Die young or live long: modeling subjective survival probabilities *

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ABSTRACT

Subjective survival scaling factors are often estimated from one observation of life expectancy and treated as constant to any target age. Using new survey data on subjective survival probabilities over a range of target ages, we propose and estimate a model incorporating cohort- and target age-varying beliefs in scaling factors. Both cohort age and target age matter: respondents are pessimistic about overall life expectancy but optimistic about survival to advanced ages, and older respondents are more optimistic than younger. We illustrate the effect of these variations on the perceived value of annuities and on optimal life cycle consumption plans.

Keywords: subjective life expectancy; life cycle model.

JEL Classifications: D14, D84, J11, I10

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1 Introduction

In most forward-looking economic models, agents' subjective survival expectations are critical. Standard life cycle models, for example, predict that people will weight utility by their subjective survival probabilities, shifting resources towards the times of life when their chances of being alive to enjoy them are highest. To make such far-sighted plans, people need to have a complete set of survival expectations, extending from their current age out to the oldest age to which they could possibly live. Since this information is usually not available to researchers, many empirical life cycle studies assume that the shape of each person's subjective survival curve matches the population average, after some constant adjustment for personal optimism or pessimism.

Here we collect and model new survey data that captures the subjective survival expectations of 920 middle aged men and women from their current age to extremely old ages, giving the comprehensive set of expectations needed for life-cycle modelling.[1] We show that even after averaging out idiosyncratic differences, individual subjective survival curves do not match the shape of population survival curves. People underestimate their chances of living to near ages and overestimate their chances at much older ages. Ludwig and Zimper (2013) find this pattern among people of different ages, and propose a learning model to account for the persistent bias. The fact that we have expectations to a range of target ages from the same individual means we can verify their view that younger age pessimism followed by later age optimism is not a cohort effect. However we go further and show that this pattern of early pessimism followed by later optimism is actually anticipated by individuals of different ages. On average, people in our survey also underestimate their overall life expectancy, women more than men, and younger cohorts more than older cohorts, consistent with results reported in many studies from a wide range of countries (e.g., Hamermesh, 1985; Wenglert and Rosén, 2000; Hurd and McGarry, 2002; Banks et al., 2004; Gan et al., 2005; Elder, 2013; O'Donnell et al., 2008; Teppa and Lafourcade,

[1] The widely-used Health and Retirement Survey (HRS) collects forecasts to a single target ages that can be different for respondents of different ages. Recent exceptions where ranges of probabilities were collected include Payne et al. (2013) and Teppa and Lafourcade (2013).

2013; Kutlu-Koc and Kalwij, 2013).

Subjective survival models that use constant or target-age-independent rescalings of population survival curves cannot match the shifting pessimism and optimism we see in our data. We estimate and reject constant rescalings using several consistency tests. Instead we propose and implement a more general cubic model that adjusts population survival by scaling factors that change with cohort age and target age. Our data allow us to make much more precise estimates of subjective survival curves than we could using only a life expectancy or one probability (Gan et al., 2005).[2]

Incorporating these new dynamics into a simple life cycle model sharpens predictions. For example, early retirement survival pessimism followed by later retirement survival optimism can partly explain the high rates of drawdown in early retirement and slow decumulation very late in life of some cohorts (Börsch-Supan and Lusardi, 2003). Pessimism among younger cohorts can help explain under-saving for retirement. Near age pessimism could motivate low rates of annuitization among younger retirees (Teppa and Lafourcade, 2013) or a dislike of deferred annuities. These results extend the literature on the effect of survival expectations on annuitization decisions (e.g., Milevsky and Young, 2007; Hainaut and Deelstra, 2014) and retirement consumption and portfolio decisions (e.g., Horneff et al., 2009; Salm, 2010).

Our study adds to the extensive literature on individual survival expectations and their use in life cycle modelling, beginning with Hamermesh (1985). Individual estimates of survival probabilities are coherent and useful for prediction and modelling (e.g., Smith et al., 2001; Hurd and McGarry, 2002; Hurd, 2009; Salm, 2010; Rohwedder and Delavande, 2011), but vary widely between people, often in ways that correlate with know risk factors such as personal health and parents' mortality (e.g., Bissonnette et al., 2012; Khwaja et al., 2007; Ludwig and Zimper, 2013; Perozek, 2008; Wang, 2014). Prior studies have shown that subjective survival expectations behave like probabilities (e.g., Hurd and McGarry, 1995; Hurd and McGarry, 2002; Gan et al.,

[2]Bernheim (1989, 1990) find that survey collected expectations contain significant reporting errors because "expectation" may not be fully understood by respondents and/or may not well defined in a survey.

2004; Smith et al., 2001) so that if complications caused by focal points can be managed (Hurd et al., 1998; Gan et al., 2005; Kleinjans and Soest, 2013), researchers can use them to model individual subjective survival curves (e.g., Bissonnette et al., 2012; Elder, 2013; Gan et al., 2005; Khwaja et al., 2007; Perozek, 2008).

In the next section, we describe the survey data. In Section 3 we test and reject the hypothesis that the subjective scaling factor is independent of target age within the same individual. Section 4 sets out a new model for subjective survival curves that allows for individual and cohort-level heterogeneity. We illustrate the effect of subjective survival probabilities on the perceived value of immediate and deferred annuities as well as on the consumption plans of forward looking agents in Section 5. Section 6 concludes.

2 Data

We collected subjective survival expectations from the Retirement Plans and Retirement Incomes: Pilot Survey, conducted in May 2011.[3] The survey was completed by a representative sample of 920 respondents aged between 50 and 74 years from the PureProfile online panel of over 600,000 Australians. Australian mortality patterns and longevity improvement rates are similar to other developed western countries.

After some deletions, our final sample comprised subjective survival probabilities of 855 respondents to seven target ages. Respondents answered the questions, *"What are the chances that you will live to be age t_a?"*, where the target age "t_a" took the values of 75, 80, 85, 90, 95, 100, 105, 110, 120, and 120^+ years respectively. Respondents chose probabilities from the list shown in Table 1 that most closely matched their expectation of survival at each age, however we exclude subjective survival probabilities to 110, 120, and 120^+ years in our analysis, because the population life tables do not report any data for these ages. We also dropped respondents who

[3] Agnew et al. (2013) gives more details about the survey sample. The full survey is available at: `http://www.censoc.uts.edu.au/researchareas/Super_Screenshots.pdf`.

chose increasing survival probabilities at older ages because their answers imply that at least some conditional survival probabilities were above one. This left 5985 ($= 855 \times 7$) observations in total.

The survey also asked respondents, *"To what age do you think you will live?"*, which gives an estimate of their subjective life expectancy. Table 2 contains summary statistics for subjective survival probabilities and life expectancies by age and gender, showing that women anticipate higher survival rates than men, although the variation between respondents of both genders is large. Women's average life expectancy is 83.9 years and men's is 82.6 years.

The survey also included socioeconomic and demographic information, such as current health, income, education, and marital status. Agnew et al. (2013) compare the sample and population demographics: age, gender, marital status, work status and income, survey sample proportions are very close to the 50-74 years Australian population. Except that survey respondents report slightly higher levels of formal education than the population, the sample is representative of middle-aged and retiring adults who are likely to be planning for retirement.

3 Consistency of subjective and population survival probabilities

In this section we compare subjective probabilities with population survival patterns. We begin with descriptive statistics for the whole sample by gender, then by cohort (current age) and by target age. We then fit re-scaling factors to each individual's projections at each target age and to their subjective life expectancy. Comparing these factors for each respondent lets us see if single constant re-scalings of population survival can match the subjective data.

3.1 Descriptive data

Average subjective survival expectations are pessimistic. Table 3 shows females underestimate lifetimes by an average of five years and males underestimate by an average of three years, consistent with Perozek (2008) and Bissonnette et al. (2012).[4] At first glance, pessimism about life expectancy seems to be at odds with observed optimism about other future life states, (e.g., Weinstein, 1980; Weinstein and Klein, 1996; Harris and Hahn, 2011) especially health (e.g., Weinstein, 1982; Weinstein, 1984 and Massey et al., 2011). But although health and life expectancy are correlated, optimism about health and pessimism about life expectancy can be harmonized if people expect their time to be spent in bad health to be much shorter than is really likely. In general, if as psychological studies show, most people are unwilling to plan for or even contemplate their own death (Kastenbaum, 2000), mis-estimations of personal mortality are likely.

Younger cohorts underestimate survival (the 50-54 age group underestimates life expectancy by more than eight years) while older cohorts tend to overestimate, especially males (Ludwig and Zimper, 2013). (Males in the 70-74 age group overestimate life expectancy by only one year, and females underestimate it by one year.) If people update their beliefs over time, information representation might affect the quality of updating so that at advanced ages, people might become more accurate at estimating survival because they observe more deaths among friends and family than when middle-aged (Hoffrage and Gigerenzer, 1996, Reber and Millward, 1971). Psychological biases, such as underestimating the mean of a left-skewed distribution (Tversky and Kahneman, 1972) or overweighting small, and underweighting large, probabilities (Kahneman and Tversky, 1979) can also help explain the relative pessimism of middle-aged to older respondents. Another explanation is that people can overestimate the probability of conjunctive events (e.g., probability of surviving this year and surviving next year, and so on,

[4] For current population survival probabilities, we use the Australian Life Tables (Australian Government Actuary, 2009), and we compute cohort probabilities from the published life tables using the 25 year improvement factors.

see Bar-Hillel, 1973 and Tversky and Kahneman, 1974).

Pessimism also falls at older target ages within cohorts. In Table 3, for any cohort, the negative difference between subjective survival probabilities and the population probabilities along the horizontal axis is biggest at nearer target ages and becomes smaller at later ages, eventually becoming positive. For our sample, average target age pessimism appears to peak at target age 80 while optimism peaks at target age 95. The within-cohort target age effect we find is different from the tendency for an individual's pessimism to switch to optimism as they themselves age (Ludwig and Zimper, 2013) since respondents anticipate decreasing future pessimism at the time they answer the survey. Ludwig and Zimper (2013) propose a model of modified Bayesian learning to explain how an individual can be pessimistic at younger ages but fail to converge to a true posterior about survival as they get older. They argue that people are relatively insensitive to data ('likelihood insensitivity') so that although they update their survival expectations with new data over time, they are also increasingly influenced by an optimism parameter that tilts subjective expectations away from the rational benchmark. Our data imply that if this updating model is true, people must anticipate learning in this way at the time they are forming expectations.

3.2 Subjective scaling factors

The usual method for adjusting life or cohort table survival probabilities for subjective variations is to re-scale using a constant subjective scaling factor (e.g., Gan et al., 2005). Based on the current life table, the objective expected life time for an individual of gender $g \in \{M, F\}$ (M is male, F is female), currently aged x, is given by:

$$\begin{aligned} e_{x,g} &= \sum_{\tau=1}^{\infty} {}_{\tau}p_{x,g} \\ &= \sum_{\tau=1}^{\infty} \prod_{s=0}^{\tau-1} 1 - q_{x+s,s,g} \end{aligned}$$

where $e_{x,g}$ is the expected lifetime for an individual aged x with gender g; ${}_\tau p_{x,g}$ is the probability of an individual aged x surviving another τ years; and $q_{x+s,s,g}$ is the one-year mortality probability of an individual aged $x+s$ at time s.

The subjective survival probability out to τ years for individual i at age x, ${}_\tau\widetilde{p}_{x,g,i}$, is

$$ {}_\tau\widetilde{p}_{x,g,i} = \prod_{s=0}^{\tau-1} 1 - \widetilde{c}_i \cdot q_{x+s,s,g} \tag{1} $$

where $\widetilde{c}_i$ is the subjective scaling factor for individual i. For now we assume $\widetilde{c}_i$ is constant for all target ages $t_a = x + \tau$.

Using Equation (1), the corresponding subjective life expectancy, $\widetilde{e}_{x,g,i}$, for individual i is

$$ \widetilde{e}_{x,g,i} = \sum_{\tau=1}^{\infty} \prod_{s=0}^{\tau-1} 1 - \widetilde{c}_i \cdot q_{x+s,s,g}. \tag{2} $$

While individual subjective scaling factors can be different from one because of private information or personal tendencies, the law of large numbers implies that the average subjective scaling factor for any cohort should equal one if individuals hold rational expectations.

3.3 Tests for constancy and consistency of subjective scaling factors

Survey responses include two sources of data for $\widetilde{c}_i$: responses to target age questions *"What are the chances that you will live to be age t_a?"* and to the life expectancy question *"To what age do you think you will live?"*. (Respondents can give any answer to the life expectancy question.) For each respondent i, we can use seven observations on target age survival, ${}_\tau\widetilde{p}_{x,g,i}$ and one observation on life expectancy, $\widetilde{e}_{x,g,i}$ and compare the subjective scaling factors implied by each. If the factors from each source are not consistent, then $\widetilde{c}_i$ is unlikely to be constant over t_a. We denote subjective scaling factors computed from subjective survival questions to target age t_a as $\widetilde{c}_i^{(1,t_a)}$ and factors computed from the subjective life expectancy question as $\widetilde{c}_i^{(2)}$.

Subjective survival probabilities come from a discrete list, so we compute a range for $\widetilde{c}_i^{(1,t_a)}$ by assuming that each reported subjective survival probability is a rounded answer, where rounding errors are within $\pm$ 0.5. If rounding errors are greater than 0.5 in magnitude, respondents should reasonably choose a subjective survival probability from the list that is closer to the number in their minds. (To the extent our assumed rounding error is too big, tests in this section may result in a even stronger rejection of consistency.) For example, we treat an answer of 0.3 as lying in $[0.25, 0.35)$, for "No chance, almost no chance" we use the interval $[0, 0.05)$ and for "Certain, practically certain" we use the interval $[0.95, 1]$. For life expectancy, computing a single point estimate of $\widetilde{c}_i^{(2)}$ is straightforward.

We compare subjective scaling factors for each individual using the following tests. First, if the life expectancy point estimate $\widetilde{c}_i^{(2)}$ falls in the interval of a target age response $\widetilde{c}_i^{(1,t_a)}$ for a given t_a, we record a binary coincidence indicator $D_i^{(1,t_a)} = 1$ for that target age. Doing this creates seven values for $D_i^{(1,t_a)}$ for each respondent. Second, we test whether any single value of $\widetilde{c}_i$ falls into *all* the intervals of $\widetilde{c}_i^{(1,t_a)}$ computed from target ages up to and including t_a. We record the coincidence indicator $D_i^{(2,t_a)} = 1$ if there exists a common value in the $\widetilde{c}_i^{(1,t_a)}$ intervals from target ages up to and including t_a. Hence, the first test compares the life expectancy answers with all the target age answers separately and the second test evaluates whether an individual uses a constant subjective scaling factor in answering all target age survival probability questions. Third, if there is a constant subjective scaling factor $\widetilde{c}_i$ that explains all the target age answers up to t_a, we then ask whether it can also explain the factor implied by the point estimate of life expectancy. If this is the case, the indicator $D_i^{(3,t_a)} = 1$. If this is not the case but $D_i^{(2,t_a)} = 1$, we infer that people consistently project multiple target age survival probabilities but their life expectancy point estimates do not match up to those projections.

Table 4 reports results for the three tests, showing very low rates of consistency. For target age 75, for both genders, only approximately 25% of $\widetilde{c}_i^{(2)}$ fall in the interval of $\widetilde{c}_i^{(1,t_a)}$, and as target age increases, consistency rates fall. By definition, the proportion of coincidence $D_i^{(2,t_a)}$ starts at 100% because $\widetilde{c}_i^{(1,75)}$ are evaluated against themselves. On average, over 60% of respondents are consistent at target ages 75 and 80 but the proportion halves when $\widetilde{c}_i^{(1,85)}$ are included in the test. The coincidence falls to less than 2% when all target ages are compared.

Combining the results from tests one and two into the third test shows that overall consistency rates are very low. The proportion of cases where $\widetilde{c}_i^{(2)}$ converges to $\widetilde{c}_i^{(1,t_a)}$ goes down to approximately 5% for ages 75, 80, and 85 and falls to 0% when all target ages are taken into consideration. Thus, even for those individuals who consistently evaluated their survival probabilities, very few choose life expectancies matching their personal beliefs of survival probabilities.

Some rejections of consistency within individuals may be due to idiosyncratic error. To check the robustness of individual level consistency results, we average across individuals. For each target age t_a, we test the hypothesis:

$$\mathbf{H}_0 : \mu_{\ln(\widetilde{c}_i^{(2)})} = \mu_{\ln(\widetilde{c}_i^{(1,t_a)})} \qquad \text{v.s.} \qquad \mathbf{H}_1 : \mu_{\ln(\widetilde{c}_i^{(2)})} \neq \mu_{\ln(\widetilde{c}_i^{(1,t_a)})}$$

where $\mu_{\ln(\widetilde{c}_i^{(2)})}$ is the mean of the natural log of $\widetilde{c}_i^{(2)}$, and for each target age t_a we have that $\mu_{\ln(\widetilde{c}_i^{(1,t_a)})}$ is equal to the mean of the natural log of $\widetilde{c}_i^{(1,t_a)}$.

Table 5 reports results for the consistency test on subjective scaling factors. For the whole sample and for each gender, on average, sample means of the natural logarithm of the subjective scaling factor for survival probabilities are all significantly smaller than those from the subjective life expectancy, exhibiting less pessimism, and in addition, the difference in means decreases with target age. From all of the tests, we conclude that treating subjective scaling factors as constant across target ages is not supported by the data, either when comparing life expectancies with target age probabilities or when target age probabilities are compared with each other.

4 Modeling subjective survival probabilities

In this section we model cohort and target age variation in subjective scaling factors, first at the individual level, allowing for the influences of observed variation in health and demographics and unobserved heterogeneity, and second at the cohort level averaging across individual differences. Cohort-gender models with cubic terms in target age fit best.

4.1 Individual subjective scaling factors

We allow subjective scaling factors to depend on target age so that

$$_{\tau}\widetilde{p}_{x_i,g,i} = \prod_{s=0}^{\tau-1} 1 - \widetilde{c}(x_i, s, g) \cdot q_{x_i+s,g},$$

and estimate

$$\ln(\widetilde{c}(x_i, t_a, g)) = f(x_i, t_a, g) + X_i\beta + \pi_i + \varepsilon_{i,t_a,g}$$

where $\ln(\widetilde{c}(x_i, t_a, g))$ is the natural logarithm of the subjective scaling factor for individual i with gender g aged x_i when projecting to target age t_a, $f(x_i, t_a, g)$ is a function of x_i, t_a and g for individual i, X_i is a set of observed individual control variables, π_i is an individual-specific error component, and $\varepsilon_{i,t_a,g}$ is an independent error term, where $\pi_i \sim N(0, \sigma_\pi^2)$ and $\varepsilon_{i,t_a,g} \sim N(0, \sigma_\varepsilon^2)$. Note that π_i is constant for individual i and can be interpreted as an unobserved individual tendency to pessimism or as additional personal information not captured by observed controls. Table 6 reports results of (1) a pooled OLS estimation with linear age and target age terms, (2) a fixed target age effects model, (3) a fixed target age and random cross-section effects model, and (4) a fixed and random effects model with a cubic form for age and target age.

4.1.1 Health and sociodemographic effects

Individuals in our sample who report physical or mental health problems also hold lower subjective survival expectations. In relation to mental health, Wright and Bower (1992) find that happy people are more optimistic, so people with *Anxiety/Depression* in our sample might therefore be more pessimistic: we estimate mortality odds of 1.49 for respondents who have depression and/or anxiety, close to the value of 1.52 estimated from a large population survey by Mykletun et al. (2009).

The coefficient on gender (binary variable *Female*) has the expected sign but is not significant, possibly because of collinearity with *Income*. A $1,000 increase in annual salary is associated with a 0.2% decrease in the level of pessimism (for example, see Hurd and McGarry, 1995 and Balia, 2014).[5] Effects of post school education are not statistically significant when income is included in the estimation, but are estimated with the expected negative sign when income is dropped. We also find larger regression errors among the low education group, in line with the finding of Hill et al. (2004).

When comparing with panel studies of realized mortality, the higher income and more educated individuals in this sample appear to be more pessimistic than is warranted, and do not fully allow for their survival advantage. Clarke and Leigh (2011) use longitudinal panel data from the Households Income and Labour Dynamics Australia (HILDA) survey to compute the effect of income and education on mortality odds. They report odds for univariate effects: 1.88 for income (lowest quintile compared to highest quintile), and 1.63 for education (less than 12 years of education compared to more than 12 years). Using univariate effects in the model in column (3) we find weaker effects: 1.52 for income and 1.13 for education. The overall fit of the models possibly could be improved by including more informative covariates such as parents' time of death (Bloom et al., 2006) and smoking status (Khwaja et al., 2007) that were not collected by the survey.[6]

[5]While the coefficient on *Wealth* is insignificant and negligible, we find that one percentage point increase in the wealth allocation to fixed interest assets is associated with a 0.8% rise in pessimism level, after controlling for total wealth (estimation results are available upon request), implying a strong relationship between asset allocation and pessimism about survival.

[6]We also test the reduced models (backward elimination, selection criterion t-value). Except for *Intercept* and *Usual Activity Problem* in columns (3) and (4) which increased from 0.455 to 0.530 when excluding non-significant covariates, the differences are negligible. *Income* becomes significant in the reduced model in column (4).

4.1.2 Current age and target age effects

Results in all models show that membership of an older cohort and/or projecting survival chances to more distant target ages reduces pessimism about survival. In the pooled OLS model (column (1)), which treats both age and target age as linear effects, estimated coefficients are both negative. In the fixed target age effect models (columns (2) and (3)), the target age indicators are jointly significant and show a monotonically decreasing trend as the target becomes more distant, while the coefficient on *Age* is significantly negative. (The only exception is the insignificant positive estimate for *Target Age 80*.) The estimate of target age in the pooled OLS model is within the confidence bounds of the estimates in the fixed effect models, and the small increase in R^2 shows that the additional explanatory power of the fixed effects is low.

Estimates confirm the relevance of higher order terms and interactions between age and target age (column(4) in Table 6). Although the main effects for *Age* and *Target Age* are positive, the marginal effect of *Age* is negative in the relevant age range for our sample. For older individuals, target age effects are U-shaped, whereas for middle-aged individuals the effects are *inverse* U-shaped.

4.2 Cohort-specific subjective scaling factors

Cohort models are useful for prediction when individual level explanatory variables are unknown, so we investigate age and gender-specific subjective scaling factors for different cohorts rather than individuals. Here we integrate out individual socioeconomic, health and idiosyncratic effects by averaging within those cohorts and propose a model to fit cohort-specific subjective scaling factors.

Table 7 reports sample means of the log subjective scaling factors by cohort and target age, and the panels of Figure 1 show first the target age effects averaged over cohorts, and second, the cohort age effects averaged over target ages. In the upper panel, we see the average log subjective scaling factor for males increases to target age 80 then decreases, and passing through one around target age 95. The lower panel shows that people become more confident of survival as they age, relative to the life tables, with pessimism switching to optimism during the 60's (males around 61, females around 67). (Women are consistently more pessimistic than males in projecting both life expectancies and survival probabilities.) Since the 60s is the decade in which many individuals retire and make decisions about retirement benefits, retirement residence and estate planning (Agnew et al., 2013), the switch is particularly important.

Next, we allow the sample average of the cohort-specific subjective factor for males and females to vary with both current age and target age. The upper panels in Figure 2 illustrate that interactions are important because these surfaces are not planes.[7] Given the shape of the cohort-specific factor surface, we model the log subjective scaling factors at the cohort level using a cubic form in *Age* and *Target Age*. The estimation results of this cohort model are reported in columns (5) and (6) in Table 6 and in the lower panels in Figure 2.

The cubic form in *Age* and *Target Age* fits the cohort-specific subjective scaling factor well, explaining about 95% of variation. For females almost all terms are statistically significant, whereas for males, only one out of four 3rd order terms is statistically significant; we continue with the cubic form model over a quadratic model, because it explains the structural part better for males and we prefer a consistent structure for both genders.[8]

The stationary points of the estimated polynomial indicate when respondents switch from being more pessimistic to being more optimistic. For females, there is a local maximum point of pessimism at current age 50 for target age 80 and a local minimum point at current age 71 to target age 97.[9] The maximum point of pessimism at age 50 and target age 80 is key to the pricing of life insurance products: if females are at the peak of pessimism when they are aged

[7]One respondent in the age 70-74 cohort females shows at the target age 75 an irregularly high level of pessimism. After conducting robustness checks via repeatedly bootstrapping and re-estimating the model, we decided not to exclude this respondent because other answers contain meaningful information and the results are substantially unchanged.

[8]We have also estimated a quadratic model, excluding the 3rd order terms. For younger individuals the quadratic model is more pessimistic for close and distant target ages than the cubic model, whereas at target ages around 90 years, it is more optimistic. For older ages, the reverse is the case.

[9]There are no local maximum/minimum points for males.

50 and projecting to the target age 80 (which would be common for decisions about products such as a life annuity), they will underestimate their survival probabilities by a lot more than life table predictions. (In fact, the perceived survival probability of females could be even lower than the life table the industry uses for pricing.) If women base their consumption and saving decisions on these subjective beliefs (Gan et al., 2004), market prices on commercial annuities will look very unfair, as will "fairly priced" offerings to delay taking up social security.

5 Applications of subjective survival probabilities

In this section we show the importance of the dynamics of subjective survival expectations for annuitization and consumption decisions later in life. We compare the money's worth (expected present value of future cash flows from an annuity divided by the purchase price) of annuities assuming time-varying or constant scaling factors. We then compare optimal consumption paths from a standard life cycle optimization model when survival expectations take several different patterns.

5.1 Impact of subjective beliefs on perceived money's worth of annuities

The money's worth of a fairly priced annuity is sensitive to the modeling of subjective survival expectations, especially at younger ages. The left panels of Figure 3 show the perceived money's worth of an actuarially fair immediate annuity for males (top panel) and females (bottom panel). The right panels show the perceived money's worth of actuarially fair deferred annuity, with a first payment starting at age 85. We use three assumptions about subjective survival to draw the graphs:

i) Scaling factors vary by current age and target age (columns 5 and 6 of Table 6);

ii) Constant scaling factors (sample average) based on the subjective survival probability to age 75 (people up to 65 years of age), 80 (for 65 to 70 years) or 85 (for over 70 years);

iii) A constant scaling factor based on subjective life expectancy (sample average).

Method *iii*, based on a single life expectancy, makes immediate annuities less attractive than *i* or *ii* since annuities look more valuable when the individual considers the whole distribution of their future lifetime, rather than only the mean. But calculating the perceived money's worth of annuities from only one point of the distribution of individual's subjective lifetime (method *ii*) instead of allowing it to vary with target age, creates a substantial underestimation of the money's worth of annuities, especially at younger ages. Around age 65, the perceived money's worth is close to one for *i* or *ii* so that subjective survival probabilities would, on average, have limited influence on the attractiveness of annuities. However, the effects of subjective pessimism of younger individuals and the optimism of older individuals indicate that improvements in annuity take up rates can be achieved by postponing the age at which individuals would face the choice of purchasing annuities.

The effect of subjective survival probabilities on the perceived money's worth of an actuarial fair deferred annuity is much larger than on an immediate annuity. Advanced-life deferred annuities –deferred annuities with a first payment at advanced ages– are advocated as an alternative to immediate annuities, because they appear to be cheap as insurance for income at advanced ages. However when subjective expectations are used in valuation, at younger ages the perceived money's worth of deferred annuities is very low and increasing only at advanced ages, making them a difficult product to market.

5.2 Impact of subjective beliefs in life cycle models

Now we turn to the effect of subjective survival probabilities on optimal life cycle consumption decisions. We assume that an individual maximizes (subjective) expected lifetime utility, represented by an inter-temporally separable CRRA utility function. For the survival probabilities, unless mentioned otherwise, we assume that the individual uses the subjective survival probabilities related to their age, and dependent on the target age. Hence, at age 65, an individual would maximize his or her expected lifetime utility given the subjective survival probabilities he or she has at the age of 65 and use this to calculate consumption in that year. A year later the individual updates their subjective beliefs – that is, has the subjective survival probabilities of a 66-year-old individual – and at the beginning of that period chooses a consumption level by re-optimizing expected lifetime utility. We set parameters equal to the values often used in the life-cycle literature (Gomes and Michaelides, 2005): relative risk aversion $\gamma = 5$; a time preference parameter (also referred to as subjective discount factor) $\beta = 0.96$; and $u = 0.17$ (Yogo, 2009) as the relative utility of bequest. The real risk-free return is set at $r = 2.6\%$ (Yogo, 2009) for all t. Let $x(t)$ be the age at time t, $W(t)$ the level of wealth (adjusted for inflation) at time t and $C(t)$ the level of consumption (adjusted for inflation) at time t, then at each time t the individual solves:

$$V(W(t), x(t)) = \max_{\{C(s)\}_{s \geq t}} \left\{ \mathbb{E}_t \left[\sum_{s \geq t} {}_s\widetilde{p}_{x(t),t} \cdot \beta^s \cdot \left(\frac{C(s)^{1-\gamma}}{1-\gamma} + \beta \widetilde{q}_{x(t),t} \cdot \frac{(uW(s+1))^{1-\gamma}}{1-\gamma} \right) \right] \right\}$$

subject to:

$$\begin{aligned} W(s) - C(s) \geq& 0, \qquad \text{for all } s; \\ W(s+1) =& (W(s) - C(s))(1+r), \end{aligned}$$

where the first constraint denotes the positive wealth requirement and the second is the budget constraint. This assumes that the individual consumes at the start of the period and dies, thus leaving the bequest, at the end of the period.

We consider five methods for computing optimal consumption patterns:

i) Mortality probabilities from the life tables;

ii) Subjective mortality probabilities whose scaling factors depend on current age and target age (using columns (5) and (6) of Table 6);

iii) Subjective mortality probabilities whose scaling factors depend on target age only (using columns (5) and (6) of Table 6);

iv) A constant scaling factor (sample average) based on the subjective survival probability to age 75 (for 50 years old) or 80 (for 65 years old) ;

v) A constant scaling factor based on subjective life expectancy (sample average).

The consumption plan under method *i* is consistent with rational expectations for a population-representative individual. The consumption plan under method *ii* is optimal for an individual using the cohort-specific subjective survival probabilities. Hence, this individual is rational in that he solves his life cycle model consistent with his beliefs, but irrational in that he uses biased subjective survival probabilities. We assume that he updates his survival beliefs each year and adjusts his consumption plan accordingly. Under method *iii*, the individual's subjective scaling factors vary with target age, similar to method *ii*, however, compared with method *ii*, the individual does not re-optimise his consumption level each year. This can be interpreted as an individual who sticks to the consumption plan he designed at age 50 or 65. The difference between consumption plans in method *ii* and *iii* measures modifications to subjective survival beliefs as the consumer gets older.

We include methods *iv* and *v* to compare our results with existing literature and to illustrate the importance of correctly incorporating age and target age in subjective survival beliefs. Methods *iv* and *v* assume that the scaling factor is the same for all target ages and individuals do not update their subjective survival beliefs. In method *v* individuals optimize at age 65 (or age 50) based on the point estimate of their subjective life expectancy and in method *iv* based on their subjective survival probability to one target age.

Figure 4 illustrates the effect of subjective survival probabilities on the optimal lifetime consumption and wealth level for an individual aged 50 (upper panel) and 65 (lower panel). For an (retired) individual aged 65 (lower panel) the consumption plan based on his subjective life expectancy (method *v*) implies that he would consume more than the optimal level (method *i*) up to age 87 and thereafter – due to a low wealth level – less than the optimal level. This is the result of pessimistic subjective life expectancy. However, when using a constant scaling factor based on the subjective survival probability to age 80 (method *iv*), he under-consumes before age 87 and over-consumes later. We find similar results using subjective mortality probabilities at age 65, which do depend on target age (method *iii*).

When individuals are constantly updating their subjective mortality beliefs (method *ii*) the optimal consumption plan changes from concave to convex, because they become more optimistic as they age. Age-varying subjective survival beliefs thus also partly explain observed conservative spending patterns in retirement (e.g., Banks et al., 1998; Benartzi et al., 2011; Poterba et al., 2011) where individuals continue to accumulate wealth early in retirement. By comparing method *ii* and *iii*, we observe that up to age 92 an individual who updates his consumption level to changes in his subjective beliefs on surviving will consume less than he initially – at age 65 – planned to consume.

Planning for retirement often gains momentum in middle age, so we conduct the same analysis starting from age 50 (Figure 4, upper panel). Method *v* produced similar outcomes as for the 65 year planning date, and using current subjective survival probabilities (methods *iii* and *iv*) indicates that individuals would over-consume early in retirement, up to age 84. In addition, individuals planning from age 50 and constantly updating their mortality beliefs (method *ii*) will also overconsume before age 60. (For the case of deterministic labor income where human capital is part of total wealth, over-consumption at age 50 is equivalent to not saving enough for retirement.) Hence, the subjective survival probabilities also play a role in explaining why individuals save too little for retirement, (e.g., Mitchell and Moore, 1998; Laibson et al., 1998).

Summarizing, we show that incorporating subjective survival beliefs which depend both on age and target age into the core expected utility model provides substantially different consumption patterns than the consumption plan based on life table (rational) expectations, and the consumption plan calibrated using a constant subjective scaling factor. While there are other explanations for both under-saving for retirement (such as hyperbolic discounting) and under-spending in retirement (such as unexpected health expenditure), the empirical pattern of subjective survival beliefs documented here contributes to explaining both puzzles rather than only one of them.

6 Conclusions

Many important economic decisions depend on subjective life expectancy. Studies have shown that cross-sectional variation in subjective survival probabilities is both large and powerfully predictive of individual economic behavior and realized mortality (e.g. Hamermesh, 1985; Hurd, 2009; Hurd and McGarry, 2002; Smith et al., 2001). However because of a lack of detailed data, it is common practice to estimate a whole individual survival curve from a single point estimate of life expectancy or a survival probability, effectively assuming each person's pattern of deviation from population life tables is constant.

Based on a more comprehensive measure of subjective survival beliefs, we reject the assumption of constancy and find that a large part of the individual variation in subjective scaling factors can be explained by a polynomial form in current age and projecting target age. While subjective survival probabilities are generally pessimistic, pessimism decreases as the target age (forecasting horizon) increases, and also decreases with the current age of the individual (cohort age) and females are more pessimistic than males (Ludwig and Zimper, 2013; Perozek, 2008; Bissonnette et al., 2012).

There are several possible explanations for our findings, first, that forecasts of desirable events are more pessimistic in the short term than in the long term (Wright and Ayton, 1992) and second, that individuals adjust probabilities (possibly over-adjusting) as they learn about mortality at advanced ages (Reber and Millward, 1971). In addition, Kahneman and Tversky (1979) argue that individuals tend to overweight small probabilities and underweight large probabilities. As a result, the low mortality probability for young cohorts (or when projecting to close target ages) and the low survival probabilities for old cohorts (or when projecting to distant target ages) are likely to be overestimated.

Our results have wide-ranging implications for explaining individual decision making in life-cycle modeling and retirement policy as well as myriad other applications. For example, the peak of pessimism among females at age 50 in projecting to a target age of 80, combined with the general pessimism among most groups, can partially explain the annuity puzzle among younger cohorts and may be a factor in apparently irrational choices around social security. We show that subjective survival probabilities have an influence on the perceived money's worth of both immediate life annuities and deferred annuities. It follows that efforts by government and industry to inform and educate people about their survival prospects are likely to create real benefits for baby-boomers entering retirement. Subjective survival beliefs can contribute to the explanation of both the retirement savings puzzle, where individuals save too little, and conservative spending patterns, where individuals spend too slowly later in retirement.

One of the limitations of our analysis is a lack of information on realized mortality for our sample. We cannot judge how well the people surveyed here predict their own survival. Future work that expands longitudinal surveys from a variety of countries to include more measures of survival expectations over a wide range of target ages, as well as tracking realized mortality for the survey respondents, would greatly improve understanding of the dynamics of survival expectations.

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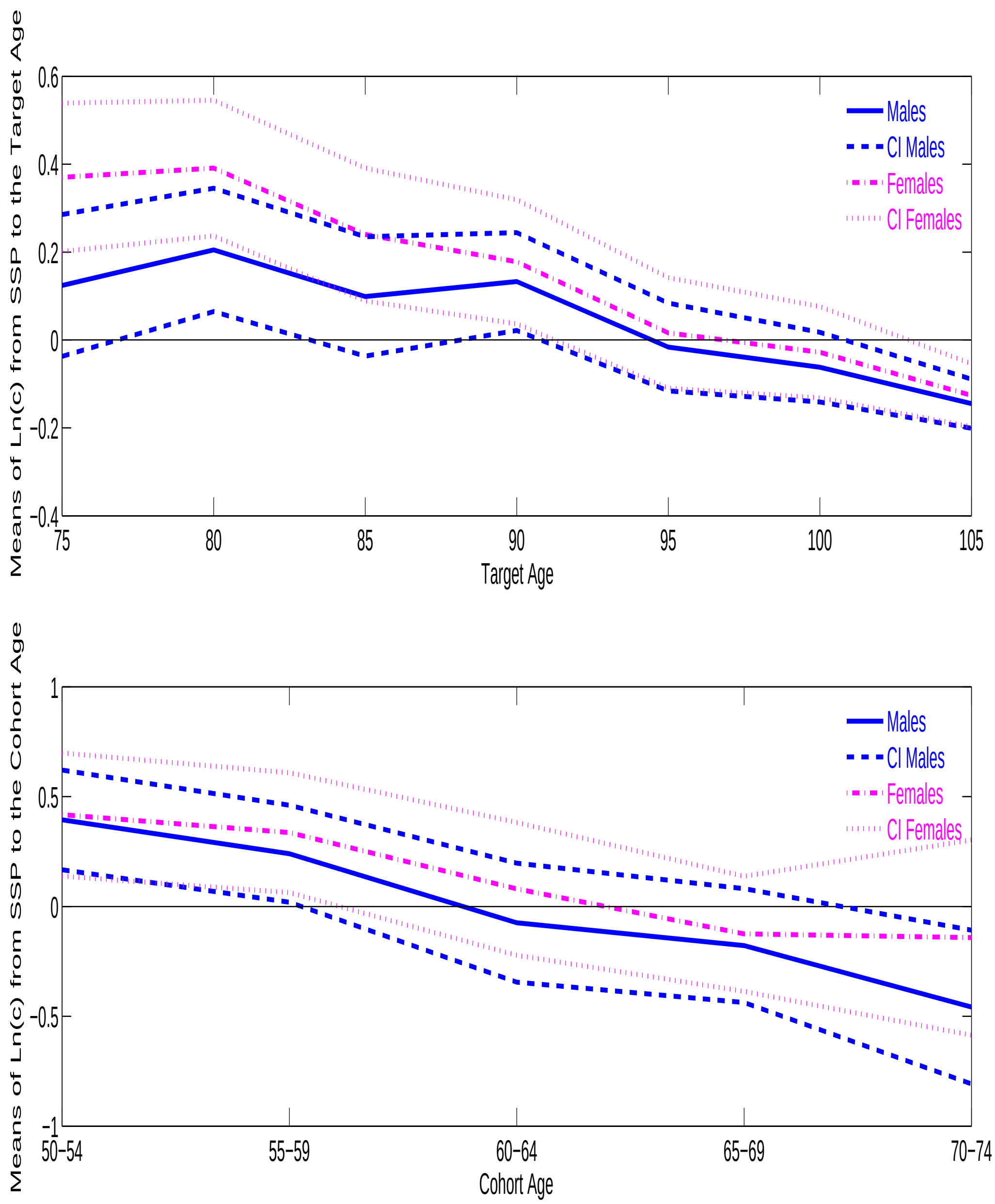
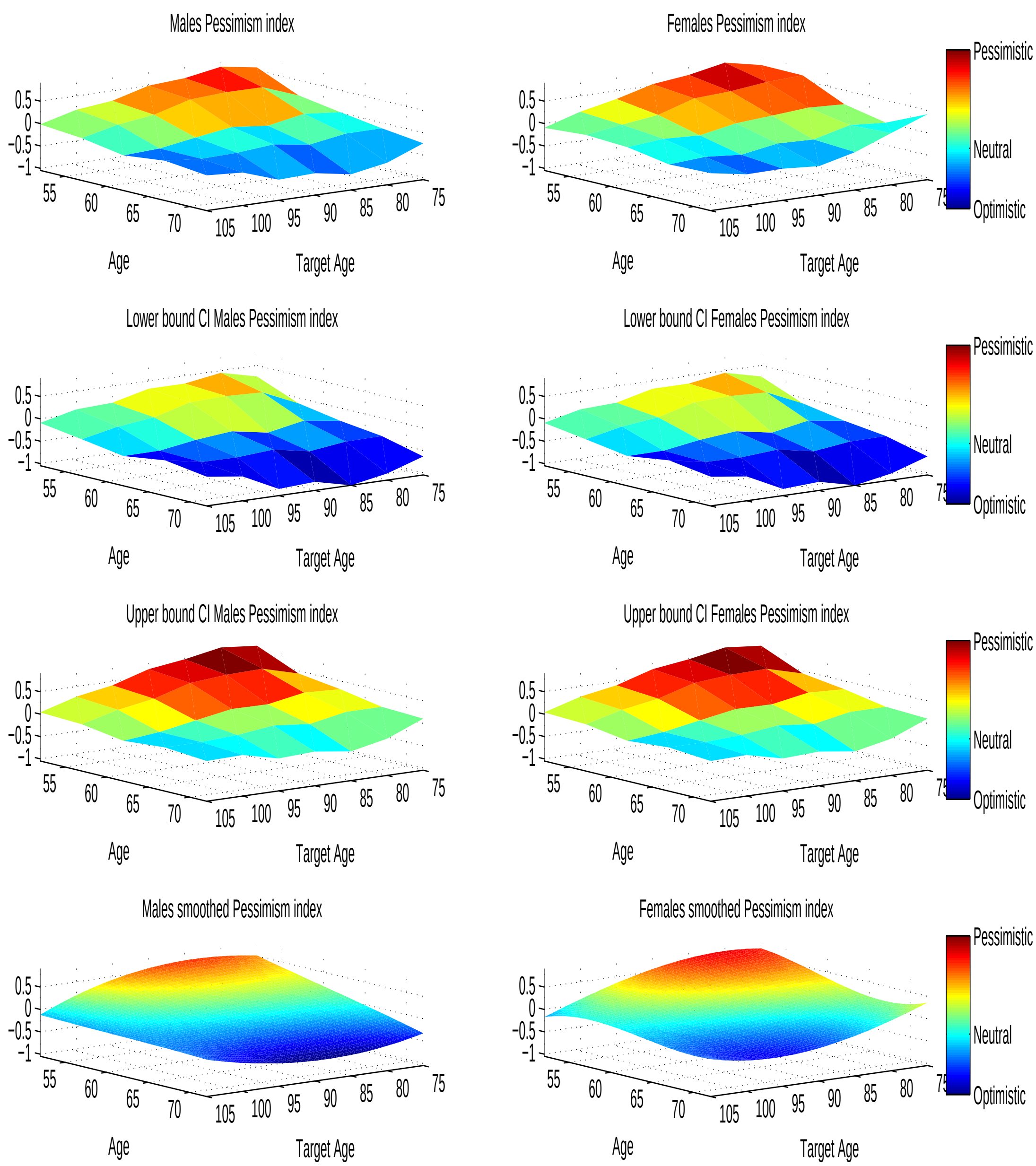
A Figures and Tables

Figure 1: Target Age and Cohort Age Effects on Pessimism



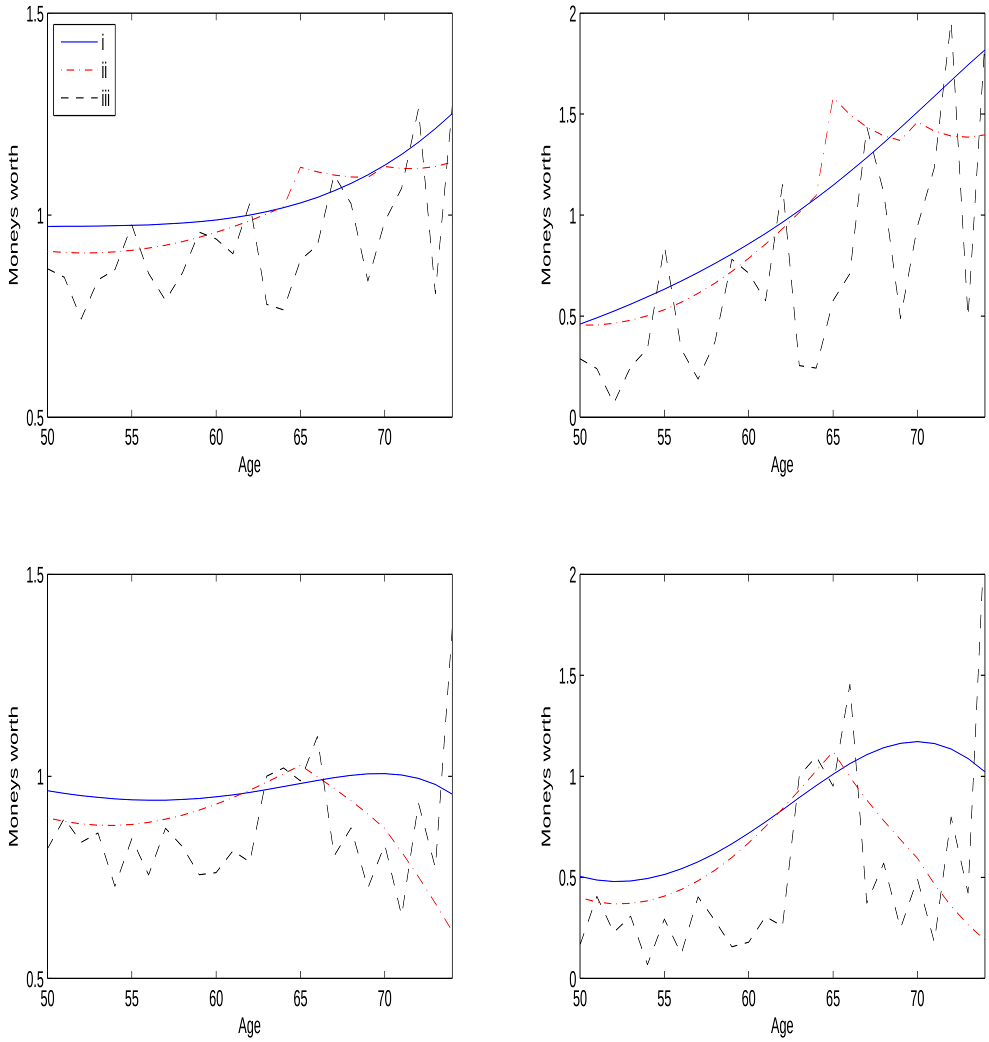
The upper panel graphs means of the natural logarithm of subjective scaling factors by target age and the lower panel graphs the means of log scaling factors by cohort age. Positive values show pessimism and negative values show optimism relative to improved cohort life table survival probabilities.

Figure 2: Pessimism Indices for Males and Females



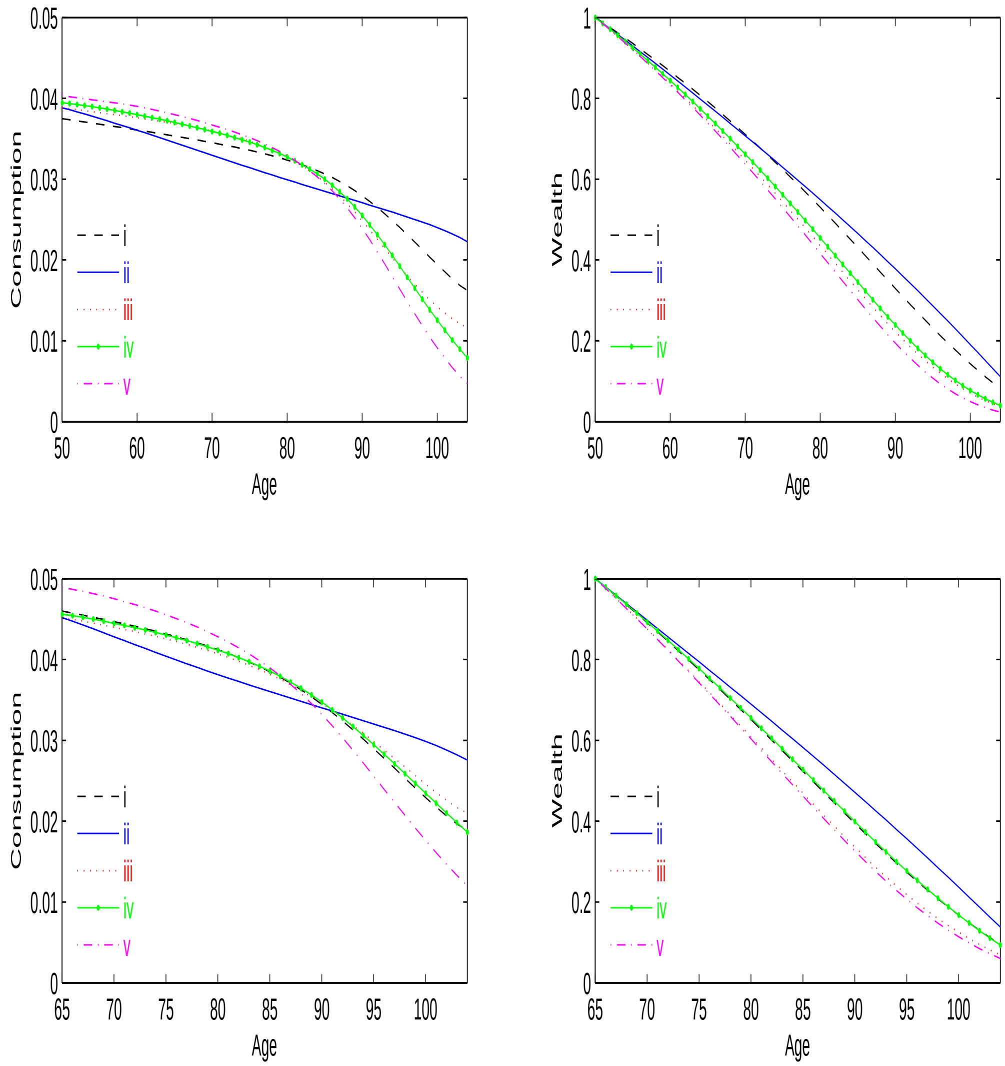
The upper panels graphs the natural logarithm of subjective scaling factors by cohort age (median age of cohort) and target age (see Table 7). The middle panels graph the lower and upper (5% and 95%) bootstrapped quantile of the subjective scaling factor. The lower panels graph the smoothed subjective scaling factor using the estimation results from Weighted Least Square regressions of cohort level subjective scaling factor, see column (5) and column (6) of Table 6.

Figure 3: Perceived Money's Worth of Annuities



The left panels graph the perceived money's worth of immediate annuities. The right panels graph the perceived money's worth of deferred annuities with a first payment at age 85. The upper panels graph values for males; the lower panels graph values for females. The assumed interest rate is 4% p.a. The solid lines graph values calculated using the subjective mortality probabilities whose scaling factors depend on current age and target age (using columns (5) and (6) of Table 6); the dot-dash lines graph values calculated assuming a constant scaling factor (sample average) based on the subjective survival probability to age 75 (for people up to 65 years old), 80 (for people from 65 up to 70 years old) or 85 (for people over 70 years old); and the dashed lines graph values assuming a constant scaling factor based on subjective life expectancy (sample average).

Figure 4: Consumption paths and wealth levels



The upper panels of the graph display the consumption path and wealth level for a 50 year old calculated using the five methods described below; the lower panels display the consumption path and wealth level for a 65 year old. The (real) consumption (left panels) and wealth level (right panels) are displayed as a fraction of the current wealth level. (i) assumes the mortality probabilities from the life tables;(ii) assumes the subjective mortality probabilities where scaling factors depend on age and target age (using columns (5) and (6) of Table 6);(iii) assumes the subjective mortality probabilities where scaling factors depend on target age (using columns (5) and (6) of Table 6); (iv) assumes a constant scaling factor based on subjective survival probability to age 75 (for 50 years old) or 80 (for 65 years old, using sample average); (v) assumes a constant scaling factor based on subjective life expectancy (sample average).

Table 1: Reference Table for Subjective Survival Probabilities

Category	Interpretation
0	No chance, almost no chance (1 in 100)
1	Very slight possibility (1 chance in 10)
2	Slight possibility (2 chances in 10)
3	Some possibility (3 chances in 10)
4	Fair possibility (4 chances in 10)
5	Fairly good possibility (5 chances in 10)
6	Good possibility (6 chances in 10)
7	Probable (7 chances in 10)
8	Very probable (8 chances in 10)
9	Almost sure (9 chances in 10)
10	Certain, practically certain (99 chances in 100)

Table 2: Summary Statistics

The sample consists of 855 Australian respondents surveyed in May 2011. *Subjective Survival Probability* (SSP) measures personal beliefs on the probability of surviving to each target age. *Subjective Life Expectancy* (SLE) is the individual's subjective estimate of expected lifetime.

	Mean and (Std. Dev.)		
Variables	Full Sample	Males	Females
Subjective Survival Probability			
Surviving to Age 75 (SSP75)	0.743	0.730	0.757
	(0.257)	(0.259)	(0.254)
Surviving to Age 80 (SSP80)	0.639	0.621	0.658
	(0.279)	(0.279)	(0.279)
Surviving to Age 85 (SSP85)	0.529	0.504	0.555
	(0.297)	(0.294)	(0.297)
Surviving to Age 90 (SSP90)	0.380	0.349	0.411
	(0.297)	(0.284)	(0.307)
Surviving to Age 95 (SSP95)	0.260	0.239	0.281
	(0.269)	(0.256)	(0.280)
Surviving to Age 100 (SSP100)	0.142	0.133	0.151
	(0.214)	(0.201)	(0.227)
Surviving to Age 105 (SSP105)	0.068	0.063	0.073
	(0.146)	(0.135)	(0.156)
Surviving to Age 110 (SSP110)	0.042	0.042	0.043
	(0.108)	(0.106)	(0.109)
Surviving to Age 120 (SSP120)	0.030	0.029	0.031
	(0.084)	(0.085)	(0.083)
Surviving to Age 120^{+} (SSP120^{+})	0.023	0.022	0.025
	(0.072)	(0.074)	(0.070)
Subjective Life Expectancy (SLE)	83.273	82.629	83.945
	(9.698)	(9.372)	(9.995)
Number of Respondents	855	437	418

Table 3: Means of Differences between Subjective Survival Probabilities and Life Table Probabilities

The table reports means of differences between subjective survival probabilities and cohort (improved) life table probabilities, sorted by cohorts in rows and target ages in columns. A significantly positive value is labelled "optimistic" and a significantly negative value is labelled "pessimistic", based on one-tailed t-tests. "Neutral" indicates that means of differences are insignificantly different from zero using a one-tailed t-test.

Panel A: Full Sample

		Differences in Survival Probability to Target Age										
Age	N	75	80	85	90	95	100	105	Mean	t-stat	Pessimistic, Optimistic or Neutral	Life Expectancy Differences
50-54	212	-0.226	-0.263	-0.247	-0.187	-0.063	0.007	0.036	-0.135***	-6.926	Pessimistic	-8.275
55-59	193	-0.172	-0.205	-0.206	-0.162	-0.035	0.022	0.037	-0.103***	-5.524	Pessimistic	-5.593
60-64	164	-0.129	-0.138	-0.120	-0.065	0.044	0.082	0.061	-0.038**	-1.766	Pessimistic	-3.353
65-69	195	-0.091	-0.097	-0.047	-0.002	0.089	0.101	0.058	0.002	0.082	Neutral	-1.117
70-74	91	-0.085	-0.063	-0.001	0.080	0.147	0.121	0.058	0.037*	1.411	Optimistic	0.178
Mean		-0.149***	-0.167***	-0.141***	-0.087***	0.021**	0.058***	0.048***				-4.717***
t-stat		-17.283	-17.462	-13.717	-8.407	2.232	7.867	9.678				-9.913
Pessimistic, Optimistic or Neutral		Pessimistic	Pessimistic	Pessimistic	Pessimistic	Optimistic	Optimistic	Optimistic				Pessimistic

Panel B: Males												
		Differences in Survival Probability to Target Age									Pessimistic, Optimistic	Life Expectancy
Age	N	75	80	85	90	95	100	105	Mean	t-stat	or Neutral	Differences
50-54	106	-0.227	-0.252	-0.225	-0.156	-0.041	0.004	0.026	-0.124***	-4.854	Pessimistic	-8.164
55-59	102	-0.148	-0.185	-0.184	-0.136	-0.017	0.027	0.036	-0.087***	-3.490	Pessimistic	-4.573
60-64	84	-0.125	-0.124	-0.087	-0.025	0.073	0.111	0.079	-0.014	-0.472	Neutral	-3.182
65-69	98	-0.092	-0.091	-0.028	0.018	0.099	0.102	0.045	0.007	0.280	Neutral	-0.259
70-74	47	-0.057	0.004	0.076	0.141	0.189	0.126	0.057	0.077***	2.299	Optimistic	1.482
Mean		-0.140***	-0.148***	-0.112***	-0.055***	0.043***	0.065***	0.046***				-3.558***
t-stat		-11.518	-11.087	-7.823	-3.961	3.422	6.666	7.149				-7.926
Pessimistic, Optimistic or Neutral		Pessimistic	Pessimistic	Pessimistic	Pessimistic	Optimistic	Optimistic	Optimistic				Pessimistic

Panel C: Females												
		Differences in Survival Probability to Target Age									Pessimistic, Optimistic	Life Expectancy
Age	N	75	80	85	90	95	100	105	Mean	t-stat	or Neutral	Differences
50-54	106	-0.225	-0.275	-0.269	-0.218	-0.084	0.010	0.045	-0.142***	-4.959	Pessimistic	-8.387
55-59	91	-0.199	-0.227	-0.230	-0.191	-0.055	0.015	0.037	-0.110***	-4.334	Pessimistic	-6.736
60-64	80	-0.135	-0.152	-0.154	-0.107	0.014	0.052	0.042	-0.061***	-2.032	Pessimistic	-3.532
65-69	97	-0.090	-0.103	-0.066	-0.022	0.078	0.100	0.072	-0.002	-0.172	Neutral	-1.984
70-74	44	-0.114	-0.134	-0.083	0.016	0.101	0.115	0.058	-0.005	-0.149	Neutral	-1.215
Mean		-0.159***	-0.186***	-0.172***	-0.121***	-0.002	0.051***	0.050***				-4.857***
t-stat		-12.958	-13.688	-11.703	-7.901	-0.142	4.572	6.588				-9.913
Pessimistic, Optimistic or Neutral		Pessimistic	Pessimistic	Pessimistic	Pessimistic	Neutral	Optimistic	Optimistic				Pessimistic

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: Individual Consistency Test on Subjective Scaling Factors

The table reports the results of individual consistency test between $\widetilde{c}_i^{(1,t_a)}$ and $\widetilde{c}_i^{(2)}$, where $\widetilde{c}_i^{(2)}$ denotes the subjective scaling factor based on subjective life expectancy data and $\widetilde{c}_i^{(1,t_a)}$ denotes the range of subjective scaling factors based on rounded subjective survival probability data. $D^{(1,t_a)} = \mathbb{E}\left[D_i^{(1,t_a)}\right]$ represents the percentage of sample respondents whose $\widetilde{c}_i^{(2)}$ is within all $\widetilde{c}_i^{(1,t_a)}$ up to and including t_a. $D^{(2,t)} = \mathbb{E}\left[D_i^{(2,t_a)}\right]$ represents the percentage of sample respondents who show a common value (range) in $\widetilde{c}_i^{(1,t_a)}$ from target age 75 to target age t_a. $D^{(3,t_a)} = \mathbb{E}\left[D_{3,i}^{(t_a)}\right]$ indicates the percentage of respondents who have a common value (range) in $\widetilde{c}_i^{(1,t_a)}$ up to and including t_a and whose $\widetilde{c}_i^{(2)}$ includes in that range.

Panel A: Full Sample							
	75	80	85	90	95	100	105
$D^{(1,t_a)}$	25.6%	23.0%	18.9%	17.1%	16.8%	14.6%	13.3%
$D^{(2,t_a)}$	100.0%	66.1%	33.3%	15.8%	6.5%	2.8%	1.2%
$D^{(3,t_a)}$	25.6%	10.9%	3.9%	1.5%	0.2%	0.2%	0.0%
Panel B: Males							
	75	80	85	90	95	100	105
$D^{(1,t_a)}$	25.9%	23.3%	19.2%	19.0%	16.9%	11.9%	13.5%
$D^{(2,t_a)}$	100.0%	66.8%	33.4%	18.1%	8.5%	3.4%	2.1%
$D^{(3,t_a)}$	25.9%	11.0%	5.3%	2.3%	0.5%	0.5%	0.0%
Panel C: Females							
	75	80	85	90	95	100	105
$D^{(1,t_a)}$	25.4%	22.7%	18.7%	15.1%	16.7%	17.5%	13.2%
$D^{(2,t_a)}$	100.0%	65.3%	33.3%	13.4%	4.5%	2.1%	0.2%
$D^{(3,t_a)}$	25.4%	10.8%	2.4%	0.7%	0.0%	0.0%	0.0%

Table 5: Population Consistency Test on Subjective Scaling Factors

The table reports the results of the population consistency test between $\widetilde{c}_i^{(2)}$ and $\widetilde{c}_i^{(1,t_a)}$'s. $\widetilde{c}_i^{(2)}$ denotes the subjective scaling factor inferred from subjective life expectancy data. $\widetilde{c}_i^{(1,t_a)}$ denotes the subjective scaling factor inferred from subjective survival probability data to target age t_a.

Panel A: Full Sample								
	$\ln(\widetilde{c}_i^{(2)})$	$\ln(\widetilde{c}_i^{(1,t_a)})$ to the Target Age						
		75	80	85	90	95	100	105
Mean	0.533***	0.244***	0.296***	0.168***	0.155***	-0.001	-0.045	-0.136***
t-stat	11.175	4.179	5.673	3.311	3.466	-0.014	-1.403	-5.996
Difference in Means $(\mathbb{E}[\ln(\widetilde{c}_i^{(1,t_a)})] - \mathbb{E}[\ln(\widetilde{c}_i^{(2)})])$		-0.289***	-0.237***	-0.365***	-0.378***	-0.534***	-0.579***	-0.669***
t-stat		-3.830	-3.355	-5.248	-5.775	-8.606	-10.035	-12.666
Panel B: Males								
	$\ln(\widetilde{c}_i^{(2)})$	$\ln(\widetilde{c}_i^{(1,t_a)})$ to the Target Age						
		75	80	85	90	95	100	105
Mean	0.437***	0.124	0.205***	0.099	0.133**	-0.016	-0.062	-0.145***
t-stat	6.638	1.538	2.920	1.457	2.391	-0.320	-1.564	-5.180
Difference in Means $(\mathbb{E}[\ln(\widetilde{c}_i^{(1,t_a)})] - \mathbb{E}[\ln(\widetilde{c}_i^{(2)})])$		-0.313***	-0.231**	-0.338***	-0.304***	-0.453***	-0.499***	-0.582***
t-stat		-3.005	-2.401	-3.569	-3.522	-5.468	-6.490	-8.134
Panel C: Females								
	$\ln(\widetilde{c}_i^{(2)})$	$\ln(\widetilde{c}_i^{(1,t_a)})$ to the Target Age						
		75	80	85	90	95	100	105
Mean	0.634***	0.370***	0.391***	0.240***	0.178**	0.016	-0.028	-0.126***
t-stat	9.192	4.382	5.064	3.180	2.519	0.254	-0.540	-3.512
Difference in Means $(\mathbb{E}[\ln(\widetilde{c}_i^{(1,t_a)})] - \mathbb{E}[\ln(\widetilde{c}_i^{(2)})])$		-0.264**	-0.243**	-0.394***	-0.456***	-0.618***	-0.662***	-0.760***
t-stat		-2.422	-2.352	-3.857	-4.610	-6.680	-7.686	-9.775

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Regressions of Subjective Scaling Factors at the Individual Level

The table reports estimates of the regression of the natural logarithm of individual subjective scaling factor from subjective survival probabilities on groups of independent variables. Column (1) presents OLS estimates of the following regression equation assuming the effects of *Target Age (TA)* is linear:

$$\begin{aligned}\ln(\widetilde{c}_i^{(1,t_a)}) =& Intercept + \beta_{Demo} Demographic\ Characteristics_i \\ &+ \beta_{Social} Socioeconomic\ Characteristics_i \\ &+ \beta_{Health} Health\ Information_i + \beta_{TA} Target\ Age + \varepsilon_{i,t_a}.\end{aligned}$$

Column (2) includes fixed target age effects. Column (3) includes fixed target age effects and cross-sectional random effects on the error term ε_{i,t_a}, i.e. $\varepsilon_{i,t_a} = \pi_i + \mu_{i,t_a}$ where π_i is considered random. Column (4) adds higher order terms in *Age* and *TA*. Columns (5) and (6) are Weighted Least Square regressions of cohort level subjective scaling factors shown in Panel B and C of Table 7 on *Age* and *TA*. *Female*, *Married*, *Prev. married*, *Working*, *Graduate* and *Vocational* are binary variables that are equal to 1 if the respondent is female, married or in a de facto relationship, divorced/separated/widowed, employed, holding a university (college) degree, and a vocational qualification, and 0 otherwise. *Income* is annual gross income and *Wealth* is net personal wealth in thousands of dollars. All health variables are binary variables equal to 1 if the respondent has the relevant heath problem and 0 otherwise.

t-statistics in parentheses are calculated from robust standard errors. F-stats are for joint significance of target age fixed effects in columns (2) and (3), and of higher order terms in age and target age in columns (4), (5) and (6). *Random effects* χ^2*-stats* are Breusch and Pagan LM test for random cross section effects. σ_ε is the standard error of regression in columns (1), (2), (5) and (6), and is the standard error of residuals from between-individual variation in columns (3) and (4). σ_π is the standard error of residuals from within-individual variation.

	Pooled OLS	Fixed TA Effects	Fixed TA & Random Cross Section Effects	Structural Model	Cohort Males	Cohort Females
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	3.418***	2.285***	2.285***	-70.984**	-70.699**	-95.435***
	(14.88)	(12.38)	(5.90)	(-2.19)	(-2.29)	(-4.33)
Demographic Characteristics						
Female	0.022	0.022	0.022	0.021		

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	(1)	(2)	(3)	(4)	(5)	(6)
	(0.64)	(0.64)	(0.30)	(0.28)		
Married	0.090	0.090	0.090	0.090		
	(1.48)	(1.48)	(0.69)	(0.69)		
Prev. Married	0.015	0.015	0.015	0.015		
	(0.22)	(0.22)	(0.10)	(0.11)		
Socioeconomic Characteristics						
Working	-0.024	-0.024	-0.024	-0.026		
	(-0.61)	(-0.61)	(-0.29)	(-0.31)		
Income	-0.002***	-0.002***	-0.002	-0.002		
	(-3.13)	(-3.13)	(-1.46)	(-1.47)		
Wealth	-0.000	-0.000	-0.000	-0.000		
	(-0.59)	(-0.59)	(-0.28)	(-0.24)		
Graduate	0.015	0.015	0.015	0.012		
	(0.36)	(0.36)	(0.17)	(0.13)		
Vocational	-0.009	-0.009	-0.009	-0.012		
	(-0.23)	(-0.23)	(-0.11)	(-0.14)		
Health Information						
Mobility	0.080*	0.080*	0.080	0.080		
-Problem	(1.75)	(1.75)	(0.81)	(0.81)		
Anxiety	0.400***	0.400***	0.400***	0.399***		
-/Depression	(11.36)	(11.36)	(5.30)	(5.28)		
Pain	0.068*	0.068*	0.068	0.069		
-/Discomfort	(1.77)	(1.77)	(0.83)	(0.83)		
Usual Activity	0.457***	0.457***	0.457***	0.457***		
-Problem	(9.89)	(9.89)	(4.62)	(4.60)		

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	(1)	(2)	(3)	(4)	(5)	(6)
Subjective Control Factors						
Age	-0.039***	-0.039***	-0.039***	0.930	0.819	2.432***
	(-14.41)	(-14.41)	(-6.73)	(0.65)	(0.83)	(3.42)
Target Age	-0.014***			1.869***	1.942***	1.693***
	(-9.00)			(4.60)	(2.95)	(3.61)
Fixed Target Age Effects						
Target Age 80		0.052	0.052			
		(0.88)	(1.37)			
Target Age 85		-0.076	-0.076**			
		(-1.29)	(-2.02)			
Target Age 90		-0.089	-0.089**			
		(-1.51)	(-2.35)			
Target Age 95		-0.245***	-0.245***			
		(-4.14)	(-6.47)			
Target Age 100		-0.290***	-0.290***			
		(-4.90)	(-7.65)			
Target Age 105		-0.380***	-0.380***			
		(-6.43)	(-10.03)			
Structural terms						
$Age \times TA/100$				-1.508***	-2.078***	-0.837
				(-3.55)	(-2.91)	(-1.64)
$Age^2/100$				-0.563	0.023	-3.510***
				(-0.24)	(0.02)	(-3.40)
$TA^2/100$				-1.592***	-1.474**	-1.636***
				(-3.94)	(-2.27)	(-3.52)

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	(1)	(2)	(3)	(4)	(5)	(6)
$Age^2 \times TA/10000$				-0.060**	0.015	-1.043***
				(-2.53)	(-0.04)	(-3.51)
$TA^2 \times Age/10000$				0.129***	1.233***	1.214***
				(7.52)	(4.41)	(6.12)
$Age^3/10000$				0.060	-0.012	2.420***
				(0.48)	(-0.02)	(4.49)
$TA^3/10000$				0.029**	-0.254	0.329**
				(2.00)	(1.09)	(1.98)
F-stat		14.67***	35.73***	15.187***	7.39***	13.46***
Random effects χ^2-stat			6222.91***	6318.36***		
σ_ε	1.222	1.222	0.783	0.776	0.095	0.068
σ_π			0.944	0.946		
R^2 (unweighted)	0.130	0.131	0.131	0.136	0.940	0.967
R^2 (weighted)			0.061	0.075		

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Means of Subjective Scaling Factors at the Cohort Level Based on the Cohort Life Table

The table reports means of the natural logarithm of subjective scaling factors, sorted by cohorts and target ages. N denotes the number of observations. A significantly positive number indicates pessimism. t-stats are for t-tests of zero means. "Pessimistic" or "Optimistic" indicates that means of subjective scaling factors are significantly different from zero according to a one-tailed t-test. "Neutral" indicates that means of differences are significant according to a two-tailed t-test.

Panel A: Full Sample												
		Means of $\ln(\widetilde{c}_i^{(1,t_a)})$ to the Target Age									Pessimistic, Optimistic	Means of
Age	N	75	80	85	90	95	100	105	Mean	t-stat	or Neutral	$\ln(\widetilde{c}_i^{(2)})$
50-54	212	0.589	0.736	0.590	0.517	0.299	0.170	-0.059	0.406***	4.508	Pessimistic	0.965
55-59	193	0.375	0.515	0.474	0.429	0.189	0.084	-0.069	0.285***	3.282	Pessimistic	0.677
60-64	164	0.100	0.158	0.051	0.065	-0.070	-0.117	-0.176	0.001	0.014	Neutral	0.470
65-69	195	-0.061	-0.032	-0.199	-0.127	-0.232	-0.209	-0.201	-0.152*	-1.647	Optimistic	0.207
70-74	91	0.078	-0.231	-0.458	-0.483	-0.470	-0.332	-0.239	-0.305***	-2.165	Optimistic	0.047
Mean		0.244***	0.296***	0.168***	0.155***	-0.001	-0.045*	-0.136***				0.533***
t-stat		4.179	5.673	3.311	3.466	-0.014	-1.403	-5.996				11.175
Pessimistic, Optimistic or Neutral		Pessimistic	Pessimistic	Pessimistic	Pessimistic	Neutral	Optimistic	Optimistic				Pessimistic

Panel B: Males

Age	N	Means of $\ln(\widetilde{c}_i^{(1,t_a)})$ to the Target Age: 75	80	85	90	95	100	105	Mean	t-stat	Pessimistic, Optimistic or Neutral	Means of $\ln(\widetilde{c}_i^{(2)})$
50-54	106	0.562	0.691	0.555	0.501	0.278	0.193	-0.022	0.394***	3.478	Pessimistic	0.955
55-59	102	0.163	0.463	0.465	0.418	0.192	0.082	-0.103	0.240***	2.173	Pessimistic	0.508
60-64	84	0.013	0.089	-0.060	0.024	-0.093	-0.222	-0.265	-0.074	-0.546	Neutral	0.422
65-69	98	-0.124	-0.126	-0.256	-0.137	-0.211	-0.231	-0.160	-0.178*	-1.374	Optimistic	0.119
70-74	47	-0.234	-0.550	-0.698	-0.559	-0.588	-0.314	-0.263	-0.458***	-2.618	Optimistic	-0.196
Mean		0.124*	0.205***	0.099	0.133**	-0.016	-0.062	-0.145***				0.437***
t-stat		1.538	2.920	1.457	2.391	-0.320	-1.564	-5.180				6.638
Pessimistic, Optimistic or Neutral		Pessimistic	Pessimistic	Neutral	Pessimistic	Neutral	Neutral	Optimistic				Pessimistic

Panel C: Females

Age	N	Means of $\ln(\widetilde{c}_i^{(1,t_a)})$ to the Target Age: 75	80	85	90	95	100	105	Mean	t-stat	Pessimistic, Optimistic or Neutral	Means of $\ln(\widetilde{c}_i^{(2)})$
50-54	106	0.617	0.782	0.626	0.532	0.319	0.147	-0.095	0.418***	2.984	Pessimistic	0.975
55-59	91	0.612	0.574	0.484	0.441	0.186	0.085	-0.030	0.336**	2.462	Pessimistic	0.867
60-64	80	0.191	0.230	0.168	0.108	-0.045	-0.006	-0.083	0.080	0.529	Neutral	0.520
65-69	97	0.003	0.063	-0.142	-0.118	-0.253	-0.187	-0.242	-0.125	-0.955	Neutral	0.296
70-74	44	0.412	0.109	-0.202	-0.401	-0.344	-0.352	-0.213	-0.142	-0.639	Neutral	0.308
Mean		0.370***	0.391***	0.240***	0.178***	0.016	-0.028	-0.126***				0.634***
t-stat		4.382	5.064	3.180	2.519	0.254	-0.540	-3.512				9.192
Pessimistic, Optimistic or Neutral		Pessimistic	Pessimistic	Pessimistic	Pessimistic	Neutral	Neutral	Optimistic				Pessimistic

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.