is greater than the probability of living up to age 75 (cases where it is likely that the individual was not able to comprehend the nature of the question). Figure A1 and A2 on the appendix summarize the sample selection process at individual and observation level.

[3] As noted in section 2.1, changing the scale causes a difference in the nature of responses in 1992 and 1994 onwards. Indeed, one is a discrete answer on a 0 to 10 scale whereas the other is a continuous answer in terms of probability. Therefore, the reasoning for the answers is different.

3 Methodology

In order to develop a method for estimating the forward-looking age, first we need subjective remaining life expectancies expressed in terms of years. As they are not measured directly in the HRS and survival expectations only exist in the form of probability of surviving up to a specified target age, we can use these self-reported subjective survival probabilities to obtain subjective life expectancies.

However, there is a challenge in the use of these subjective survival probabilities due to the structure of the survival questions in the HRS. As indicated by Bissonnette et al. (2014) among others, these self-reported probabilities are subject to rounding and focal answers. Indeed, when people are asked to choose a real number within a range between 0 and 100, most of them report the nearest multiple of some integer rather than their exact subjective expectations (Dominitz and Manski, 1997). Moreover, a significant fraction of the responses heaps at the end points and in the middle of the given scale. In fact, it is found that subjective survival probabilities at the individual level cluster around some focal responses of 0, 50, and 100, even though they seem reasonable when averaged across respondents (for discussions, see, for example, Hurd and McGarry 2002; Manski 2004, Bissonnette et al. 2014). Particularly, serious bunching at 50 percent is considered to be either non-informative focal answers which do not correspond to respondents' underlying beliefs (De Bruin et al. 2000; De Bruin and Carman 2012; De Bresser and van Soest 2013; Hill et al. 2005; Hudomiet and Willis 2013), or an extreme form of rounding (Gan et al. 2005; Kleinjans and Soest 2014; Manski and Molinari 2010). On the other hand, Bissonnette et al. (2014) find little support for the idea that 50 percent answers are used to avoid answering questions. Therefore, using these subjective survival probabilities in an empirical analysis without correcting for rounding and measurement errors may give us biased results. We propose a three step procedure to calculate forward-looking ages from self-reported survival probabilities:

1. Tackling the focal points problem using random effects ordered probit to obtain refined probabilities which depend on the characteristics of each individual.
2. Non Linear Least Squares estimation of subjective survival functions using these refined probabilities and construction of life tables for groups with various characteristics.
3. Using the life tables based on estimated subjective survival curves to apply the 'Characteristic Approach' proposed by Sanderson and Scherbov (2013, 2014) to calculate forward-looking ages for different groups.

3.1 Tackling the Focal Points Issue in the Data

In the existing literature, various approaches are used to deal with the focal responses (e.g., Gan et al. 2005; Kleinjans and Soest 2014; Bissonnette et al. 2014), but still there is no consensus. Gan et al. (2005) propose a method which takes responses from other subjective probability questions to estimate the probability of giving a focal point answer to the questions about subjective survival probabilities. Therefore, by doing so, they are limiting their analysis to people from whom other information is available related to subjective probabilities. Kleinjans and Soest (2014) and later Bissonnette et al. (2014) deal with the focal point problem using an ordered response model to estimate the probability of using a certain rounding rule when giving an answer to the survival probabilities question. Alternatively, Ludwig and Zimper (2013) propose a method where they model the answering of survival probability questions in a Bayesian update framework. However, as they point out, the aim of their approach is to explain the individual differences between subjective probabilities and objective data, which is far from our purpose. Moreover, their method is oblivious to individual characteristics, which lies in the core of our approach, and they focus solely on the information update process.

In order to tackle the focal point issue, we take a path different from the literature, and we use random effects ordered probit to estimate the probability that people's given subjective survival probabilities fall in a particular interval. In our method, we do not intend to model the individual reasoning process behind giving a certain probability as an answer. Instead, we directly estimate the probability of an individual giving an answer according to characteristics. We also include random effects, as individual randomness clearly plays a role in the process of giving a subjective probability of survival. In this way, we attempt to better capture the influence of the characteristics in the survival probabilities, treating other individual effects (such as the rounding process or individual optimism/pessimism) as part of the random term. By using probit, we stand under the assumption that the randomness factor and the disturbances are normally distributed.

Formally, we estimate the probability that a given subjective probability of survival is greater than a particular cut point given all cut points, the individual characteristics and the randomness factor. This probability is given by:

$$Pr(SPS_{i,a,A} > k|\kappa, X_{i,a}, v_i) = \Phi(X_{i,a}\beta + v_i - \kappa_k)$$

where $SPS_{i,a,A}$ is the subjective probability of survival up to target age A for individual i aged a; κ is the vector of cut points - 21 cut points are defined depending on key focal points, v_i is the vector of random effects for individual i and $X_{i,a}$ corresponds to a set of characteristics for individual i at age a including: education dummies (less than high school, high school graduate, more than high school), cohort dummies (cohort 1 if the year of birth is in the interval of 1930-1945; cohort 2 if the year of birth is in the interval of 1946-1959), a dummy for place of birth (created depending on whether the respondent was born in the US), an array of health variables (whether the respondent was diagnosed with some adverse health conditions such as diabetes, cancer, high blood pressure, arthritis, stroke, heart problems, lung problems, psychological problems), and a dummy for smoking. Detailed descriptions of the regression variables are presented in Table A1.

Table A2 shows the estimated marginal effects of personal characteristics on the subjective probability of survival up to different target ages. Column (I) and Column (III) of the table present the estimates for target age 75, while Column (II) and Column (IV) present the estimates for target age 85. The coefficients are estimated separately for men and women but only the results for white individuals are presented here. We evaluate gender differently, as the story of females is very different from males in terms of actual life expectancy at age 50 (Glei et al., 2010). Thus, the coefficients represent the gender specific effects of the characteristics.

Clearly, subjective survival probabilities increase by age. We also find that the older cohort has higher subjective survival probabilities compared to the younger cohort. This finding is in line with (Bissonnette et al., 2014). We also control for the place of birth by considering that individuals who were born and grew up in a country different from the US may have followed a different ageing path.

The coefficients of education dummies are negative and strongly statistically significant for both men and women at both target ages. This implies that education has a positive effect on subjective survival probabilities and this effect is much larger for women than for men. On the other hand, this effect is smaller for both genders at the older target age.

Hurd and McGarry (1995, 2002) also find a similar effect on subjective survival probabilities. This is not surprising, as education contributes to life expectancy in different ways including healthier behavior, higher earnings and higher rates of employment (Hummer and Lariscy, 2011).

The particular causes and the contributing factors of mortality at older age demonstrated by Crimmins et al. (2011) may be the same factors lowering subjective survival probabilities. For the US, Crimmins et al. (2011) show that the prevalence of heart disease, stroke and diabetes is very high and cancer is the most important cause of death. Thus, our list of health measures roughly corresponds to that used by Crimmins et al. (2011) and includes high blood pressure, diabetes, cancer, lung condition, heart condition, stroke, arthritis and psychological conditions. Among others, arthritis and psychological conditions may not be life-threatening, but we may still presume that they may reduce the subjective survival probabilities. As expected, we found that the coefficients on these indicators are negative and strongly statistically significant. Also, in line with the results in Hurd and McGarry (1995, 2002), the association between these adverse health conditions and survival probabilities is different for men and women. In particular, for both target ages, coefficients on smoking, high blood pressure, diabetes, and arthritis are larger for men than for women, whereas the opposite is true for coefficients on cancer and stroke. Furthermore, coefficients on adverse lung and heart conditions are found to be larger for women at the younger target age. Similar results are observed for men at the older target age.

As smoking increases the risk of numerous causes of death and people are aware of its associated mortality risk, we can expect smoking to be negatively correlated with subjective survival probabilities. Indeed, the coefficient is found to be negative and strongly statistically significant for men and women at each of the target ages, with its magnitude being larger for men at both target ages.

After calculating the probabilities for each of the cut points for each individual, we rebuild the subjective survival probabilities. These 'refined' probabilities will be simply the expected value of the subjective survival probabilities given the cut points and the characteristics.

3.2 Estimation of Individual Subjective Survival Functions

In the second step, we estimate subjective survival curves using the above 'refined' subjective survival probabilities. At this point, the choice of the method for the estimation of subjective survival curves changes depending on how many observations exist for each respondent (for an overview of these methods see, for example, Bissonnette and Bresser 2014). As explained in the data section, HRS has either one or two observations for each individual depending on the age of the respondents. The most common method in current literature for age intervals where there is only one observation for each individual is using a scaling factor to estimate the whole individual subjective survival curve from a single point of subjective survival probability. This scaling factor can be defined assuming that either it does not change with the target age (Gan et al., 2005) or follows a predefined distribution such as the Gamma distribution over different target ages (e.g., Bissonnette et al. 2014; Khwaja et al. 2007). However, if there are more than one observation for each individual, using one of these methods may give biased results (see Wu et al. 2015 for more details). For this case, Perozek (2008) fits subjective survival functions to predefined distributions using the two subjective survival probabilities and forcing it to converge to an end point derived from the aggregate observed life tables. This applies the method of fitting parametric, observation-specific survival functions by non-linear least squares introduced by Dominitz and Manski (1997) to the case of subjective survival probabilities. Alternatively, if the assumption that expectations follow a known parametric distribution is relaxed, then non-parametric approaches may be applicable if there are more than two observations, but we are not discussing them here, as it is not our case. However, De Bresser and van Soest (2013), using a sample of Dutch adults, show that the life expectancies calculated from fitted parametric distributions are similar to those calculated from non-parametric spline functions.

We estimate the survival curves following an approach similar to the one applied by Perozek (2008), but using only our refined self-reported probabilities. We use a Non Linear Least Square (NLLS) method to estimate the parameters of the subjective survival functions. In particular, we assume that

$$SPS_{i,t} = S_{i,t}(\alpha_i, \beta_i) + \epsilon_{i,t}$$

where $SPS_{i,t}$ is the subjective probability that individual i lives to age t, $S_{i,t}$ is a general representation of a two-parameter survival function, and $\epsilon_{i,t}$ is the error term, which is assumed to be homoskedastic, independent and identically distributed with a mean of 0.

The NLLS estimators are the values of α_i and β_i that minimize the following expression:

$$\sum_{t \in A} [SPS_{i,t} - S_{i,t}(\alpha_i, \beta_i)]^2$$

where A is the set of target ages.

As four functional forms - Gompertz, Weibull, logistic and log-logistic distribution- are commonly used in the survival analysis, we separately find two sets of parameter estimates under these different functional form assumptions. We find that Gompertz is the one which seems to have a better fit to the data.[4] Therefore, the parameters of the survival function $(\hat{\alpha_i}, \hat{\beta_i})$ are calculated under the assumption that it takes the form of a Gompertz survival function, which is defined by:

$$S_{i,t}^{Gompertz}(\alpha_i, \beta_i) = exp\left[\frac{\alpha_i}{\beta_i}\left(1 - exp\left[\beta_i(t - age_i)\right]\right)\right]$$

Under these assumptions, NLLS provides unbiased and efficient estimates of the underlying parameters of the survival function for each individual.

3.3 Calculation of Forward-Looking Ages for Different Characteristics

After having constructed the subjective life tables based on estimated subjective survival curves, we obtain the subjective remaining life expectancies in terms of years for each group of individuals who share the same characteristics. As subjective remaining life expectancy is one of the characteristics of people, we can apply the 'Characteristic Approach' of Sanderson and Scherbov (2013, 2014) which provides a framework for measuring ageing based on people's characteristics that change with chronological age, such as life expectancy. Along those lines, we express the characteristic schedule as:

$$k_r\left(a\right) = C_r\left(a\right)$$

where k is the subjective remaining life expectancy (in terms of years) at chronological age a in a characteristic schedule r. The schedule r can refer to different years, different

[4]Results under other distributional forms will be provided upon request.

education levels, different cohorts, different gender or any other features that distinguishes people. If $C_r(a)$ is continuous and monotonic in chronological age over the relevant range, holding r fixed, we can take the inverse of this function in terms of a different set of characteristics s to find the associated forward-looking age, α:

$$\alpha = C_s^{-1}(C_r(a))$$

As the equation above shows, to calculate forward-looking ages (α), we need two sets of characteristics, r and s, and we keep characteristic schedule s constant while characteristic schedule r varies.

We illustrate how forward-looking ages are calculated in the following example.

Example 1: We draw a sample which consists of white-female individuals at chronological age 52 who were born in the US between 1930 and 1945. None of the individuals in this sample either smokes or has any adverse health condition. Now, we divide this sample into three subgroups depending on the education level of individuals:

1. Group X represents the subgroup which has more than high school education;
2. Group Y represents the subgroup which has only high school education;
3. Group Z represents the subgroup which has less than high school education.

Based on their estimated subjective life tables, the subjective remaining life expectancy at age 52 is 35.2, 32.7, and 31.1 years for the individuals in group X, Y and Z respectively. In this example, our aim is to estimate the pure effect of education for the given sample. To do this, we calculate the forward-looking age of the individuals in group Y and group Z respectively, taking the group X as a standard. We start with group Y:

- Characteristic ($C(.)$) : subjective remaining life expectancy;
- Constant parameters : s more than high school education, at age 52;
- Variable parameters : r high school education.
- Based on the estimated subjective life tables for group Y and X:
  - $C_r(52) = 32.7$, where r is high school education
  - $C_s(52) = 35.2$, where s is more than high school education.

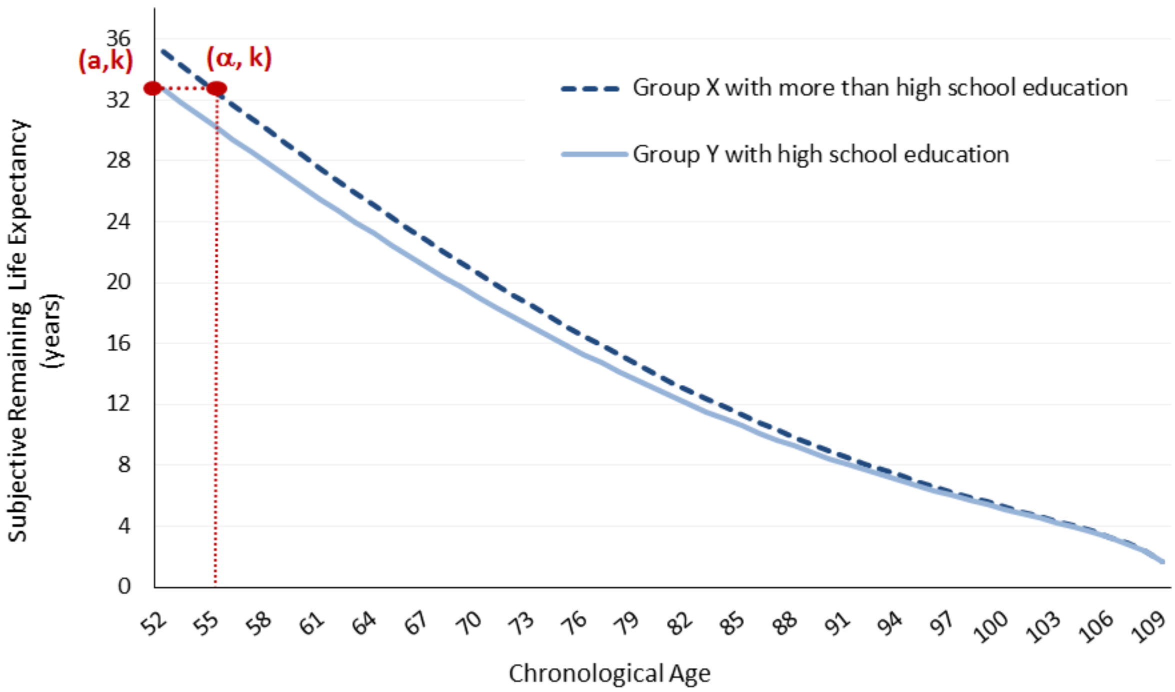
Then the forward-looking age is:

$$C_s^{-1}(C_r(52)) = 55 \Rightarrow C_s^{-1}(32.7) = 55$$

Therefore, in this example, the forward-looking age of the 52 years old individuals of group Y in schedule r (high school education), would be 55, using schedule s (more than high school education) as a standard. Put differently, the forward-looking age of individuals of group Y is 55 using the age profile of their more than high school educated counterparts (group X) as a standard.

This process can be illustrated as shown in Figure 1. It presents the distribution of subjective remaining life expectancy by chronological age for the individuals in group X and Y. The curve of group Y, which lies below the curve of group X, indicates that the ones with high school education have lower subjective remaining life expectancy in terms of years. For our specific example, we are only interested in the subjective remaining life expectancy at the (chronological) age of 52. For illustration purposes, we added two dots on the curves to mark the different chronological ages corresponding to the respective subjective remaining life expectancy. The projection of the subjective remaining life expectancy of group Y, represented by the point (a, k) on the graph, on the subjective remaining life expectancy curve of group X (presented by point (α, k)) gives us the forward-looking age of group Y. In this case, it is equal to 55. It can be interpreted as follows: individuals of group X will have the equivalent subjective remaining life expectancy of individuals of group Y (that is 32.7 years) when they reach age 55.

Figure 1: Illustration of the calculation of a forward-looking age using a sample of US-born, white, female, born between 1930 and 1945, no-smoking individuals with no adverse health conditions



Notes: Characteristic $(C(\cdot))$: subjective remaining life expectancy;
Constant parameters: s more than high school education and a age 52;
Variable parameter: r high school education

Next, we calculate the forward-looking age of the individuals in group Z using the age schedule of group X. At chronological age 52, the subjective remaining life expectancies of group Z and group X obtained from their estimated subjective life tables are:

- $C_r(52) = 31.1$, where r is less than high school education;
- $C_s(52) = 35.2$, where s is more than high school education.

Based on their subjective life table, we find that individuals of group X will have the equivalent subjective remaining life expectancy of individuals in group Z (that is 31.1 years) when the members of group X reach the (chronological) age of 57. Thus, the forward-looking age of the individuals of group Z is 57, using the age profile of their counterparts with more than high school education (group X) as a standard. Formally,

$$C_s^{-1}(C_r(52)) = 57 \Rightarrow C_s^{-1}(31.1) = 57$$

We can summarize the findings of this example in the following table:

Table 1: Forward-looking ages calculated using a sample of US-born, white, female, born between 1930 and 1945, no-smoking individuals with no adverse health condition

	Forward-Looking Ages
More than high school education*	52
High school education	55
Less than high school education	57

Notes: Characteristic ($C(\cdot)$): subjective remaining life expectancy;
Constant parameters: s more than high school education and a age 52;
Variable parameters: r high school education and less than high school education respectively. (*) indicates standard schedule, that is, more than high school education.

4 Results

In this section we present results that show the effects of certain characteristics such as education, cohort and some particular health conditions and smoking. The results are presented for different cohorts and gender using only white, US born individuals. In Tables A3-A16 the columns marked with (*) indicate the standard schedule for the calculation of forward-looking ages.

First, we can see that the level of education is important for forward-looking age. Indeed, from Table A4, at each cohort, forward-looking ages for high school and less than high school educated males are on average 2 years more than those with more than high school education. Furthermore, this difference is even higher in the case of females as indicated in Table A3. For high school educated females, the difference starts at 3 years and goes up to 5 years in the younger cohort, whereas for the less than high school educated, it starts at 5 years and increases up to 7 years, again for the younger cohort. These results are derived using non-smoking individuals who have no adverse health conditions.

We can also look at the effect of education on smokers or those that have one of the selected adverse health conditions. Tables A5 to A16 show different forward-looking ages corresponding to individuals that have one of the selected conditions using their non-smoking counterparts who have no particular adverse health condition as a standard. The results show that the detrimental effect of the selected adverse health conditions and smoking is decreasing by education. For example, Table A8 shows that, for the given sample consisting of female members of the younger cohort (cohort 2), the forward-looking age of those with lung conditions at age 60 would be 63 at an education level higher than high school (taking their non-smoker counterparts with no adverse health condition as standard). If we do the same comparison separately for high school educated and less than high school educated individuals, we find that the forward-looking ages are 64 and 67, respectively (Tables A9 and A10). For males of cohort 2, these forward-looking ages correspond to 62, 64 and 65 for education levels of more than high school, high school and less than high school respectively, as shown in Tables A14, A15 and A16.

Furthermore, it is possible to see the cohort effects in these results. Keeping education levels constant for both genders, we observe that the forward-looking age of cohort 2 is always greater than or equal to the forward-looking ages of the older cohort (cohort 1) at the given conditions. For example, at an education level of more than high school, if we look at females at the age of 60 with lung condition, the forward-looking age in both cohorts is 63 (Tables A5 and A8). Now, if we make the same comparison at high school level, the forward-looking age for cohort 1 is 63, while it is 64 for cohort 2 (Tables A6 and

A9). Finally, for less than high school education, the forward-looking ages are 65 and 67 for cohort 1 and 2, respectively (Tables A7 and A10). The same pattern can be observed in all different cases that we present.

Our results in terms of education are consistent with the findings of the literature on observed life expectancy. In particular, Hendi (2015) and Olshansky et al. (2012) show that life expectancy increases with education and this increase is larger for females. However, cohort effects tend to vary across different education levels and gender. Also, for white individuals with less than high school education, life expectancy of the younger cohorts is decreasing, in line with our results. However, contrary to what we see in subjective life expectancy, Hendi (2015) and Olshansky et al. (2012) show that, for white individuals, the increase in education has implied an increase in life expectancy for younger cohorts.

5 Concluding Remarks

In this paper, we develop a new age measure which takes people's expectations about their own longevity into consideration. As backward looking conventional age measures cannot capture neither the heterogeneity nor the dynamism in people's forward looking expectations, there is a need for an alternative age measure which captures these features. We call this new age measure 'forward-looking age'. This age measure can be relevant for studies in which people's forward-looking expectations play a significant role, such as retirement and saving decisions.

We propose a three-step method to calculate the forward-looking age starting from subjective survival probabilities. To exemplify our method, we use a subsample of white individuals from HRS, a panel study of elderly Americans over age 50. However, this method can be used with other data sets which include questions on subjective survival probabilities and an array of other demographic and health related characteristics.

Overall, we see that education level is the factor that has the greater effect on subjective life expectancy, and therefore, on forward-looking age. Especially, when the individual has an adverse health condition, the effect of the level of education on forward-looking age tends to increase. Also, keeping education levels constant, we observe that the forward-looking age of the younger cohort is always greater than or equal to the forward-looking age of the older cohort, at the given conditions. It implies that younger cohorts are older in terms of forward-looking age for the given conditions. Besides, the difference between forward-looking age and chronological age is increasing as individuals get older. The speed of this change varies depending on the education level, cohort and conditions.

The main shortcomings of this method come from the assumptions that we need to calculate the subjective remaining life expectancy from subjective survival probabilities. For datasets where subjective life expectancies are measured in terms of years or which include more observations of subjective survival probabilities, forward-looking ages should provide more precise information about people's expectations.

In subsequent studies, we will test whether the forward-looking age is more predictive on people's behavior than their chronological age. As we can see in the results that are presented here, forward-looking ages show a considerable degree of variation depending on people's characteristics, and we expect to see this reflected in the heterogeneous behavior of people with different characteristics.

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7 Appendix

7.1 Figures and Tables

Figure A1: Health and Retirement Study (HRS) Individuals Sampling Criteria

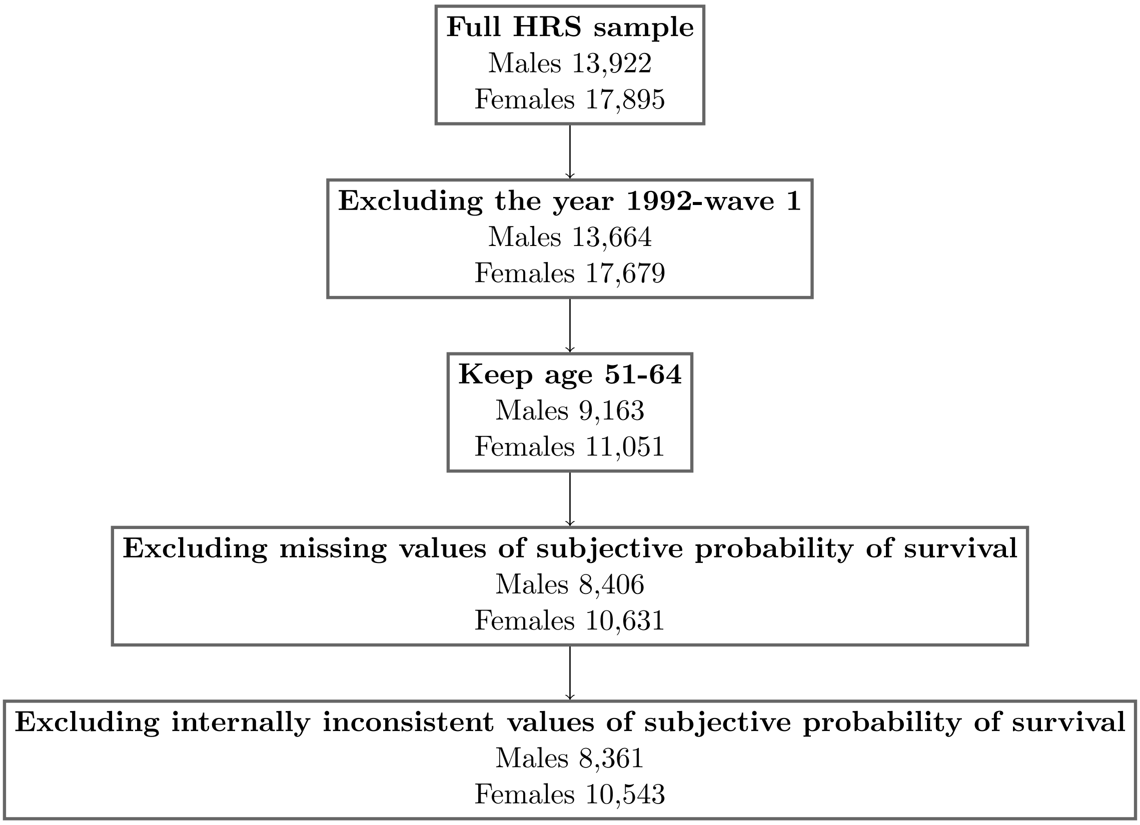
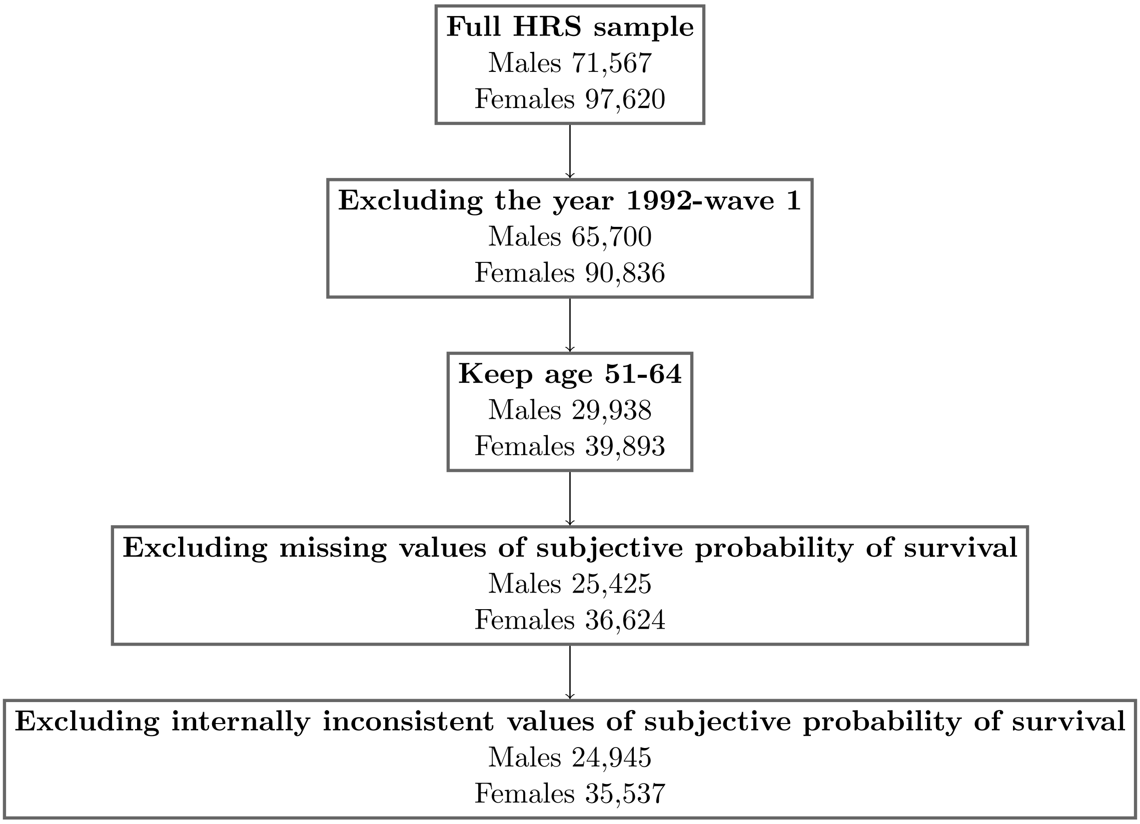


Figure A2: Health and Retirement Study (HRS) Observations Sampling Criteria



7.2 Tables

Table A1: Variable Definitions

Variable Name	**Description**
Age	Age in years
Cohort 1	=1 if 1930 $\leq$ year of birth $\leq$ 1945
Cohort 2	=1 if 1945 $<$ year of birth $<$ 1959
Born Outside	=1 if born outside of the US
Education	
Less than High School	=1 if years of schooling $<$ 12
High School	=1 if years of schooling = 12
More than High School	=1 if years of schooling $>$ 12
Health	
Smoking	=1 if smoke now
High Blood Pressure	=1 if has ever been diagnosed with high blood pressure
Diabetes	=1 if has ever been diagnosed with diabetes
Cancer	=1 if has ever been diagnosed with cancer
Lung Condition	=1 if has ever been diagnosed with lung condition
Heart condition	=1 if has ever been diagnosed with heart condition
Stroke	=1 if has ever had a stroke
Arthritis	=1 if has ever been diagnosed with arthritis
Psych Condition	=1 if has ever been diagnosed with a psychiatric condition
White	=1 if white
Female	=1 if female
SPS75	Subjective probability of surviving to age 75
SPS85	Subjective probability of surviving to age 85
Cut 1	SPS75 or SPS85 in $[0, 3)$
Cut 2	SPS75 or SPS85 in $[3, 8)$
Cut 3	SPS75 or SPS85 in $[8, 13)$
Cut 4	SPS75 or SPS85 in $[13, 18)$
Cut 5	SPS75 or SPS85 in $[18, 23)$
Cut 6	SPS75 or SPS85 in $[23, 28)$
Cut 7	SPS75 or SPS85 in $[28, 33)$
Cut 8	SPS75 or SPS85 in $[33, 38)$
Cut 9	SPS75 or SPS85 in $[38, 43)$
Cut 10	SPS75 or SPS85 in $[43, 48)$
Cut 11	SPS75 or SPS85 in $[48, 53)$
Cut 12	SPS75 or SPS85 in $[53, 58)$
Cut 13	SPS75 or SPS85 in $[58, 63)$
Cut 14	SPS75 or SPS85 in $[63, 68)$
Cut 15	SPS75 or SPS85 in $[68, 73)$
Cut 16	SPS75 or SPS85 in $[73, 78)$
Cut 17	SPS75 or SPS85 in $[78, 83)$
Cut 18	SPS75 or SPS85 in $[83, 88)$
Cut 19	SPS75 or SPS85 in $[88, 93)$
Cut 20	SPS75 or SPS85 in $[93, 98)$
Cut 21	SPS75 or SPS85 in $[98, 100]$

Table A2: Estimation Results for the White Sample in HRS

	White-Female		White-Male	
	SPS75 (I)	**SPS85 (II)**	**SPS75 (III)**	**SPS85 (IV)**
Age	0.010 ***	0.018 ***	0.014 ***	0.015 ***
	(0.002)	(0.003)	(0.003)	(0.004)
Cohort 1 (1930≤year of birth≤1945)	0.148 ***	0.183 ***	0.080 *	0.149 ***
	(0.031)	(0.036)	(0.034)	(0.040)
Born outside of the US	-0.337 ***	-0.038	-0.249 ***	0.120
	(0.053)	(0.065)	(0.060)	(0.075)
EDUCATION				
Less than high school	-0.797 ***	-0.516 ***	-0.645 ***	-0.351 ***
	(0.041)	(0.047)	(0.047)	(0.054)
High school	-0.344 ***	-0.298 ***	-0.376 ***	-0.256 ***
	(0.032)	(0.037)	(0.035)	(0.042)
HEALTH				
Smoking	-0.217 ***	-0.355 ***	-0.325 ***	-0.400 ***
	(0.029)	(0.031)	(0.035)	(0.039)
High blood pressure	-0.163 ***	-0.168 ***	-0.188 ***	-0.225 ***
	(0.023)	(0.027)	(0.029)	(0.034)
Diabetes	-0.215 ***	-0.175 ***	-0.222 ***	-0.188 ***
	(0.027)	(0.029)	(0.032)	(0.035)
Cancer	-0.256 ***	-0.382 ***	-0.168 ***	-0.338 ***
	(0.037)	(0.048)	(0.046)	(0.065)
Lung condition	-0.361 ***	-0.356 ***	-0.345 ***	-0.397 ***
	(0.037)	(0.046)	(0.047)	(0.061)
Heart condition	-0.252 ***	-0.425 ***	-0.226 ***	-0.478 ***
	(0.033)	(0.033)	(0.041)	(0.042)
Stroke	-0.306 ***	-0.410 ***	-0.281 **	-0.347 ***
	(0.066)	(0.071)	(0.087)	(0.096)
Arthritis	-0.143 ***	-0.117 ***	-0.159 ***	-0.170 ***
	(0.022)	(0.026)	(0.027)	(0.032)
Psychiatric condition	-0.219 ***	-0.316 ***	-0.252 ***	-0.200 ***
	(0.027)	(0.039)	(0.034)	(0.050)
Cut1	-2.598 ***	-1.936 ***	-1.741 ***	-1.528 ***
	(0.122)	(0.151)	(0.158)	(0.203)
Cut2	-2.500 ***	-1.827 ***	-1.578 ***	-1.282 ***
	(0.122)	(0.151)	(0.158)	(0.203)
Cut3	-2.205 ***	-1.481 ***	-1.126 ***	-0.686 **
	(0.122)	(0.151)	(0.158)	(0.202)
Cut4	-2.187 ***	-1.462 ***	-1.090 ***	-0.623 **
	(0.122)	(0.151)	(0.158)	(0.202)
Cut5	-2.008 ***	-1.253 ***	-0.752 ***	-0.234
	(0.122)	(0.151)	(0.158)	(0.202)
Cut6	-1.880 ***	-1.104 ***	-0.522 **	0.041
	(0.122)	(0.151)	(0.157)	(0.202)
Cut7	-1.765 ***	-0.955 ***	-0.285	0.301
	(0.122)	(0.151)	(0.157)	(0.202)
Cut8	-1.756 ***	-0.940 ***	-0.264	0.334
	(0.121)	(0.151)	(0.157)	(0.202)
Cut9	-1.639 ***	-0.802 ***	-0.023	0.601 **

(Continued on next page)

Table A2 *(Continued from previous page)*

	White-Female		White-Male	
	SPS75 (I)	**SPS85 (II)**	**SPS75 (III)**	**SPS85 (IV)**
	(0.121)	(0.150)	(0.157)	(0.202)
Cut10	-1.630 ***	-0.792 ***	-0.009	0.617 **
	(0.121)	(0.150)	(0.157)	(0.203)
Cut11	-0.410 **	0.386 *	0.908 ***	1.473 ***
	(0.121)	(0.150)	(0.158)	(0.203)
Cut12	-0.407 **	0.390 *	0.916 ***	1.484 ***
	(0.121)	(0.150)	(0.158)	(0.203)
Cut13	-0.264 **	0.561 ***	1.114 ***	1.715 ***
	(0.121)	(0.150)	(0.158)	(0.203)
Cut14	-0.245 *	0.593 ***	1.161 ***	0.203 ***
	(0.121)	(0.150)	(0.158)	(0.200)
Cut15	-0.084	0.773 ***	1.361 ***	1.965 ***
	(0.121)	(0.150)	(0.158)	(0.203)
Cut16	0.313 *	1.150 ***	1.706 ***	2.265 ***
	(0.121)	(0.150)	(0.158)	(0.204)
Cut17	0.911 ***	1.666 ***	2.128 ***	2.574 ***
	(0.121)	(0.151)	(0.159)	(0.204)
Cut18	1.003 ***	1.751 ***	2.229 ***	2.669 ***
	(0.121)	(0.151)	(0.159)	(0.204)
Cut19	1.365 ***	2.069 ***	2.532 ***	2.919 ***
	(0.121)	(0.151)	(0.159)	(0.205)
Cut20	1.453 ***	2.143 ***	2.600 ***	2.974 ***
	(0.121)	(0.151)	(0.159)	(0.205)
N	28,461	18,017	20,788	13,477

Standard errors in parentheses
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, '$p < 0.1$

7.3 Forward-Looking Ages by Chronological Ages

7.3.1 Effect of Education for Different Cohorts

Table A3: White, Female, Born in the US, No-Smoking with No Particular Health Conditions

Cohort 1			Cohort 2		
More than HS*	High School	Less than HS	**More than HS****	High School	Less than HS
51	54	56	**51**	54	56
52	55	57	**52**	55	57
53	56	58	**53**	56	58
54	57	59	**54**	57	59
55	58	60	**55**	58	60
56	59	61	**56**	59	61
57	60	62	**57**	60	62
58	61	63	**58**	61	63
59	62	64	**59**	63	64
60	63	65	**60**	64	65
61	64	66	**61**	65	67
62	65	67	**62**	66	68
63	67	68	**63**	67	69
64	68	69	**64**	69	71

(*) Standard schedule at cohort 1.
(**) Standard schedule at cohort 2.
HS : High School.

Table A4: White, Male, Born in the US, No-Smoking with No Particular Health Conditions

Cohort 1			Cohort 2		
More than HS*	High School	Less than HS	**More than HS****	High School	Less than HS
51	53	54	**51**	53	54
52	54	55	**52**	54	55
53	55	56	**53**	55	56
54	56	57	**54**	56	57
55	57	57	**55**	57	58
56	58	58	**56**	58	59
57	59	59	**57**	59	60
58	60	60	**58**	60	61
59	61	61	**59**	61	62
60	62	62	**60**	62	62
61	63	63	**61**	63	63
62	64	64	**62**	64	64
63	65	65	**63**	65	65
64	66	66	**64**	66	66

(*) Standard schedule at cohort 1.
(**) Standard schedule at cohort 2.
HS : High School.

7.3.2 Effect of Smoking or One of the Selected Adverse Health Conditions at Different Education Levels

Table A5: White, Female, Born in the US, Cohort 1, More than High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	53	53	52	53
52	55	54	53	54
53	56	55	54	55
54	57	56	55	56
55	58	57	56	57
56	59	58	57	58
57	60	59	58	60
58	61	60	59	61
59	62	61	60	62
60	63	62	61	63
61	64	63	62	64
62	66	64	63	65
63	67	65	64	66
64	68	66	65	67

(*) Standard schedule.

Table A6: White, Female, Born in the US, Cohort 1, High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	53	53	52	54
52	55	54	53	55
53	56	55	54	56
54	57	56	55	57
55	58	57	56	58
56	59	58	57	59
57	60	59	58	60
58	61	60	59	61
59	62	61	60	62
60	63	62	61	63
61	65	63	62	64
62	66	64	63	65
63	67	65	64	67
64	69	67	65	68

(*) Standard schedule.

Table A7: White, Female, Born in the US, Cohort 1, Less than High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	54	53	53	55
52	55	54	54	56
53	57	55	55	57
54	58	57	56	58
55	59	58	57	59
56	60	59	58	60
57	61	60	59	61
58	63	61	60	63
59	64	62	61	64
60	66	63	62	65
61	67	65	63	67
62	69	66	64	69
63	72	68	66	71
64	75	71	68	74

(*) Standard schedule.

Table A8: White, Female, Born in the US, Cohort 2, More than High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	54	53	54	54
52	55	54	53	55
53	56	55	54	56
54	57	56	55	67
55	58	57	56	58
56	59	58	57	59
57	60	59	58	60
58	61	60	59	61
59	63	61	60	62
60	64	62	61	63
61	65	63	62	64
62	66	64	63	65
63	68	65	64	67
64	69	67	65	68

(*) Standard schedule.

Table A9: White, Female, Born in the US, Cohort 2, High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	54	53	52	54
52	55	54	53	55
53	56	55	54	56
54	57	56	55	57
55	58	57	56	58
56	59	58	57	59
57	60	59	58	60
58	62	60	59	61
59	63	61	60	63
60	64	62	61	64
61	65	64	62	65
62	67	65	63	66
63	68	66	64	68
64	70	67	65	69

(*) Standard schedule.

Table A10: White, Female, Born in the US, Cohort 2, Less than High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	55	54	53	55
52	56	55	54	56
53	57	56	55	57
54	58	57	56	59
55	60	58	57	60
56	61	59	58	61
57	62	60	59	62
58	64	62	60	64
59	65	63	61	65
60	67	64	63	67
61	69	66	64	69
62	72	68	66	71
63	75	71	68	74
64	79	74	71	78

(*) Standard schedule.

Table A11: White, Male, Born in the US, Cohort 1, More than High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	54	52	53	54
52	55	53	54	55
53	56	54	55	56
54	57	55	56	57
55	58	56	57	58
56	59	57	58	59
57	60	58	59	60
58	61	59	60	61
59	62	60	61	62
60	63	61	62	63
61	64	62	63	64
62	65	63	64	65
63	66	64	65	66
64	67	66	66	67

(*) Standard schedule.

Table A12: White, Male, Born in the US, Cohort 1, High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	54	52	54	54
52	55	53	55	55
53	56	54	56	56
54	57	55	57	57
55	58	56	58	58
56	59	58	59	59
57	60	59	60	60
58	61	60	61	61
59	62	61	62	62
60	64	62	63	63
61	65	63	64	65
62	66	64	65	66
63	67	65	66	67
64	68	66	67	68

(*) Standard schedule.

Table A13: White, Male, Born in the US, Cohort 1, Less than High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	55	53	54	55
52	56	54	55	56
53	57	55	56	57
54	58	56	57	58
55	59	57	58	59
56	60	58	59	60
57	61	59	60	61
58	62	60	61	62
59	63	61	63	63
60	65	62	64	64
61	66	63	65	66
62	67	64	66	67
63	69	66	67	69
64	70	67	69	70

(*) Standard schedule.

Table A14: White, Male, Born in the US, Cohort 2, More than High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	54	52	54	54
52	55	53	55	55
53	56	54	56	56
54	57	55	57	57
55	58	56	58	58
56	59	57	59	59
57	60	58	60	60
58	61	59	61	61
59	62	61	62	62
60	63	62	63	63
61	64	63	64	64
62	66	64	65	66
63	67	65	66	67
64	68	66	67	68

(*) Standard schedule.

Table A15: White, Male, Born in the US, Cohort 2, High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	54	53	54	54
52	55	54	55	55
53	56	55	56	56
54	57	56	57	57
55	58	57	58	58
56	59	58	59	59
57	61	59	60	61
58	62	60	61	62
59	63	61	62	63
60	64	62	63	64
61	65	63	64	65
62	66	64	65	66
63	68	65	67	68
64	69	66	68	69

(*) Standard schedule.

Table A16: White, Male, Born in the US, Cohort 2, Less than High School Education

No-Smoking with No Particular Health Conditions*	Smoking	Diabetes	Cancer	Lung Condition
51	55	53	55	55
52	56	54	56	56
53	57	55	57	57
54	58	56	58	58
55	59	57	59	59
56	60	58	60	60
57	61	59	61	61
58	63	60	62	63
59	64	61	63	64
60	65	62	64	65
61	67	64	66	67
62	68	65	67	68
63	70	66	68	70
64	72	68	70	72

(*) Standard schedule.