DISCUSSION PAPER SERIES

IZA DP No. 8658

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November 2014

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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Discussion Paper No. 8658
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IZA Discussion Paper No. 8658
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ABSTRACT

Individual Survival Curves Comparing Subjective and Observed Mortality Risks*

In this paper, we compare individual survival curves constructed from objective (actual mortality) and elicited subjective information (probability of survival to a given target age). We develop a methodology to estimate jointly subjective and objective individual-survival curves accounting for rounding on subjective reports of perceived mortality risk. We make use of the long follow-up period in the Health and Retirement Study and the high quality of mortality data to estimate individual survival curves which feature both observed and unobserved heterogeneity. This allows us to compare objective and subjective estimates of remaining life expectancy for various groups, evaluate subjective expectations of joint survival and widowhood by household, and compare objective and subjective mortality with standard life-cycle models of consumption.

JEL Classification: C81, D84, I10

Keywords: subjective probabilities, old age mortality, joint survival of couples

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* We want to thank Rob Alessie, Charles Bellemare, Eric Bonsang, Juan Juan Cai, Katherine Carman, Martin Salm, Arthur van Soest, and the participants at the Health and Health Care Session at the 2010 Canadian Economic Association Meeting and the 2011 International Pension Workshop in Zurich for their insightful comments. Research support from the National Institute on Aging under grant P01AG008291 is gratefully acknowledged. Remaining mistakes are ours.

1 Introduction

Mortality expectations play a key role in economic models of saving behavior (Yaari, 1965; Hamermesh, 1985; Hurd, 1989). Examining these models with data requires modelling of mortality expectations. Earlier work assumed individuals expected mortality to follow population mortality risk. Most studies use aggregate mortality found in life tables (e.g. Hubbard et al., 1995; Scholz et al., 2006). Recognizing that mortality risk is heterogeneous across individuals, recent work has used actual mortality risk conditional on observable characteristics (e.g. De Nardi et al., 2011). Indeed, rich datasets such as the Health and Retirement Study accurately record the mortality experience of respondents over a period of more than 20 years. Hence, analysis of mortality can be conditioned on known socio-economic covariates. Despite being an improvement, using observed (or objective) mortality in models of economic behavior, whether from life tables or from panel data, requires that individuals correctly assess their mortality risk. Groups may vary in their ability to predict their own mortality risk (Lichtenstein et al., 1978; Khwaja et al., 2006). Since longevity risk is paramount for retirement preparation, misperceptions of mortality risk could have far reaching implications for well-being in retirement.

The Health and Retirement Study has pioneered the collection of perceived, or subjective, mortality risk. It asks respondents to provide a point estimate of their probability of surviving to a target age. Several studies show that subjective survival probabilities aggregate well to life-table probabilities and that they covary with various characteristics in expected ways (Hurd and McGarry, 1995). Also, they are predictive of actual mortality risk, even when conditioning on a rich set of socio-economic and demographic variables (Hurd and McGarry, 2002). Several studies analyze the predictive power of subjective report of mortality risk for a number of economic decisions (Hurd et al., 2004; Dominitz and Manski, 2007; Salm, 2010). Yet subjective mortality risk has not been used extensively in life-cycle models of saving behavior.

There are two important impediments to using these data in economic models. First, a single point estimate of a subjective survival probability to a target age cannot be directly transformed into subjective survival curves to compute expected utility. One could compare the predicted life-table survival probability to the same target age to apply a proportional shift to the life-table mortality profile. Gan et al. (2005) adopt a sophisticated variant of this strategy. The main limitation of this approach is that the life-table may not be an appropriate benchmark due to cohort and selection effets. Another limitation is that some respondents do not answer subjective risk questions. Such respondents typically have greater mortality risk than others.

Second, subjective reports of survival probabilities appear to be rounded. This introduces additional complexity as reports of a subjective probability of zero or one yields impractical survival curves. There is also evidence that reports of focal points, such as 0.5, are quite frequent and may reflect epistemic uncertainty (de Bruin et al., 2000).

In this paper, we use 16 years of actual mortality experience for Health and Retirement Study respondents who also answered mortality-risk expectation questions. We estimate jointly objective and subjective mortality-risk models, which allows direct testing of parametric restrictions imposed by the assumption that respondents correctly perceive their actual mortality risk. We also account for rounding in reports of subjective mortality risk. Once rounding is filtered we recover individual subjective survival curves which vary both due to observable socio-economic characteristics and unobserved heterogeneity in subjective reports. In one illustration, we use the objective and subjective curves to investigate whether couples correctly perceive the risk of becoming widowed. This risk is important due to the high prevalence of old-age poverty, in part resulting from widowhood. Finally, we use the standard life-cycle model to show how consumption paths derived from subjective survival expectations may differ from those using objective (or rational) survival expectations.

The paper is structured as follows. In Section 2, we describe the data and discuss the questions used to elicit subjective survival probabilities. In Section 3, we present the models of subjective survival. In Section 4, we present the estimation results. Section 5 discusses subjective and objective remaining life expectancy by respondent characteristics (e.g., by whether respondents smoke). Section 6 presents an application to consumption trajectories in retirement. Section 7 concludes.

2 Data

We use data from the *Health and Retirement Study* (HRS) relying on nine waves from 1992 to 2008. The sample includes respondents aged 50 and older, and their spouses. Death is recorded in exit interviews and confirmed with matches to the National Death Index (NDI).

Respondents for whom the vital status is unknown are also matched to the NDI to collect death information of deceased respondents. We use covariates measured in the current wave to predict mortality by the following interview.

2.1 Observed Survival

Figure 1 compares between-period life-table and one-year survival rates from the survey in three waves of the HRS. For this, we use all respondents answering in that wave as well as year-of-death from the HRS/NDI information to compute the fraction who are known to have survived one year. These data from the HRS use respondent-level weights for each of these three years. We obtain period life tables from the *Human Mortality Database* (www.mortality.org).

For all three years, the HRS survival and period life-table survival rates match well prior to age 75. HRS survival is somewhat higher at older ages in 1994, but this difference vanishes by 2006. This difference is likely due to the sampling frame the HRS used. The HRS samples the non-institutionalized population for each entering cohort entering the study. The non-institutionalized population has more favorable survival prospects than the overall population. The gap vanishes as the study progresses because HRS follows respondents who enter nursing homes. Hence, the objective is to compare actual and expected survival it is therefore important to use the actual mortality experience of those answering the expectations questions.

2.2 Subjective Survival

The HRS elicits subjective survival expectations through the following question:

> [Using any] number from 0 to 100 where "0" means that you think there is absolutely no chance and "100" means that you think the event is absolutely sure to happen... What do you think are chances that: You will live to at least A?

where A is a target age that varies for each respondent. Respondents 65 or younger were asked to report a probability of survival to age 75. Respondents older than 65 were asked

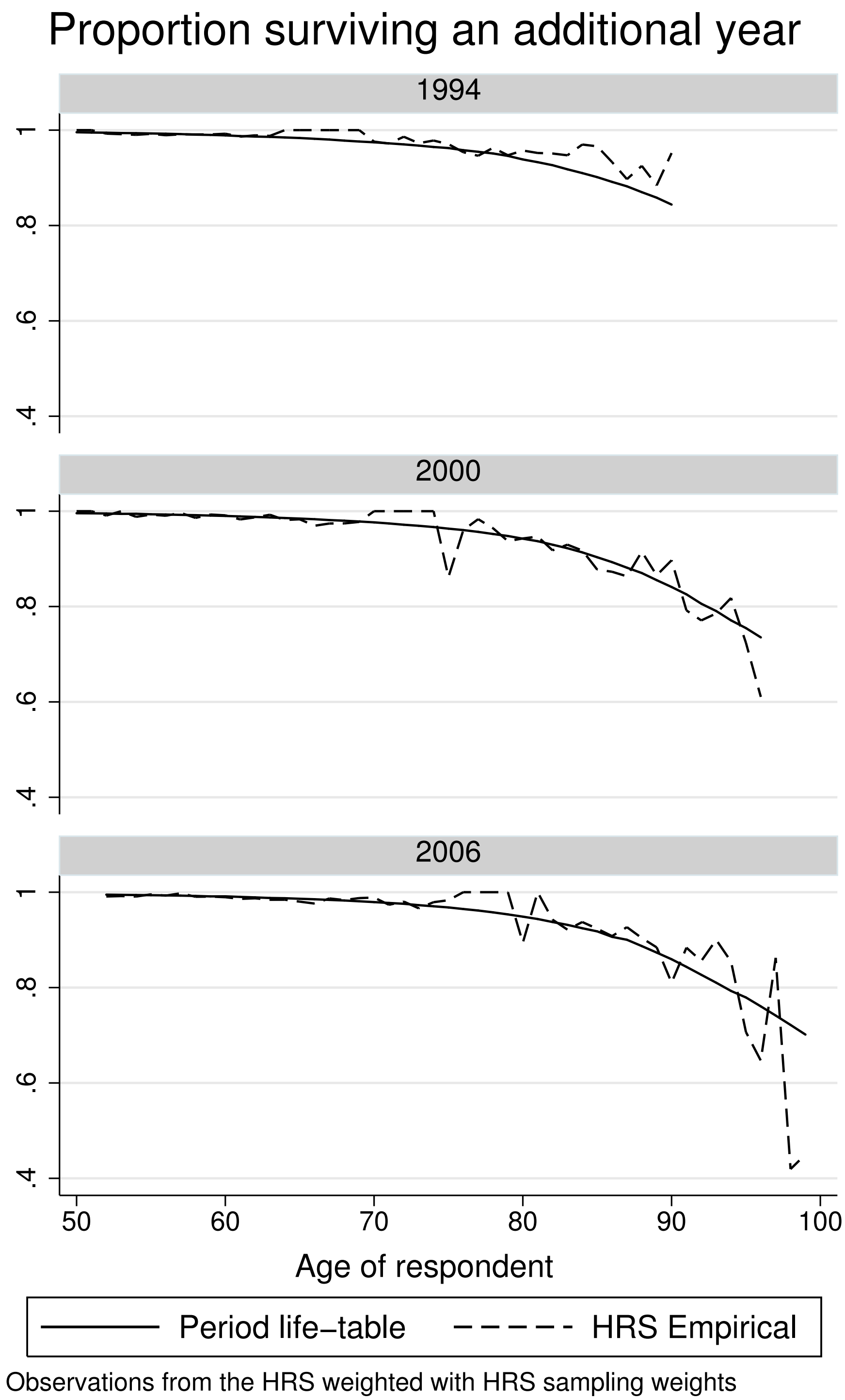


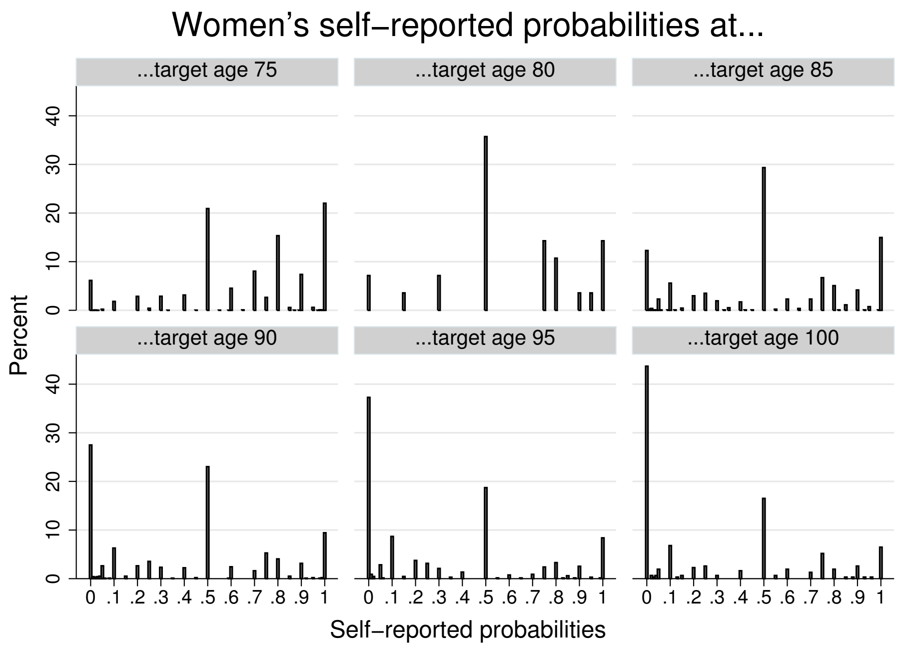
Figure 1: Comparison of the survival rate over one year at various ages between the HRS respondents in 1994, 2000, and 2006 with the period life-table for these years.

about survival to another target age. This target age was determined as an age 11 to 15 years in the future that is also a multiple of 5 (e.g. 90 for an individual aged 78). Our analysis includes 18,791 respondents who answered the probability questions, were observed at least once alive, and provided information on the covariates included in the analysis. When using the full sample, the number of observations (i.e. respondent-wave) is 80,298. Because we compare actual mortality of individuals who respond to the subjective probability question, we do not need to account for the selective nature of non-response to this question.

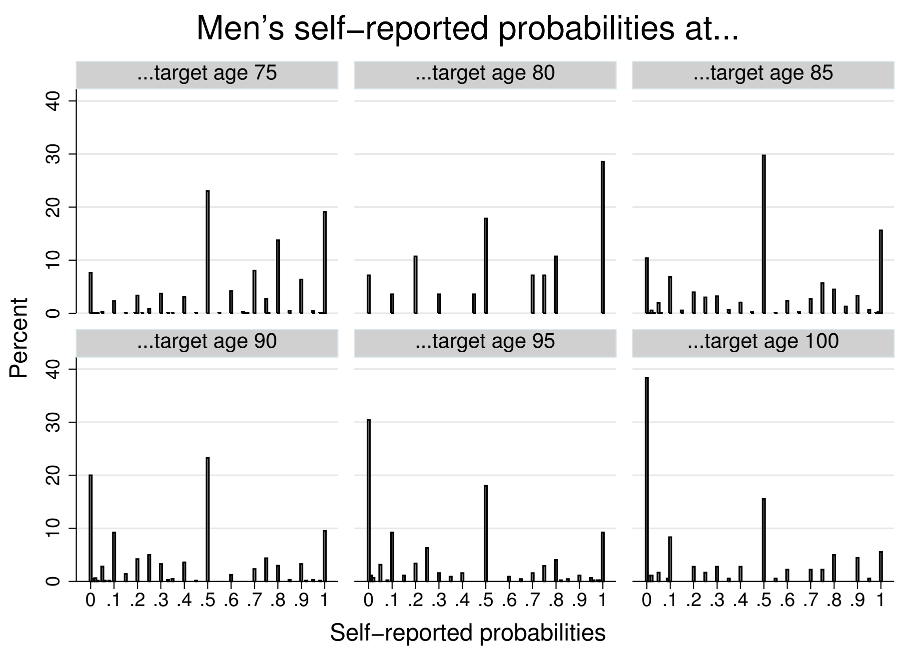
The self-reported probabilities are subject to rounding and focal answers (0, 0.5 and 1). Figures 2 (a) and (b) present histograms showing the distribution of the elicited subjective probabilities for the 6 target ages separately for females and males. There is substantial heterogeneity in the reported probabilities but significant heaping at the multiples of 50%-points (0, 50 and 100%). The proportion of such answers is rather stable for each target age. Answers of 0% and 100% are particularly problematic given that they imply degenerate hazard rates (infinity or 0). We also find evidence of rounding at multiples of 25, 10, and 5, and also find very precise answers reported with a 1%-precision. Our empirical strategy allows for the possibility of rounded answers.

2.3 Observed Characteristics

We use several dummy variables (taking a value of 1) throughout our analyses. These are for respondents who are male, black, Hispanic, whose highest educational attainment is a high-school diploma, whose highest educational attainment is a college degree, and who were smoker at one point in their life. The selected covariates are known to influence mortality and are typically constant over time for a given respondent. We include cohort dummies to control for variations in survival probabilities among older respondents that would not be captured by observable characteristics. We only consider characteristics which can be assumed not to vary with age because we seek to predict survival curves that covary with observable characteristics.



(a)



(b)

Figure 2: Histograms of the self-reported probabilities of survival to various target ages for women (a) and men (b). The target age depends on the respondent's age, hence respondents in the same sub-figures are close in age.

3 Econometric Model

We develop an econometric model for reports of subjective survival expectations which allows us to compare subjective and objective mortality hazards. Since both hazards are parametrized in similar ways, we can also reconstruct subjective and objective survival curves. The model accounts for rounding in subjective survival probabilities. The model consists of three components:

1. the objective hazard to predict survival among a population of respondents with given characteristics;
2. the subjective hazard perceived by respondents with given characteristics, and for whom the objective hazard is a special case;
3. the reporting model, accounting for the rounding behavior of respondents.

3.1 Objective hazard

Consider a respondent i at age a when reporting a probability of survival to target age t. We are interested in the probability that the age of death of the respondent, denoted T, will be greater than t. This probability is given by:

$$S_a^O(t|\boldsymbol{x_i}, \nu_i^O) = \exp\left(-\nu_i^O \int_a^t \lambda^O(\tau|\boldsymbol{x_i}))d\tau\right) = \exp(-\nu_i^O \Lambda_a^O(t|\boldsymbol{x_i})) \tag{1}$$

where $\lambda^O(t|\boldsymbol{x_i})$ is the objective hazard of respondents with characteristics $\boldsymbol{x_i}$, $\Lambda_a^O(t|\boldsymbol{x_i})$ is the integrated objective hazard from age a to age t, and ν_i^O is a frailty term added to capture unobserved heterogeneity (unobserved to analysts).

We assume the hazard is proportional with baseline hazard taking the Gompertz form.[1] The hazard at age t, for a respondent with characteristics $\boldsymbol{x_i}$, constant over time, is given by:

$$\lambda^O(t|\boldsymbol{x_i}) = \exp(\boldsymbol{x_i}\boldsymbol{\zeta}^O)\exp(\alpha^O t). \tag{2}$$

Respondents are first observed after age 50. We therefore use age 50 as our initial time at risk. The integrated hazard from the initial time period (notice that we omit the subscript a in this case) is then given by:

$$\Lambda^O(t|\boldsymbol{x_i}) = \frac{\exp(\boldsymbol{x_i}\boldsymbol{\zeta}^O)}{\alpha^O}(\exp(\alpha^O t) - 1). \tag{3}$$

The individual frailty term ν^O is assumed to follow a gamma distribution with unit expectation at the initial time at risk. The probability density function of the Gamma distribution $\mathcal{G}(c, d)$ is given by

$$f(x) \quad = \quad \frac{d^{-c}\, x^{c-1} \exp\left(-\frac{x}{d}\right)}{\Gamma(c)}$$

and this distribution has an expected value of cd and a variance of cd^2. Notice that if $d = 1/\delta^O$ and $c = \delta^O$, the distribution has a unit expectation and a variance of $1/\delta^O$.

We can derive the expected survival probability from age a to age t as follows:

$$S_a^O(t|\boldsymbol{x_i}) = \int \frac{S^O(t|\boldsymbol{x_i}, \nu)}{S^O(a|\boldsymbol{x_i}, \nu)} f(v|T > a)dv$$

which, given that

$$f(v|T > a) = S^O(a|\boldsymbol{x_i}, \nu)f(v)/S^O(a|\boldsymbol{x_i})$$

[1]We chose the Gompertz specification as it yields the best results for predicting survival based on a likelihood criterion. As a robustness check, we also tried a Weibull hazard, obtaining results similar to those of the Gompertz specification. We chose parametric specifications of the baseline hazard over a semi-parametric piece-wise constant hazard because of the small sample of deaths at older ages (yielding high variance in the form of the hazard at older ages). The shape of the piece-wise constant hazard at younger ages was indistinguishable in terms of fit from a Gompertz specification.

yields

$$S_a^O(t|\boldsymbol{x_i}) = \frac{1}{S^O(a|\boldsymbol{x_i})}\int S^O(t|\boldsymbol{x_i},\nu)f(v)dv = \frac{S^O(t|\boldsymbol{x_i})}{S^O(a|\boldsymbol{x_i})}.$$

We can use known results for the integration of the hazard over the gamma distribution to obtain a closed-form solution (see for instance Cameron and Trivedi, 2005, pp. 615-616),

$$S_a^O(t|\boldsymbol{x_i}) = \left(\frac{\delta^O + \Lambda^O(a|\boldsymbol{x_i})}{\delta^O + \Lambda^O(t|\boldsymbol{x_i})}\right)^{\delta^O}. \tag{4}$$

Each respondent is observed last at a given age, either the age at death or the age at the last interview for respondents still alive. We denote this age by t_i^O. We observe respondent i entering the survey at age a_i. Additionally, as some respondents are still alive at time t_i^O, we account for right censoring. The likelihood contribution of an individual i is given by:

$$L^O(\zeta^O,\alpha^O,\delta^O|\boldsymbol{x_i},a_i,t_i^O) = \lambda^O(t_i^O|\boldsymbol{x_i})^{d_i}S_a^O(t_i^O|\boldsymbol{x_i}) \tag{5}$$

where d_i is a dummy variable taking the value 1 if the respondent is deceased at time t_i^O.

3.2 Subjective Hazard

We use the superscript S to denote the subjective components of the model. We use the same parametric specification so as to compare objective and subjective parameters directly. Should the agents correctly perceive their mortality risk, their subjective and objective hazards would be identical. Using a similar notation for subjective probability of survival, we define:

$$S_a^S(t|\boldsymbol{x_i},\nu_i^S) = \exp\left(-\nu_i^S\int_a^t \lambda^S(\tau|\boldsymbol{x_i}))d\tau\right) = \exp(-\nu_i^S\Lambda_a^S(t|\boldsymbol{x_i})). \tag{6}$$

To interpret directly differences between objective and survival hazards we reparametrize using:

$$
\begin{aligned}
\alpha^S &= \alpha^O + \psi_\alpha \\
\boldsymbol{\zeta}^S &= \boldsymbol{\zeta}^O + \boldsymbol{\psi}_\zeta \\
\delta^S &= \delta^O + \psi_\delta.
\end{aligned}
$$

Hence, under the null hypothesis of correctly perceived mortality risk, $\boldsymbol{\psi}_\zeta$, ψ_α, and ψ_δ are equal to 0.

Conditional on $\boldsymbol{x_i}$, the survival probabilities follow a gamma distribution. Given that we need the distribution of survival probabilities to age t given survival to a in order to model rounding, denote the conditional distribution of subjective survival rates $F_s(s^S|T > a, \boldsymbol{x_i})$. To obtain an expression for this distribution, we can use $F_{\nu s}(v|T > a, \boldsymbol{x_i})$, the distribution of ν^S conditional on surviving to time a:

$$
F_s(s^S|T > a, \boldsymbol{x_i}) = 1 - F_{\nu s}\left(-\frac{\ln s^S}{\Lambda_a^S(t|\boldsymbol{x_i})}\middle| T > a, \boldsymbol{x_i}\right).
$$

This is due to the fact that for two random variables (Y, X), if $Y = g(X)$, then $F(y) = F_X(g^{-1}(y))$.

Let $d = \delta^{-1}$ such that ν^S at $a = 0$ is distributed gamma $\mathcal{G}(\delta, d)$. Given the value of d , ν^S has unit expectation. The distribution of ν^S conditional on being alive at age a is:

$$
\begin{aligned}
F_{\nu s}(\nu|T > a, \boldsymbol{x_i}) &= \frac{1}{S^S(a|\boldsymbol{x_i})}\int_0^\nu S^S(a|\boldsymbol{x_i}, u)f(u)\mathrm{d}u \\
&= \frac{1}{S^S(a|\boldsymbol{x_i})}\int_0^\nu \exp(-u\Lambda^S(a|\boldsymbol{x_i}))\frac{d^{-\delta}u^{\delta-1}\exp(-\frac{u}{d})}{\Gamma(\delta)}\mathrm{d}u \\
&= \frac{d^{-\delta}}{S^S(a|\boldsymbol{x_i})}\int_0^\nu u^{\delta-1}\frac{\exp(-u(\Lambda^S(a|\boldsymbol{x_i}) + \delta))}{\Gamma(\delta)}\mathrm{d}u.
\end{aligned}
$$

For the sake of exposition, let $k = 1/(\Lambda^S(a|\boldsymbol{x_i}) + \delta)$, and remember that $S^S(a|\boldsymbol{x_i}) = (d/k)^{-\delta}$

$$
\begin{aligned}
F_{\nu s}(\nu|T > a, \boldsymbol{x_i}) &= \frac{d^{-\delta}}{S^S(a|\boldsymbol{x_i})} \int_0^{\nu} u^{\delta-1} \frac{\exp(-\frac{u}{k})}{\Gamma(\delta)} \mathrm{d}u \\
&= \frac{1}{S^S(a|\boldsymbol{x_i})} \frac{d^{-\delta}}{k^{-\delta}} \int_0^{\nu} k^{-\delta} u^{\delta-1} \frac{\exp(-\frac{u}{k})}{\Gamma(\delta)} \mathrm{d}u \\
&= \int_0^{\nu} k^{-\delta} u^{\delta-1} \frac{\exp(-\frac{u}{k})}{\Gamma(\delta)} \mathrm{d}u.
\end{aligned}
$$

Then it follows directly that $F_{\nu s}(v|T > a, \boldsymbol{x_i})$ is distributed gamma $\mathcal{G}(\delta, k)$. This makes explicit that the mean and variance of the frailty term decreases as age increases, as the integrated hazard is expected to increase with age, leading to a decrease in k.

3.3 Self-reports and Rounding

We assume that the self-reported survival probability p_{iat} is a rounded report of $s_a^S(t|\boldsymbol{x_i}, \nu_i^S)$. We use a latent-variable reporting model following Heijtan and Rubin (1990,1991) and Kleinjans and van Soest (2013). We do not know the rounding rule used by the respondents. The problem of unknown rounding is comparable to a problem of unknown mixture of distributions. Suppose that we observe a respondent answering 25% to a probability question. The answer could be the result of rounding of a subjective probability in the [12.5, 37.5) range, rounding at the nearest multiple of 25. It could also come from the [22.5, 27.5) range if a respondent rounded to the nearest multiple of 5, or even from the [24.5,25.5) range should a respondent give a very precise answer. Based on distributional assumptions, we can estimate a model predicting the probability that respondents will use various rules in rounding and use that for maximum likelihood inference.[2] We consider the following rules based on what we observe from data:

1. Throw-away 50%-points, where respondents use 50%-points in order to avoid answering;[3]

[2] See Manski and Molinari (2010) for alternative methods used to uncover rounding rules

[3] While this rule is not rounding, strictly speaking, we treat this as any answer from the interval [0,100] that is reported at the middle point. In this regard, we depart from Kleinjans and van Soest (2013) who specifically modeled the probability of giving a throw-away answer in a first step, and then modeled rounding

2. Rounding to a multiple of 50%-points;
3. Rounding to a multiple of 25%-points;
4. Rounding to a multiple of 10%-points;
5. Rounding to a multiple of 5%-points;
6. Precise answers rounded at 1%-points.

We treat the rounding rule as an unknown random variable R. We denote the realization of R with r, an integer from 1 to 6 according to the above list. Hence, a higher value means a more precise answer or less rounding. Each rounding rule leads to a set of admissible p_{iat}. This set of admissible values is denoted by Ω_r. Finally, for each rounding rule, a self-reported probability of p_{iat} can result from rounding of values between $l_r(p_{iat})$ and $u_r(p_{iat})$. In cases where rounding is made with equally spaced intervals, we would have $l_r(p_{iat}) = p_{iat} - e_r$ and $u_r(p_{iat}) = p_{iat} + e_r$, with e_r being one half of the rounding interval.

We are interested in estimating the probability of observing a self-reported answer of p_{iat} given a subjective survival probability. The rounding process we described can be summarized as follows:

$$\begin{aligned}\text{Prob}(p_{iat}|s_a^S(t|\boldsymbol{x_i}, \nu_i^S), z_i) = &\sum_{r=1}^{6} 1(p_{iat} \in \Omega_r)\text{Prob}(R_i = r, |z_i) \\ &\times 1(l_r(p_{iat}) \leq s_a^S(t|\boldsymbol{x_i}, \nu_i^S) < u_r(p_{iat}))\end{aligned} \tag{7}$$

where z_i corresponds to a set of characteristics which affect the likelihood of rounding. In order to estimate the probability of using one of these six rounding rules, we follow an approach similar to the one discussed by Kleinjans and van Soest (2013). We consider that each respondent has a "propensity to provide a precise answer", which is represented by r_i^*. A higher value for this variable implies that respondents are more likely to use a precise rounding rule. To capture the propensity to round, we use an ordered response model. We assume that:

conditional on giving a meaningful answer. Our approach differs by assuming that throw-away 50s are very imprecise answers, not non-responses.

$$r_i^* = z_i \boldsymbol{\gamma} + \varepsilon_i$$

and that a respondent uses rounding regime r if $m_{r-1} < r_i^* \leq m_r$, where where $m_0 = -\infty$, $m_1 = 0$, and $m_6 = \infty$. It follows that m_2 to m_5 are parameters to be estimated. We assume that ε_i follows a standard normal distribution. Equation 7 can be rewritten as:

$$\begin{aligned}
\text{Prob}(p_{iat}|s_a^S(t|\boldsymbol{x_i}, \nu_i^S), z_i) = \\
&\sum_{r=1}^{6} 1(p_{iat} \in \Omega_r)(\Phi(m_r - \boldsymbol{z_i\gamma}) - \Phi(m_{r-1} - \boldsymbol{z_i\gamma})) \\
&\times 1(l_r(p_{riat}) \leq s_a^S(t|\boldsymbol{x_i}, \nu_i^S) < u_r(p_{iat})). \qquad (8)
\end{aligned}$$

We include two additional explanatory variables in the reporting mode, leading to two exclusion restrictions. The first one is based on the number of words that a respondent could recall in a memory exercise, in order to capture cognitive skills. The variable used is a period z-score, to correct for the varying number of words asked in total and for possible variation in the difficulty of the list in a given period. The second variable is the proportion of answers that were multiples of 50 in the other probability questions of the HRS.

3.4 Likelihood

We estimate the model by maximum likelihood. We maximize the joint likelihood of observing self-reported subjective probabilities and actual mortality. The likelihood for the subjective reports is

$$L^S(\zeta^O, \alpha^O, \delta^O, \boldsymbol{\psi}_\zeta, \psi_\alpha, \psi_\delta, \gamma|\boldsymbol{x_i}, a_i, z_i) = \Pr(p_{iat}|\boldsymbol{x_i}, z_i)$$

where this probability is given by

$$\begin{aligned}
\text{Prob}(p_{iat}|\boldsymbol{x_i}, z_i) = &\sum_{r=1}^{6} 1(p_{iat} \in \Omega_r)(\Phi(m_r - \boldsymbol{z_i\gamma}) - \Phi(m_{r-1} - \boldsymbol{z_i\gamma})) \\
&\times (F_s(u_r(p_{iat})|\boldsymbol{x_i}, T > a) - F_s(l_r(p_{iat})|\boldsymbol{x_i}, T > a)).
\end{aligned}$$

The complete likelihood is given by:

$$\ln L = \ln L^O + \ln L^S. \tag{9}$$

Given that we estimate both objective and subjective hazards jointly, we can test whether parameters differ.

3.5 Subjective Frailty and Individual Curves

Using parameter estimates, we generate individual subjective survival curves for each respondent. Conditional on ν_i^S we can reconstruct survival curves. We can use self-reports to obtain a distribution of ν_i^S for a given p_{iat}. We impute for each respondent the expected value ν_i^S, conditional on the answer to the self-reported survival probability. The expression for this expectation is given by

$$E(\nu_i^S | p_{iat}, \boldsymbol{x_i}, z_i) = \frac{\int_0^\infty u \text{Prob}(p_{iat} | u, \boldsymbol{x_i}, z_i) f_{\nu s}(u | \boldsymbol{x_i}, T > a) \mathrm{d}u}{\text{Prob}(p_{iat} | \boldsymbol{x_i}, z_i)}. \tag{10}$$

Hence, the resulting survival curves account for both differences in observable and unobservable determinants of subjective mortality risk.

4 Estimation Results

4.1 Objective Survival Curves

We report estimates of objective hazard parameters in the first column of Table 1. A positive parameter implies higher mortality risk and thus lower survival probability. Mortality risk covaries in expected ways with demographic characteristics. Cohort-effect estimates suggest that mortality risk is higher for younger cohorts. This would suggest a decrease in longevity in years to come. An alternative explanation is that this is due to selection in HRS. The HRS samples from the non-institutionalized population and the entry cohort in AHEAD

(70+ at entry) could well be healthier than younger cohorts who reach age 70 whether they are institutionalized or not.

In Figure 3, we present for men and women separately the distribution individual curves based on objective risk for the respondents born in 1945 or later and aged 50 to 53 at baseline –the youngest respondents of our sample. We report 10th, 50th (median) and 90th percentile of the curves. We also report the period life-table survival curve for the year the median respondent answered the survey (i.e., 1998). We use sample weights.

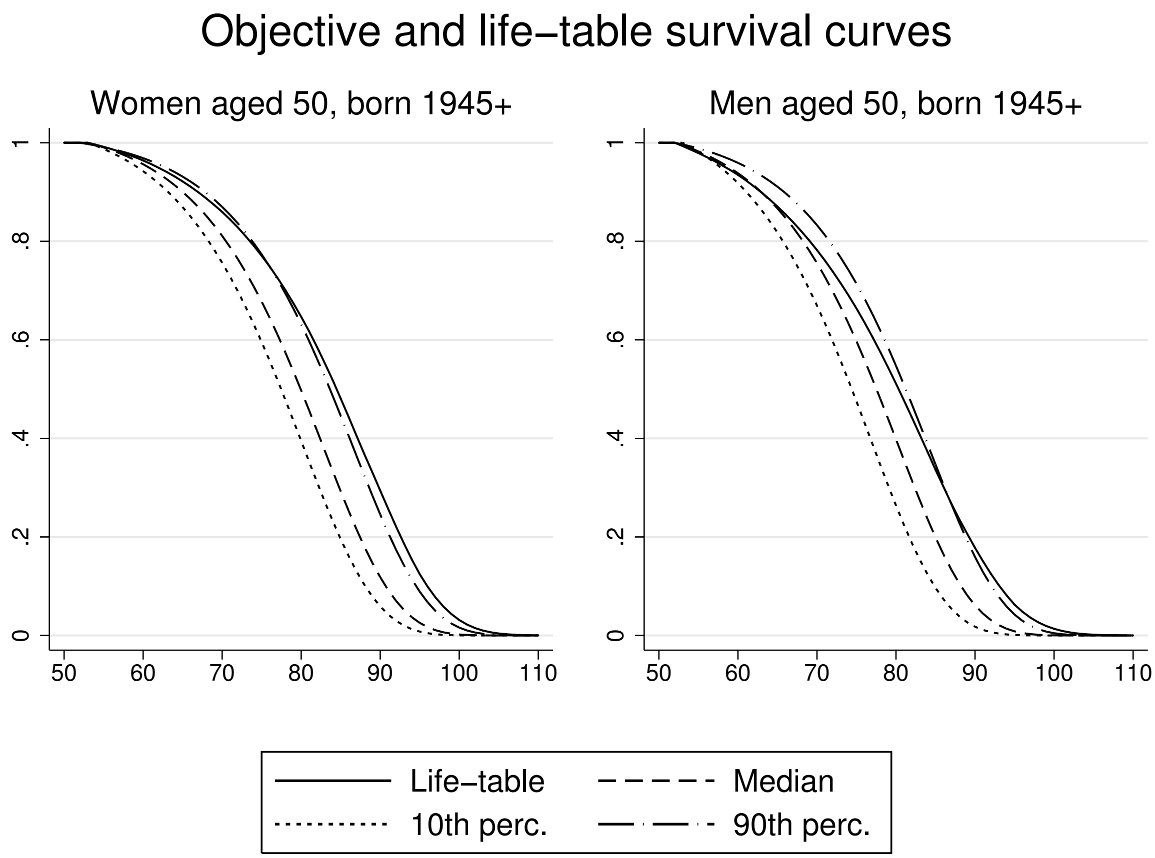


Figure 3: Comparison of the objective and of the life-table-based survival curves. Percentiles in this figure were determined using HRS weights.

The median life-table and objective curves are close for men but differ for women. The median survival curve for women lies below the life-table survival curve. Hence, the HRS features higher mortality for women than the life-table. Hurd and McGarry (2002) report

Table 1: Estimation results

	Objective model[a] ($\boldsymbol{\zeta^O}$, α^O, and δ^O)	Subjective model[b] ($\boldsymbol{\psi}$, ψ_α, and ψ_δ)	Reporting model ($\boldsymbol{\gamma}$ and m_r)
Male	0.272	-0.151	0.012
	(0.029)	(0.031)	(0.010)
Black	0.216	-0.220	-0.101
	(0.040)	(0.042)	(0.015)
Hispanic	-0.092	0.403	0.004
	(0.058)	(0.062)	(0.020)
High School	-0.210	-0.103	-0.008
	(0.033)	(0.036)	(0.013)
College	-0.379	-0.220	0.188
	(0.035)	(0.037)	(0.013)
Ever Smoked	0.427	-0.245	0.013
	(0.034)	(0.035)	(0.011)
Cohort 1900-1915	-0.537	0.791	0.274
	(0.071)	(0.125)	(0.026)
Cohort 1915-1930	-0.440	0.253	0.199
	(0.056)	(0.063)	(0.013)
Cohort 1930-1945	0.146	-0.195	-0.000
	(0.098)	(0.099)	(0.017)
α	0.109	0.006	
	(0.004)	(0.004)	
δ^{-1}	0.016	1.080	
	(0.042)	(0.043)	
Immediate word recall (z-score)			0.018
			(0.007)
Prop. of 0/50/100 in other quest.			-1.288
			(0.021)
Constant (ζ_0, ψ_0, or γ_0)	-5.984	0.851	4.560
	(0.077)	(0.081)	(0.245)
m_2			3.629
m_3			4.063
m_4			5.290
m_5			6.322
N	18,791	80,298	
Log-likelihood		-219,686.042	

Standard errors in parentheses

[a] Survival model estimated using age 50 as initial time period.

[b] Subj. parameters expressed in terms of differences as in equations 5.7 to 5.9.

a similar finding over earlier waves.[4] This finding highlights one of the main advantages of the approach we propose: even with a nationally representative sample like the HRS, the life-tables may not be a valid measure of within-sample survival probabilities. Deviation from the life-tables in subjective expectations may not be due to erroneous predictions of respondents.

4.2 Subjective Survival and Reporting

The second column of Table 1 contains estimated parameters for the subjective hazard $\boldsymbol{\psi}_\zeta$, ψ_α, and ψ_δ, capturing differences between the objective and subjective parameters.

We find that men, black and more educated (either with a high school or college degree), younger-cohort, and smoking respondents have higher subjective survival than objective survival. Hence, they are more optimistic than other groups. Hispanic respondents appear to have lower subjective survival rates. Hence, they are more pessimistic. The negative signs of the estimates of both education dummies also show that respondents overestimate the benefits of education for survival.

Differences between α^O and α^S are small and statistically insignificant (p-value = 0.154) which suggest that respondents do well at predicting the rate of decline in their survival probabilities. The difference in baseline risk (intercept) is larger than zero. Hence, respondents are more pessimistic at younger ages about their survival regardless of differences in characteristics.

The variance of the frailty term is much larger for subjective frailty than it was for objective frailty, implying higher perceived variation among respondents regarding mortality than we found with actual data. This is consistent with Hamermesh (1985).

A Wald test of joint significance rejects strongly the null hypothesis that all differences in parameters across hazards are zero. Hence, evidence suggest that there is little support for using objective risk in models of behaviour because respondents make decisions based on subjective survival curves which deviate substantially from objective curves.

[4] We also performed sensitivity analysis using alternative specifications and estimating the model separately by gender, but mortality among women remained higher than predicted. Results obtained with these alternative specifications were hardly different from the ones presented here.

In the last column of Table 1, we present results for the rounding model. We find that being male, Hispanic, having a high school diploma, and ever smoking are very weakly related to rounding behavior. College education and cognitive skills increase the likelihood of more percise answers. We also find that a higher proportion of focal answers in other HRS questions leads to a higher probability of coarse rounding in the self-reported survival probability, reinforcing the idea that some respondents are simply less prone to give "precise" answers. We find little support for the idea that 50%-point answers are used to avoid answering questions. In our model, the predicted probability of such behavior is practically zero for all respondents. On average, we predict that 33.7% of the respondents round to the nearest multiple of 50, while 15.8% round to a multiple of 25, 37.8% to a multiple of 10, 11.0% to a multiple of 5, and 1.7% report very precise answers.

We assess whether rounding is important by re-estimating a model where we fixed the propensity to report precise answers to one. This implies that we assume that respondents report their subjective probabilities with a 1%-point precision. The variance of the subjective frailty term in that model is about twice as large when we do not take rounding into account, increasing to a value of 2.63 with a standard error of 0.04. The variation in frailty needed to accommodate the large fraction of respondents who used 0% and 100% is quite substantial when there is no rounding. Other parameters adjust in terms of magnitude.

In Figure 4, we present the distribution of subjective curves. We also plot the median objective survival curve. For each respondent, we compute the expected subjective frailty term as described in Equation 10 and use those to trace survival curves.

We observe that the median objective and subjective curves are quite close. This would imply that women are conscious of the higher-than-predicted mortality risk. We also see evidence that both men and women are slightly optimistic. There is substantial heterogeneity in subjective curves, more so than in objective curves.

4.3 Subjective Remaining Life Expectancy

We can use subjective survival curves to compute subjective remaining life expectancy. In Figure 5, we report remaining subjective life expectancy at age 50. Estimates of average remaining objective life expectancy risk are 26.5 years for men and 29.2 years for women.

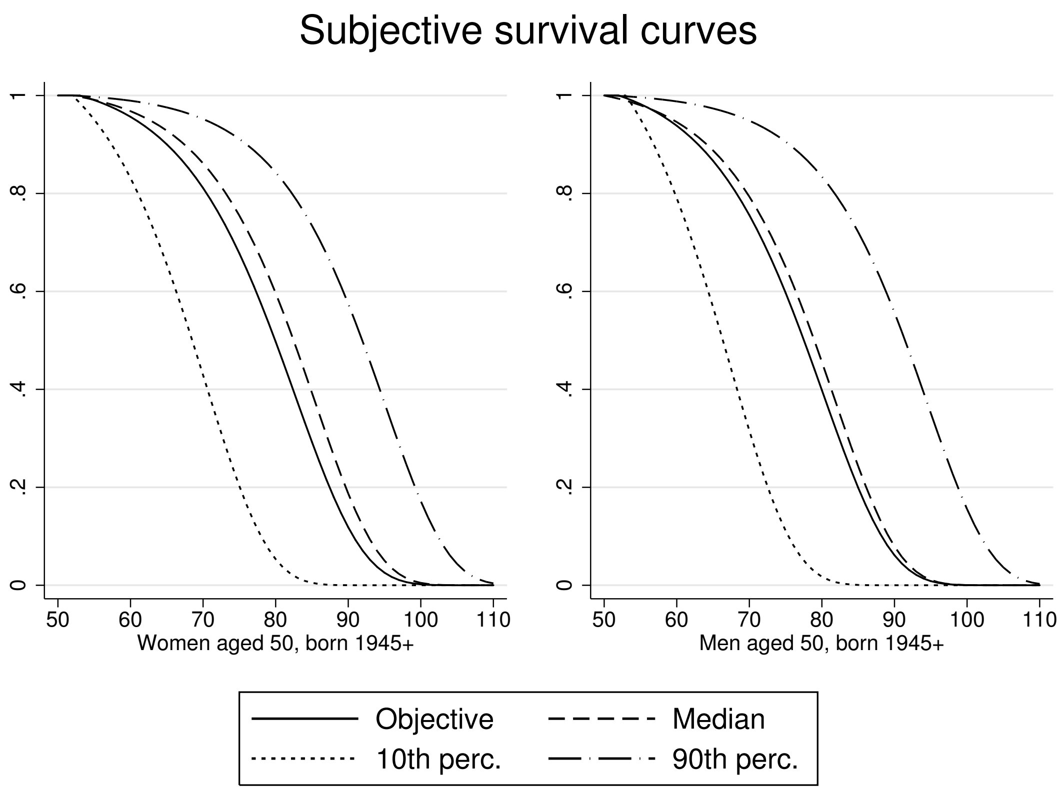


Figure 4: Subjective survival curves conditional on the respondents' self-reported probabilities (expected subjective frailty used).

The average subjective remaining life expectancy is 28.0 years for men and 30.0 years for women.

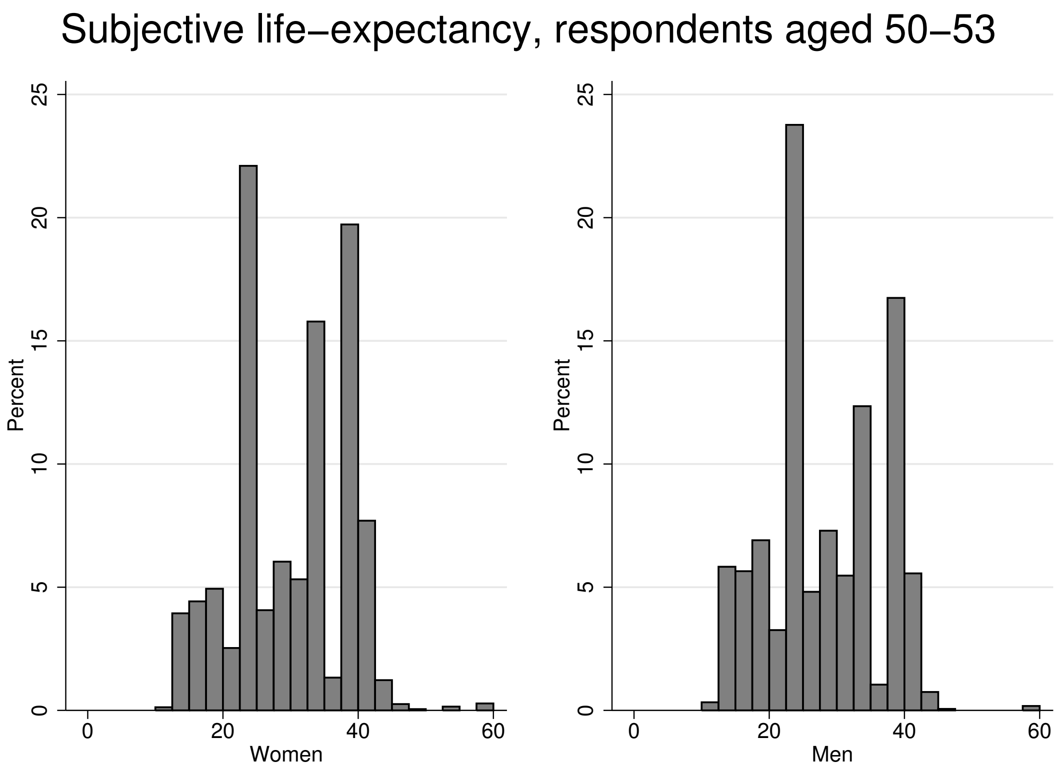


Figure 5: Distribution of the conditional life-expectancy (in remaining years) for the respondents aged 50-53, all cohorts combined.

We also report the distribution of remaining life expectancy by age, gender and cohort in Figure 6 along with median objective survival prediction at each age. These profiles are smoothed in order to focus on variation induced by the model rather than sampling variation.

Median subjective and median objective predictions are very similar for all groups. As expected from Figure 4, median respondents have subjective expectations that are quite close to the objective ones. There is considerable dispersion in the subjective estimates.

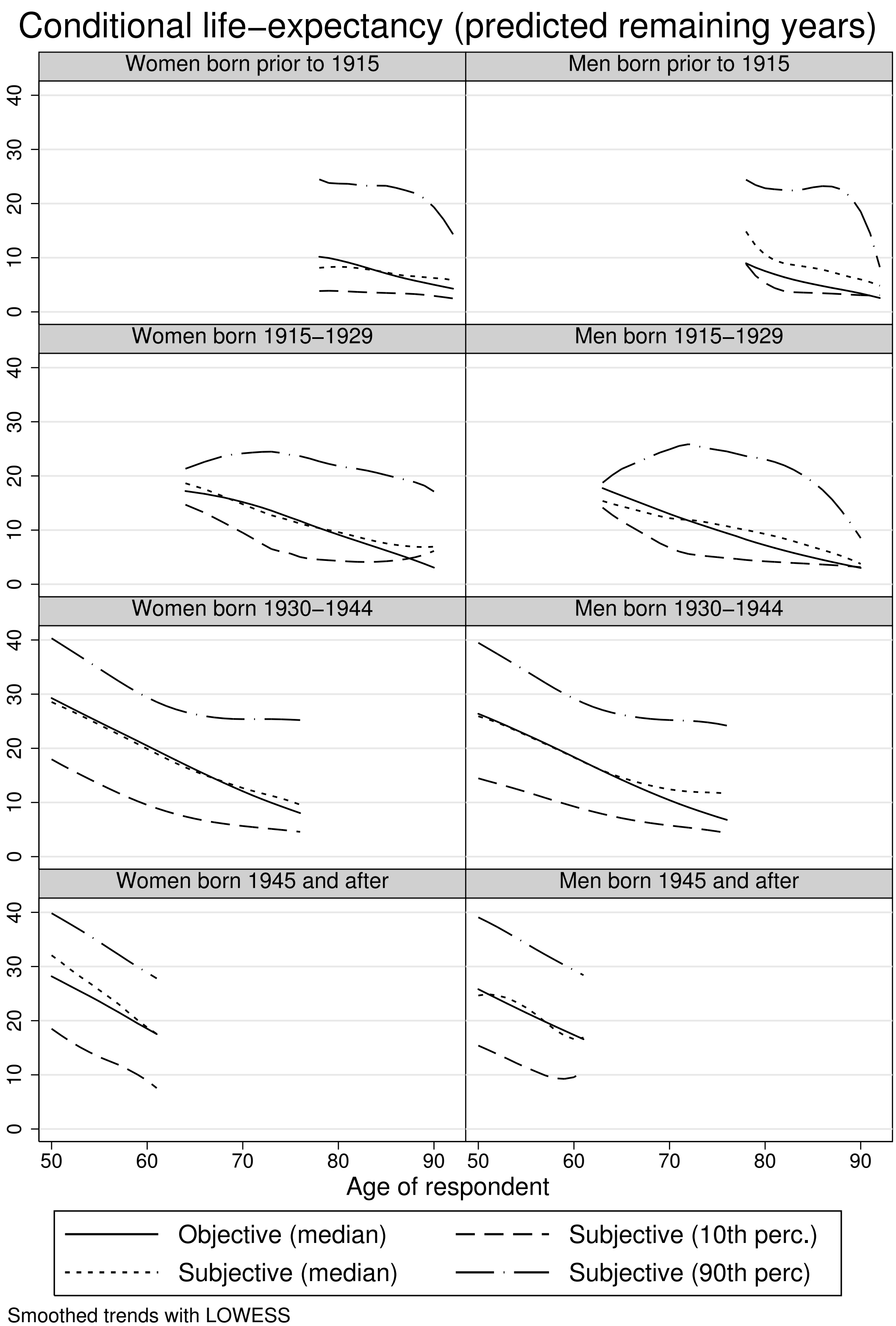


Figure 6: Objective and subjective life-expectancy (in remaining years) at various ages, by gender and cohort

5 Comparisons of Remaining Life Expectancy

5.1 Smoking

The accuracy of the expectations of smokers was previously studied by Khwaja et al. (2007) who found, using the HRS and relying on a similar comparison between subjective and objective probability of survival, that smokers tend to be optimistic concerning their own survival probabilities. Here we can compare entire survival curves for both smokers and non-smokers. In Figure 7, we present subjective survival curves of smokers and non-smokers for respondents aged 50 to 53 from the 1945 cohort. We also report the objective survival curve of the median respondent.

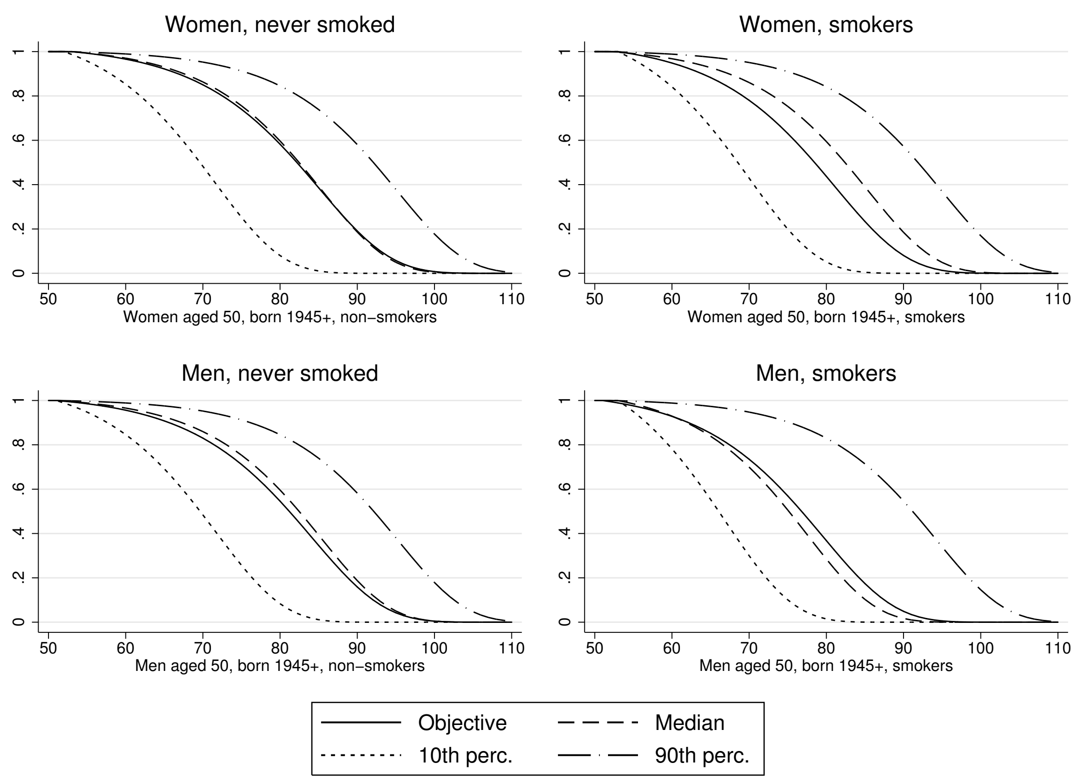


Figure 7: Subjective survival curves conditional on the respondents' self-reported probabilities (expected subjective frailty used) presented separately for smokers and non-smokers.

The median smokers and non-smokers appear to correctly perceive mortality risk. Yet this hides considerable heterogeneity. If we take the ratio of subjective to objective remaining life expectancy, we see non-smokers on average perceive correctly their mortality risk, with an average ratio of 0.99 for women and 1.03 for men. However, smokers tend to be too optimistic with an average ratio of 1.10 in subjective to objective life expectancy for both women and men. Hence, individual survival curves allow us to assess not only differences in averages but also quantify the distribution of mortality risk across individuals.

5.2 Joint Survival

Given that we estimate individual survival curves for each spouse in a couple, we can recover joint survival curves and thus estimate expected number of years together as well as widowed. Accuracy in estimating years of joint survival and widowhood may be an important reason why some households are in poverty at older ages, particularly widows who may have erroneous expectations regarding longevity risk. We restrict our analysis to couples where both members are observed and provide enough information to be included in our estimation. Altogether, we examine joint survival for 13,919 households.

In Figure 8, we first illustrate graphically the joint distribution of remaining life expectancy, both subjective and objective by focusing on those (2,349) households where the husband is aged 63 to 67 in order to control for the correlation in age. We estimate non-parametric bivariate densities. We use a fairly wide bandwidth (4 years), leading to over-smoothing. This informally compensates for our use of the expected value of the distribution rather than the full range of realization of the random variables. The left panel presents subjective expected remaining years, conditional on the answer to the probability question. The right panel presents objective expected remaining years.

The variance for both spouses is much larger in the subjective density than in the objective density. There is considerable correlation across spouses. While the average and median respondents have subjective life expectancy close to their objective measure, it seems that the skewness of the distribution is quite different when we compare the measures. We ran regressions of subjective and objective reports of the husband on the wife's expected remaining years, controlling only for age of both spouses. We find a partial correlation of 0.40 for subjective reports and 0.66 for objective reports. The fact that subjective reports are less

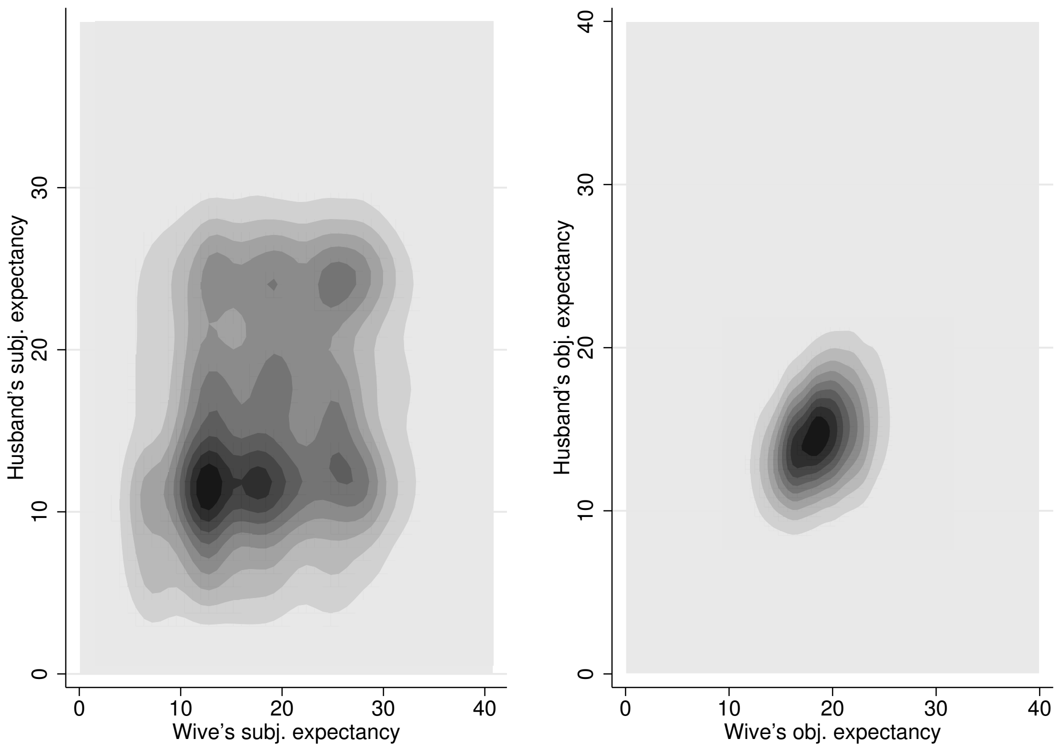


Figure 8: Estimated joint density of subjective (left panel) and objective (right panel) life expectancy of both couple's members (gaussian kernel, 4 years bandwidth).

correlated is an interesting result and suggests that spouses may make joint decisions based on perceived mortality risk which is less correlated than actual mortality risk.

To understand better the implications of these correlations, we use individual curves to construct the number of years a couple can expect to live jointly and as widowed. This assumes that survival curves do not change when a spouse dies and thus omits perceived or actual bereavement effects. Table 2 presents this information by five-year age groups of respondents. The upper part of the table presents the information ordered by husband's age and the lower part by wife's age.

Households in which the husband is young tend to overestimate the number of years they will live together and underestimate the number of years they may be widowed. Households with older husbands then to overestimate the number of years the wife will live as a widow.

In the lower panel, we see that households with younger wives tend to predict accurately the number of years they will live together. Households tend to underestimate the number of years the husband may live as a widower.

Widows are most prone to poverty in old age. However, it does not appear that misperceptions about the risk of becoming a widow is a likely explanation as we do not find large differences in perceived and actual expected number of years in widowhood. We do observe that males are much more likely to incorrectly perceive their risk of being widowed. This is largely because of their relative optimism regarding their survival prospects.

5.3 Education

Differences in life expectancy may be important for understanding lack of preparation for retirement. Scholz et al. (2006) find that roughly 20% of households, particularly those with less education in the HRS appear to be saving too little relative to savings predicted from a model which uses lifetable mortality risk. This would also imply that 80% may be saving too much for retirement. Savings behavior has important welfare implications.

Figure 9 compares survival curves for three education groups of men and women. For men, those with low education tend to correctly perceive their mortality risk at the median. Women with low education are slightly pessimistic about their survival prospects. For both

Table 2: Joint Survival, Objective and Subjective.

	Husband's age					
	Objective			Subjective		
Age	Both alive.	Husb. widow	Wife widow	Both alive.	Husb. widow	Wife widow
50-54	18.82	5.99	7.54	19.64	4.35	7.11
55-59	16.37	5.24	7.80	16.76	3.68	7.56
60-64	12.93	4.51	7.53	13.53	3.17	7.51
65-69	10.63	4.42	6.92	10.22	2.75	6.90
70-74	9.15	4.78	5.93	8.24	2.71	5.90
75-79	7.59	4.17	5.61	6.77	2.26	5.71
80-84	6.25	3.83	5.10	4.89	1.74	5.36
85-89	5.28	3.62	4.48	3.52	1.17	5.29
90-94	5.87	2.99	3.12	2.77	0.94	5.38
Total	12.54	4.75	6.95	12.51	3.08	6.89

	Wife's age					
	Objective			Subjective		
Age	Both alive.	Husb. widow	Wife widow	Both alive.	Husb. widow	Wife widow
50-54	18.28	5.03	8.53	18.59	3.48	8.40
55-59	15.13	4.88	7.94	15.59	3.44	7.70
60-64	11.94	4.89	6.66	12.40	3.28	6.90
65-69	10.06	4.77	6.10	9.30	3.02	5.90
70-74	8.59	4.48	6.11	7.82	2.52	5.98
75-79	6.92	4.24	5.17	5.99	2.15	5.33
80-84	5.49	3.90	4.30	4.41	1.98	4.33
85-89	5.20	3.90	3.73	3.33	1.80	3.43
90-94	4.31	6.77	1.75	2.86	1.67	2.89
Total	12.54	4.75	6.95	12.51	3.08	6.89

men and women of low education, there is considerable heterogeneity in survival expectations, more so than for more educated groups (high school, college). There tends to be less variance in survival curves for college-educated men. At the median, such men tend to be optimistic about their survival prospects. Given that they overestimate the number of years for which they need to finance retirement consumption, they may be saving more than necessary.

6 Consumption and Mortality Risk

The differences shown above suggest that consumers may make different decisions when using subjective rather than objective risk. For example, suppose a 65 year old believes his remaining life expectancy is 20 years but that in fact his objective remaining life expectancy is 15 years. He will plan to have enough savings to finance five additional years of consumption. Exactly how this may impact his savings and consumption will depend on his preferences. The standard life-cycle model with mortality risk dates back to Yaari (1962). In what follows, we show using a simple model how the consumption path derived from subjective survival curves may differ from those using objective risk and compute a welfare measure that captures the loss in well-being from using incorrect beliefs.

Denote the subjective survival probability s_t^S, and the objective s_t^O. Define c_t^S, c_t^O to be consumption at age t derived using subjective and objective probabilities respectively. Let r be the interest rate with $R = (1 + r)$ and W be wealth at $t = 0$ which we will assume to be age 65. We will assume preferences are constant relative risk aversion, $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$ and the consumer discounts the future with a factor β. Expected discounted utility conditional on using particular survival probabilities j is given by

$$U(c^j, s^j) = \sum_{t=0}^{T} \beta^t s_j^j u(c^j) \tag{11}$$

for $j = S, O$.

Given that $s^j > 0$ for all t and that marginal utility is infinity at $c_t = 0$, optimal wealth is always positive at $t + 1$ (the consumer will not want to run the risk of surviving with no

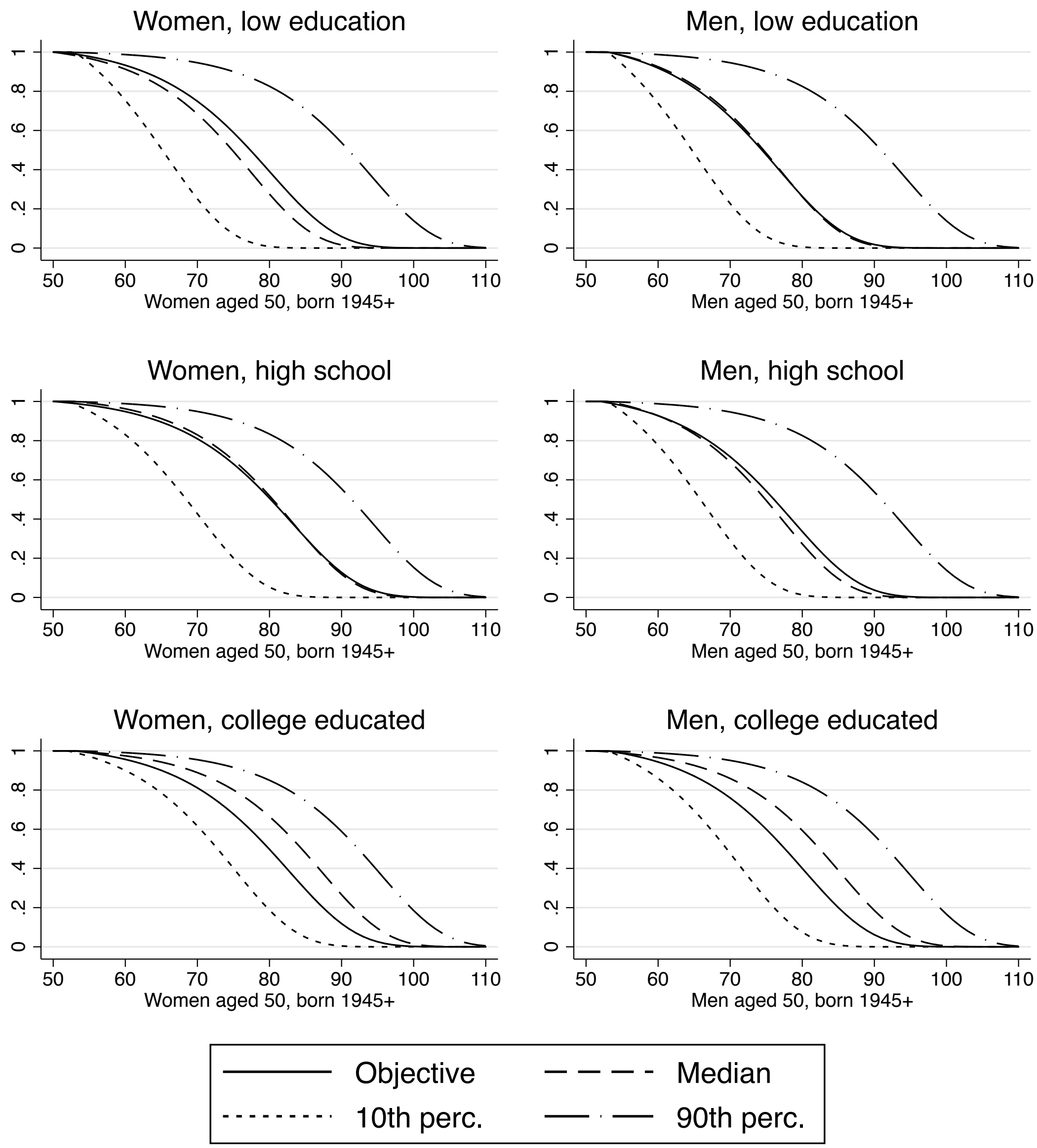


Figure 9: Subjective survival curves conditional on the respondents' self-reported probabilities (expected subjective frailty used) presented separately by level of education.

resources). Using that, the budget constraint is given by

$$W = \sum_{t=0}^{T} R^{-t} c_t^j \tag{12}$$

This simply says that wealth at $t = 0$ is equal to the present value of the consumption flow. We abstract from annuity income for this illustration which would make the problem more complicated (Hurd, 1989).

From the first-order condition to the maximization of U, we know that

$$\frac{c_{t+1}^j}{c_t^j} = \left(\frac{s_{t+1}^j}{s_t^j} R\beta \right)^{\frac{1}{\sigma}} \tag{13}$$

and therefore

$$c_t^j = c_0^j (s_t^j (R\beta)^t)^{\frac{1}{\sigma}} = c_0 g_t(s_t^j) \tag{14}$$

which in turn implies that the path of consumption over time can be written as a function of W:

$$c_t^j(W) = \frac{g_t(s_t^j)}{\sum_{t=0}^{T} R^{-t} g_t(s_t^j)} W. \tag{15}$$

Hence, the optimal consumption path given s^j and W is $c^j(W) = \{c_t^j(W)\}_{t=0}^T$. If $R = \beta$ consumption still declines with age due to mortality risk (Hurd, 1989).

Given that consumption is proportional to wealth, we will normalize accumulated wealth to one at age 65. Following Scholz et al. (2006), we will assume $\gamma = 3$, $\beta = 0.96$ and $R = 1/\beta$ so as to focus on the role of mortality risk. Choosing a lower value for γ would make consumption more sensitive to mortality risk.

A pessimistic respondent will tend to consume her wealth more quickly than an optimistic one. One way to characterize pessimism would then be to compare the ratio of consumption chosen under objective and subjective survival probabilities. A low ratio would then be a sign of pessimism, while a high ratio would be a sign of optimism. To illustrate the difference in consumption level between pessimistic and optimistic respondents, we compute the optimal consumption path of every respondent under both subjective and objective survival expectations, order them in terms of this ratio and present the consumption levels of respondents assuming they hold one dollar of wealth at age 65. Figure 10 presents these paths for the 10th, 25th, 50th, 75th and 90th percentile when respondents are sorted by this ratio. We see

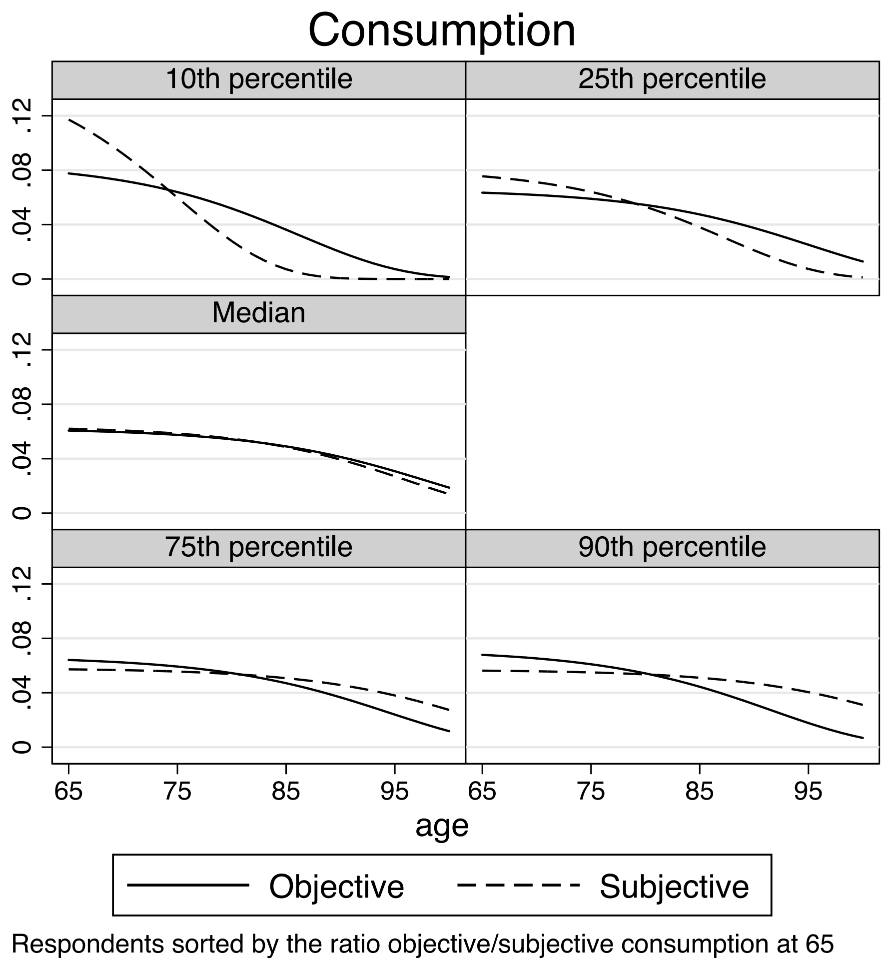


Figure 10: Evolution optimal consumption at every age for a dollar of wealth at 65 using either subjective or objective expectations on survival probabilities.

on the figure that the median respondent has a consumption path that is very close to the optimal objective path. The 10th and the 25th percentile illustrate two level of pessimism. We find that if the subjective consumption of the 10th percentile would be very low beyond age 85. This is explained by the fact that the respondent barely expects to survive past this age. The figure also hints that the optimistic respondents in the 75th and 90th percentile have consumption patterns that are closer to their objective measure if we compare them to their pessimistic peers.

The same information can be presented in terms of wealth held by the agent at every period in time. Figure 11 presents the wealth of the same respondents selected for Figure 10. We see again that the median respondents has a wealth level at every period that is very close to the path chosen under objective survival probability, with very little pessimism seen by the fact that the subjective curve lies below the objective one. The figure shows that the

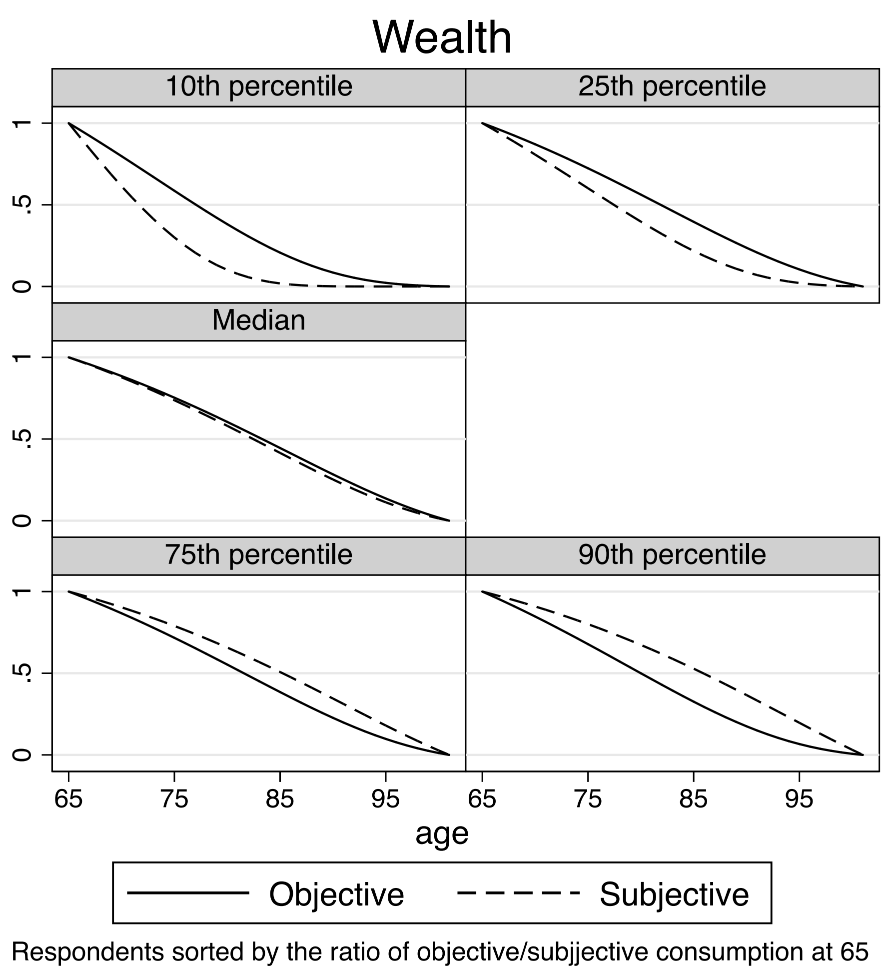


Figure 11: Evolution optimal wealth held at every age for a dollar of wealth at 65 using either subjective or objective expectations on survival probabilities.

10th percentile is the one with what seems to be the most important deviation between the two curves.

When subjective expectations differ from objective ones, the consumer will suffer a welfare loss by not choosing the optimal path of consumption ex ante. To get a sense of the magnitudes involved, we derive how much compensation we should give each respondent so that his expected utility at age 65 when using subjective beliefs is equal to the expected utility he could have reached had he used objective beliefs and thus implemented the optimal consumption plan. By doing this, we can also assess whether the welfare loss is larger for being pessimistic or optimistic.

Suppose subjective risk is different from objective risk. The agent will decide on the consumption path $c^S(W)$ based on maximizing $U(c^S, s^S)$. However, he will experience $V_S(W) = U(c^S(W), s^O)$ which leads to a welfare loss compared to what he would have obtained had he used correct expectations: $V_O(W) = U(c^O(W), s^O)$. It is easy to show under the preferences we use that the wealth needed relative to what the consumer has at age 65 is given by

$$W_C = \left(\frac{V_O}{V_S}\right)^{\frac{1}{1-\sigma}} \tag{16}$$

where V_O is expected indirect utility using objective beliefs and the optimal plan under objective beliefs and V_S is expected utility using objective beliefs but the optimal plan chosen under subjective beliefs.

We compute the value of W_C for every respondent aged 65 or less, assuming that they do reach age 65. We present here various quantiles of the distribution of W_C according to some characteristics.[5]

Table 3 presents some quantiles of the distributions based on gender and educational level. At the median, the welfare loss amounts to 7% of wealth at age 65. This loss is larger for males than females at higher education levels. In terms of education, the welfare loss is

[5] For clarity of presentation, we censored the distribution at an arbitrary value of 10. This is needed in cases where the expected probability of survival to older ages was so low that compensation needed to achieve the same utility reached extremely high values. These respondents would simply never prepare adequately for ages they barely expect to reach.

larger for low-educated households than for college-educated households. The welfare loss is very heterogeneous, reflecting the heterogeneity in survival curves found earlier. More than 25% of respondents have welfare losses larger than 60% of their current wealth. The large losses are found all across the distribution and in particular among low-educated women.

Table 3: Compensating wealth to correct for erroneous expectations by education

		10^{th}	25^{th}	Median	75^{th}	90^{th}
Women	Low. ed.	1.012	1.044	1.136	6.131	>10
	H. School	1.003	1.018	1.065	1.875	>10
	College	1.002	1.010	1.039	1.444	3.391
Men	Low. ed.	1.014	1.048	1.115	1.863	>10
	H. School	1.009	1.036	1.094	1.502	>10
	College	1.003	1.019	1.068	1.298	>10
Total	All levels	1.004	1.022	1.077	1.621	>10

We can test whether welfare losses are larger for those who are pessimistic than for those who are optimistic. We split the content of Table 3 according to whether respondents are optimistic (i.e. with subjective life expectation larger than their objective measures) or pessimistic. Table 4 presents the results. At the median, the welfare loss is larger for pessimistic respondents (54% against 3.3%). The 75th and 90th percentile tell us that these errors can be very costly. Although being optimistic implies a welfare loss, this welfare loss is small. The concavity of utility function probably explains this finding. Being pessimistic implies that at some age the marginal utility of consumption will be low (because the consumer overspent at earlier ages). Hence the discounted value of the marginal utility is larger than it is if the consumer underspent at younger ages and those had consumed too much at older ages. Although simplistic, because it avoids dealing with annuity income and other types of risk (e.g., medical expenditures), this exercice gives an idea of the magnitudes involved.

One way to increase experienced welfare in this setting would be to provide an annuity to the respondents who spend their own wealth too quickly because of misperception in their survival probabilities. The problem is that these same respondents who spend their wealth too fast are also those who would believe that an annuity is not an interesting investment. To illustrate this, we computed a fairly priced immediate fixed annuity based on the average objective survival probabilities in our sample. Denoting the yearly average survival probabil-

Table 4: Compensating wealth to correct for erroneous expectations by education and optimism

		10^{th}	25^{th}	Median	75^{th}	90^{th}
Pessimistic						
Women	Low. ed.	1.057	1.246	2.203	>10	>10
	H. School	1.015	1.184	1.712	3.882	>10
	College	1.005	1.028	1.457	2.554	>10
Men	Low. ed.	1.031	1.105	1.408	>10	>10
	H. School	1.031	1.105	1.408	>10	>10
	College	1.013	1.089	1.349	6.122	>10
Total		1.015	1.098	1.540	>10	>10

Optimistic						
Women	Low. ed.	1.003	1.021	1.047	1.079	1.107
	H. School	1.001	1.009	1.023	1.052	1.071
	College	1.001	1.006	1.019	1.040	1.058
Men	Low. ed.	1.004	1.035	1.088	1.123	1.155
	H. School	1.004	1.018	1.044	1.089	1.114
	College	1.001	1.008	1.029	1.067	1.089
Total		1.001	1.011	1.033	1.067	1.099

ity to age t as $\bar{s}_t^O$, the yearly payout of this annuity bought at 65 for the price of one dollar is given by:

$$a = \frac{1}{\sum_{t=65}^{100} \frac{\bar{s}_t^O}{(1+r)^t}} = 0.0877 \tag{17}$$

So 100,000$ in wealth is equivalent in actuarial terms, to an amount of 8,770$ paid every year. Even if this amount is more generous than what can usually be obtained on the annuity market, 5.8% of the agents are going to prefer to self-insure based on our estimation. Those who prefer self-insurance are all concentrated below the 12th percentile, and are precisely those who would benefit the most from the annuity. We estimate that another 45.6% of respondents would buy an annuity at a fair price despite having pessimistic expectations. This could result in an important welfare gain. We know however that annuities found in the market place are not actuarially fair. For instance, Mitchell et al. (1999) reported that the annuities on the market had expected present value about 20% below the actuarially fair present value. In our framework, this would lead to a payout of 0.0701, which roughly corresponds to the market payout of the immediate fixed annuity at the time of writing. Using this payout, we find that 15.5% of respondents would prefer to self-insure themselves. These respondents are concentrated below the 38th percentile and are all pessimistic respondents. No respondents in the 10th percentile and below would choose the annuity.

7 Conclusion

In this paper, we estimate jointly subjective and objective survival curves where there is rounding on subjective reports of perceived mortality risk. We use data from the Health and Retirement Study covering a 16 year period, in particular mortality dates and measurements of subjective survival to a target age. Hence, this framework allows us to investigate whether in aggregate respondents correctly perceive their mortality risk. Instead of using life-tables as a benchmark, we use their actual mortality experience which we show is important because both non-response and survey design make inappropriate the life-table as a benchmark. Since we obtain individual objective and subjective survival curves, we are also able to obtain a full distribution of joint curves which allows us to assess distributional issues rather than look at aggregate predictions. For example, we can investigate whether particular sub-groups are too optimistic or pessimistic regarding their own mortality risk. While doing this exercise, we adjust for rounding which is important for investigating the distribution of individual survival curves.

We find that at the median, both men and women are slightly optimistic regarding their survival prospects. Other subgroups such as black, more educated respondents, and respondents from younger cohorts are also optimistic regarding their survival prospects. It is important to note that these comparisons do not involve making assumptions about cohort or composition effects because we look at the mortality experience of the same respondents who answered subjective probability questions. The case of smokers is particularly interesting. While non-smokers appear to correctly perceive their mortality risk, smokers are too optimistic. This approach also enables us to look at joint survival of couples. Overall, there is no evidence that households misperceive the risk of the wife to become a widow but some evidence that they underestimate the risk for the husband to become a widower. Finally, we compute the welfare loss of using erroneous beliefs in retirement when it comes to spending down wealth. This exercice shows that welfare loss can be large and more so for pessimistic expectations. Pessimistic expectations can be a barrier for annuitization for a small but important fraction of the population.

Individual survival curves can be used directly in the context of economic models. They are smooth, non-degenerate, and with finite life expectancy. One interesting exercise would be to investigate how the estimation of preferences in life-cycle models of economic decision making is impacted by using subjective rather than objective individual survival curves.

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