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ARC Centre of Excellence in Population Ageing Research

Working Paper 2013/19

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Shang Wu[1], Ralph Stevens[2] and Susan Thorp[3]

[1] CEPAR, School of Risk and Actuarial Studies, University of New South Wales. Email: shang.wu@unsw.edu.au.

[2] CEPAR, School of Risk and Actuarial Studies, University of New South Wales and Netspar. Email: Ralph.Stevens@unsw.edu.au.

[3] Finance Discipline Group, UTS Business School, University of Technology Sydney, Email: Susan.Thorp@uts.edu.au.

We are grateful to the Australian Research Council for generous financial support.

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Shang Wu*, Ralph Stevens†, and Susan Thorp‡

July, 2013

ABSTRACT

Modeling of subjective survival is critical to the use of mortality expectations in economic models and the life insurance industry. Subjective scaling factors that are used to adjust average survival probabilities for individual expectations are often based on a single observation of personal life expectancy and assumed to be constant for any projected target age. Using survey data on subjective survival probabilities over a range of target ages and from an array of age cohorts, we estimate individual subjective scalings of population mortality probabilities. We show that both cohort age and target age matter: comparing subjective survival probabilities with the cohort life table, we show that respondents are generally pessimistic about overall life expectancy, but are optimistic about their probability of surviving to advanced ages; and that older respondents in our middle-aged sample are more optimistic than younger ones. Hence, our data suggests that individuals tend to expect to either die young or to live long. We propose a new model to incorporate cohort- and target age-varying subjective survival beliefs and illustrate the effect of these variations on optimal life cycle consumption plans. The proposed model contributes to the explanation of both the retirement savings puzzle and conservative spending patterns in retirement.

Keywords: subjective life expectancy; unobservable heterogeneity; rational expectations; life cycle model.

JEL Classifications: D14, D84, J11, I10

*CEPAR, School of Risk and Actuarial Studies, University of New South Wales, NSW 2052, Australia. Phone: +61 2 9385 7056. Fax: +61 2 9385 1883. Email: shang.wu@unsw.edu.au.

†CEPAR, School of Risk and Actuarial Studies, University of New South Wales, NSW 2052, Australia, and Netspar. Phone: +61 2 9385 7714. Fax: +61 2 9385 1883. Email: Ralph.Stevens@unsw.edu.au.

‡Finance Discipline Group, UTS Business School, University of Technology Sydney, PO Box 123, Broadway, NSW 2007, Australia. Phone: +61 2 9514 7784. Fax: +61 2 9514 7711. Email: Susan.Thorp@uts.edu.au.

1 Introduction

In most forward-looking economic models, agents' subjective survival expectations are critical. For example, in the core life-cycle model of Modigliani and Brumberg (1954), an individual's consumption plan is very sensitive to his or her expectations of survival. A recent calculation by Salm (2010) using data from the Health and Retirement Study (HRS) found that a 1% increase in the subjective probability of mortality resulted in an annual reduction in future consumption of non-durable goods of around 1.8%, and that using subjective mortality expectations improved estimation precision. However estimates of subjective mortality are not often available or, when they are available, offer very limited information about an individual's expectations. Consequently, researchers usually assume agents hold rational expectations and rely on the population life tables for survival probabilities.

Although many studies, beginning with Hamermesh (1985), confirm that individual estimates of survival probabilities are coherent, useful for prediction and conform to actuarial data (e.g., Hurd, 2009; Hurd and McGarry, 2002; Smith et al., 2001), there is evidence for large variations between people (e.g., Bissonnette et al., 2012; Khwaja et al., 2007; Ludwig and Zimper, 2013; Perozek, 2008; Wang, 2009). Variations in subjective expectations often correlate with known risk factors, such as personal health and parents' lifetimes, but also include an unobservable component that predicts actual mortality (Hurd and McGarry, 2002). Aggregate biases in subjective expectations have also been found. Research by Banks et al. (2004) and O'Donnell et al. (2008) using UK data, and Teppa (2012) using Dutch data, found that, as a group, women underestimate lifetimes, whereas Gan et al. (2005) and Hurd and McGarry (2002) find that men tend to overestimate. Overall, younger age groups of both genders tend to underestimate survival and older groups tend to overestimate (e.g., Hamermesh, 1985; Elder, 2007).

Prior studies have verified that subjective survival expectations behave like probabilities (e.g., Hurd and McGarry, 1995; Hurd and McGarry, 2002; 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 may model individual subjective survival curves (e.g., Bissonnette et al., 2012; Elder, 2007; Gan et al., 2005; Khwaja et al., 2007; Perozek, 2008) and add them to life cycle models (e.g., Rohwedder and Delavande, 2011; Gan et al., 2004; Salm, 2010). But even when subjective expectations data exist, they are often just single point estimates. For example, in the widely used HRS data, each respondent forecasts survival to a single target age.[1] Far fewer studies attempt to measure a range of survival expectations.[2]

[1]The target age may differ among respondents, for example respondents who are between the ages of 50 and 65 years only provide subjective survival probabilities to the target age of 75, however respondents who are between ages 66 and 69 years may be asked to supply probabilities for a target age of 80.

[2]Recent exceptions where ranges of probabilities were collected include Payne et al. (2012) and Teppa

Here we extend the existing literature by using data from a survey in which respondents answer eleven different questions about their subjective survival probabilities at a range of target ages. This allows us to make much more precise estimates of their subjective survival curve than we could using only a life expectancy or one probability.

Subjective survival (mortality) curves are usually modeled as a scaling of objective mortality experience, where the scaling is achieved using 'subjective scaling factors'. If only one point estimate is available for each respondent, the rest of the subjective survival curve must be drawn on the assumption that the distribution of subjective scaling factors does not change with target age. For example, Gan et al. (2005) develop a model for individual subjective survival curves with a subjective scaling factor[3] called an "optimism index", that is constant over all target ages. In other studies (e.g., Bissonnette et al., 2012; Khwaja et al., 2007), the authors assume the subjective scaling factor follows a specific distribution, such as the Gamma distribution, with target-age-independent parameters.

If the distribution of subjective scaling factors is not independent of target age, then a survival curve calculated by assuming independence will be biased. For example, a 50 year old individual may be 'pessimistic' (relative to objective experience) about his survival probability to age 75 and 'optimistic' about his survival probability to age 95. This pattern, observed in some aggregate data (Elder, 2007), cannot be modeled at the individual level by a constant scaling factor estimated from a single target age point estimate. A subjective scaling factor estimated on a 'pessimistic' expectation of reaching age 75 will underestimate the individual's current ('optimistic') expectation of reaching age 95 and hence may not match up to his views on very old age survival. A biased forecast of survival expectations at older ages would matter to major decisions such as deferred annuity or long-term care insurance purchases.

To address these problems, we work with survey data from more than 900 middle-aged to elderly respondents. The survey asked people to choose subjective probabilities of survival from their current age to target ages out to 120 years, in steps of five years. Because we collected a series of probabilities at many target ages for each respondent to the survey, we can model the the distribution of, and identify patterns in, the subjective survival curves. To our knowledge, we are the first to examine how individual subjective expectations vary by target age, and to test whether constant subjective scaling factors computed from point-estimates are a good approximation.

We find that subjective scaling factors estimated from the same person's subjective sur-

(2012).

[3]The heterogeneity in individuals' subjective scaling factor can be explained by for example private information or personal tendencies. This implies that "optimism/pessimism" at an individual level might be rational and thus does not have to be related to psychological optimism/pessimism.

vival probabilities to different target ages vary a great deal, highlighting the need to extend the standard single scaling factor model. Panel regression of individuals' subjective scaling factors on demographic characteristics, socioeconomic characteristics and health information shows the relevance of many of these covariates. Results show decreasing pessimism with target age. Consistent with existing papers (e.g., Hurd et al., 1998; Ludwig and Zimper, 2013; Bissonnette et al., 2012), we also find a general increase of optimism with cohort age. We fit a cubic model of subjective scaling factors by cohort age and target age. Our findings highlight possible weaknesses in models based on single point estimates of survival. For example, early retirement survival pessimism followed by later retirement survival optimism may 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), or low rates of annuitization among younger retirees (Teppa, 2012).

Next we describe the survey data.[4] In Section 3 we test the hypothesis that the subjective scaling factor is independent of target age within the same individual. Section 4 investigates the structural form of the subjective survival probabilities allowing for individual and cohort-level heterogeneity. Moreover, we illustrate the effect of subjective survival probabilities on the consumption plans of forward looking agents. Section 5 concludes.

2 Data

Data on subjective survival expectations come from the Retirement Plans and Retirement Incomes: Pilot Survey, conducted in May 2011.[5] We selected a representative sample of 920 respondents aged between 50 and 74 years from the PureProfile online panel of over 600,000 Australian subscribers. 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.[6] Respondents chose probabilities from the list shown in Table 1 that most closely matched their expectation of survival at each target age. Respondents who chose increasing survival probabilities at older ages were dropped from the sample because their answers imply that at least some conditional survival probabilities were above one. This left 855 respondents and 5985 ($= 855 \times 7$) observations in total.

Respondents were also asked: *"To what age do you think you will live?"*, which gives an estimate of their subjective life expectancy. The survey also included socioeconomic and

[4]Further information about the survey can be found in Agnew et al. (2012).

[5]The full survey is available at: `http://www.censoc.uts.edu.au/researchareas/Super_Screenshots.pdf`.

[6]We exclude subjective survival probabilities to age 110, 120, and 120^+ in our analysis, because the population life tables do not report any data for these ages. After the exclusion of those subjective survival probabilities the remaining survey responses consist of subjective survival probabilities to seven target ages.

demographic information, such as current health, income, education, and marital status. Sample and population demographics are compared in Agnew et al. (2012): by age, gender, marital status, work status and income, survey sample proportions are very close to the 50-74 years population. However survey respondents report slightly higher levels of formal education than the population. 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 either gender is large. Women's average life expectancy is 83.9 years and men's is 82.6 years.

3 Comparing subjective expectations with population and cohort data

3.1 Descriptive data

Average subjective life expectancies are close to current population data but fall below (improved) cohort life expectancies.[7] Table 3 shows an average underestimation of lifetimes by five years for females and three years for males, consistent with Perozek (2008) and Bissonnette et al. (2012). Further, younger cohorts underestimate survival on average while older cohorts tend to overestimate, especially males, in line with Ludwig and Zimper (2013). (Younger cohorts may fail to account for future improvements in their survival prospects when forming expectations.) In fact, the 50-54 year old group underestimates their life expectancy by more than eight years, whereas the 70-74 year old group are much closer to (improved) life table predictions. Males in this older cohort overestimate life expectancy by only one year and females underestimate it by one year.

In line with existing literature, we find overall pessimism about life expectancy. This pessimism is at odds with other findings of optimism about future life events, (e.g., Weinstein, 1980 Weinstein and Klein, 1996; Harris and Hahn, 2011). General optimism is particularly marked for health events (e.g., Weinstein, 1982, Weinstein, 1984 and Massey et al., 2011). Although health and life expectancy are correlated, the well-documented 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. Unrealistic optimism over health events is commonly explained by the hypothesis that people believe negative events are less likely to happen to themselves than to others, and positive events are more likely. For extremely undesirable or desirable events this bias is larger. Moreover, previous personal

[7]For current population survival probabilities, we use the latest published Australian Life Tables (Australian Government Actuary, 2009). Cohort probabilities are computed from the published life tables using the 25 year improvement factors.

experience of an event increases an individual's tendency to over-estimate their own chances. And while people update their beliefs over time, information representation might affect the quality of updating. It follows that at advanced ages, survival probability updating might be more accurate because people observe more deaths. Moreover,Tversky and Kahneman (1972) show that for non-symmetric distributions, individuals estimate the mean towards the long tail: for middle aged individuals this implies that they would underestimate the mean of their remaining lifetime distribution. Another explanation is that people overweight small probabilities and underweight large probabilities (Kahneman and Tversky, 1979). Accordingly, pessimism (optimism) could be caused by underestimation (overestimation) of survival probabilities by younger (older) cohorts when projecting to close (distant) target ages because the survival probability is relatively large (small).

Table 3 also shows a target age effect within cohorts: the negative difference between subjective survival probabilities and the life-table probabilities across the horizontal axis is biggest at lower target ages and becomes smaller at more distant ages, eventually becoming positive. This finding is distinct from existing results that show how the tendency to pessimism decreases with cohort age (Ludwig and Zimper, 2013). Target age pessimism appears to peak at age 80 while optimism peaks at 95. These findings suggest that assuming a constant scaling across target ages may not be a correct model for subjective survival beliefs.

3.2 Constant 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 with 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 life time for an individual aged x with gender g; ${}_{\tau}p_{x,g}$ is the probability of surviving another τ years for an individual aged x; and $q_{x+s,s,g}$ is the one-year mortality probability for 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. Here, 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 an individual's subjective scaling factor can vary away 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 Consistency of life expectancy and target age survival probabilities

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?"*. 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 from each set of responses. 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 $\widetilde{c}_i^{(2)}$.

Respondents choose subjective survival probabilities from the discrete list in Table 1. As a result, we compute a range for $\widetilde{c}_i^{(1,t_a)}$ by assuming that each reported subjective survival probability is a rounded answer. For example, we treat an answer of 0.3 as lying in $[0.25, 0.35)$ and infer a subjective scaling factor.[8] For life expectancy, computing a single point estimate of $\widetilde{c}_i^{(2)}$ is straightforward.[9]

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 $\widetilde{c}_i$ fall 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 seperately and the second test evaluates whether an individual uses a constant subjective scaling factor in answering all target age

[8]For "No change, almost no change" we use the interval $[0, 0.05)$ and for "Certain, practically certain" we use the interval $[0.95, 1]$.

[9]Note that the subjects can give any answer to the question *"To what age do you think you will live?"*.

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 consistency tests. For target age 75, for both genders, only approximately 25% of $\widetilde{c}_i^{(2)}$s fall in the interval of $\widetilde{c}_i^{(1,t_a)}$. 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 the sample with only males (i.e., Panel A and Panel B of Table 5), 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 more pessimism. Moreover, 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

4.1 Individual subjective scaling factors

To test the effects of cohort age and target age on subjective scaling factors, we estimate a panel model of factors, controlling for demographic characteristics, socioeconomic factors, and health information. All results are summarized in Table 6. We estimate four models where the specification of *Age* and *Target Age* are different. The first model is a pooled OLS model, which is linear in age and target age. The second and third model are fixed target age effect models, which allows us to estimate seven separate period effects. Those can be interpreted as the effects of target age on subjective scaling factors. The third model also allows for random cross section effects. The fourth model is a random effects model with a cubic form for the effect of age and target age. Hence, the natural logarithm of the subjective scaling factor for individual i with gender g aged x_i when projecting to target age t_a by:

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

where $f(x_i, t_a, g)$ 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 the 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 time-invariant. This can be interpreted as an unobserved individual tendency to pessimism and/or as additional personal information not captured by controls.

The models estimated in here differ from existing literature by that we allow the subjective scaling factor to be dependent on the target age. Therefore, we have to generalize Equation (1) to:

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

We will first describe the effect of individual characteristics, and then the effect of age and target age, on subjective scaling factors.

First, we consider the effect of individual characteristics on subjective survival beliefs in all four models. Individual characteristics can influence both the individual's survival probabilities and the individual's bias. We use age and gender specific mortality probabilities from the life tables as our benchmark, implying that the estimated age effect (less pessimistic for older cohorts) and gender effect (females are more pessimistic) are purely due to individual bias. However, socioeconomic factors and the health information will also change an individual's survival probabilities and a rational individual should incorporate such information into his or her subjective life expectation. Due to lack of data, we are unable to include other factors in the benchmark mortality probabilities.

We find that in all models, in line with expectations, health problems adversely affects subjective survival probabilities. Also consistent with earlier studies, (Hurd and McGarry, 1995 and Balia, 2011) the estimated coefficient of *Income* -0.003 (indicating that a $1,000 increase in annual salary is associated with a -0.3% change in the level of pessimism) shows that high income people are less pessimistic. Although not significant, estimated coefficients on *High School* and *College* are unexpectedly positive. However, excluding *Income* and *Wealth* from the regression produces the expected negative coefficients on education, and more so for *College* than *High School*. It seems that income rather than education is the key influence on subjective mortality expectations among the middle-aged. Surprisingly, the coefficient on gender (binary variable *Female*) is not significant, though it has the expected sign. This might be due to collinearity with *Income*. The overall fit of the models is relatively low,[10] and possibly could be improved by 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.

Clarke and Leigh (2011) use longitudinal panel data from the HILDA survey to compute the effect of income and education on mortality odds. We find that the increase in odds for realized mortality as income and education decline computed by Clarke and Leigh (2011) are larger than the difference in odds estimated from the subjective survival probabilities used here.[11] In other words, the higher income and higher education individuals in this sample are generally more pessimistic than is warranted, only partly taking their survival advantage into account when estimating their own lifetimes.

Wright and Bower (1992) found that happy people are more optimistic. Individuals with *Anxiety/Depression* might therefore be more pessimistic. Using a large population survey Mykletun et al. (2009) found that the case-level depression is associated with mortality odds of 1.52, a value close to the mortality odds of 1.49 estimated from respondents in this sample who reported high rates of depression and/or anxiety. Hence, we do not have evidence that individuals with *Anxiety/Depression* are more pessimistic about their survival than they rationally should be.

[10] We also tested the reduced models (backward elimination in stepwise regression with as selection criterion the t-value). Except for *Intercept* and *Usual Activity Problem* in the models in columns (3) and (4) which increased from 0.456 to 0.530 when excluding non-significant parameters, the differences between excluding and including non-significant variables is negligible. For the model in column (4), *Income* becomes significant at 1% level in the reduced form model.

[11] Clarke and Leigh (2011) report odds for univariate effects: for income, 1.88 (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 fixed target age and random cross-section effects model we find effects of 1.52 for income and 1.13 for education.

While the effect of individual characteristics are similar in the four models, age and target age are specified differently in each. In the pooled OLS model (column (1) in Table 6), that treats both age and target age as linear effects, estimated coefficients are both negative. Together these results show that membership of an older cohort and/or projecting survival chances to more distant target ages reduce pessimism about survival. As noted earlier, two possible explanations for these tendencies are, first, that forecasts for 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 survival at advanced ages (Reber and Millward, 1971).

In the fixed target age effect models (columns (2) and (3) in Table 6) we include indicator variables for the different target ages. Consistent with model one, 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.[12] The estimate of target age in the pooled OLS model, assuming linear effect, falls within the confidence bounds of the estimates in the fixed target age effect models. Moreover, the R^2 only slightly increases, indicating that the additional explanatory power of the six dummies compared to single linear effect is low. The significance of the parameters, the improved fit of the model and the different shapes of the effect of target age on the subjective scaling factor for middle ages and advanced age individuals indicate that if there are no interaction effects between age and target age, target age effects might be linear.

Finally, in the structural model (column(4) in Table 6) we allow for interaction effects between age and target age. All terms are significant except for the coefficient on *Age* squared and explanatory power is higher. Note that 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. This indicated the importance of allowing for interaction effects between age and target age.

Summarizing our results, on average, being in older cohorts and projecting to more distant target ages lowers pessimism (compared with cohort life table projections), a finding that again highlights the weakness of relying on constant scalings based on point estimates. This can be explained by older individuals who are better able to update their beliefs, see Hoffrage and Gigerenzer (1996), and/or the perception of having more control on mortality further in the future, which would be in line with the observed optimism for health events. Another explanation of the cohort effect is that people generally overestimate the probability of

[12]Note that the estimate for *Target Age 80* is positive, indicating that individuals are more pessimistic for target age 80 than 75. This would indicate a non-monotonic trend. However, this is estimate is not significant at a 10% significance level.

conjunctive events (e.g., probability of surviving this year and surviving next year and etc., see Bar-Hillel, 1973 and Tversky and Kahneman, 1974).

4.2 Cohort-specific subjective scaling factors

In this section we investigate age and gender-specific subjective scaling factors for different cohorts rather than individuals. Cohort models are useful for prediction when individual level explanatory variables are unknown. The cohorts are based on gender, age and target age. We integrate out the effects of idiosyncratic effects, such as socioeconomic indicators and health, by averaging within those cohorts. In the remainder of this section we will discuss the empirically calibrated cohort-specific subjective scaling factors and thereafter we propose a model to fit those cohort-specific subjective scaling factors.

Table 7 displays the sample mean of the natural logarithm of subjective scaling factors for each of the cohort groups. The upper panel of Figure 1 graphs the average over cohorts of the log subjective scaling factor as a function of target age for both genders. We observe that before target age 80 there is an increase and after target age 80 there is a general decrease in the average subjective scaling factor for all males. This is the case to a lesser extent for females. The average subjective scaling factors pass through one around target age 95 for both males and females. The lower panel shows cohort age subjective scaling factors averaged over target ages. Again, people become more confident of survival as they age, relative to the life tables. This relationship seems to be more linear, with the point where pessimism switches to optimism during the 60's (males around 61, females around 67). 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., 2012), the switch is particularly important. Women are consistently more pessimistic than males in projecting both life expectancies and survival probabilities, in line with existing literature (e.g., Wenglert and Rosén, 2000).

Next, to investigate possible interaction effects, we allow the sample average of the cohort-specific subjective factor for males and females to be dependent on both age and target age. The upper panels in Figure 2 illustrate the surface of cohort-specific subjective scaling factors for cohorts shown in Table 7 against *Age* and *Target Age*.[13] Figure 2 indicates that the effect of *Age* and *Target Age* are not linear, because the empirically calibrated subjective scaling factors are not perfect a plane. This is in line with the results in the previous subsection where we showed that individual subjective scaling factors are best modeled using a cubic

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

form in age and target age.

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 displayed 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 males all terms are statistically significant, whereas for females, only one out of four 3$^{\text{rd}}$ 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.[14]

The stationary points of the estimated polynomial can give us some idea about key ages at which respondents switched from lower to higher cohort-specific scaling factors. There is a local maximum point of pessimism at current age 50 for target age 80 and a local minimum point at current age 72 to target age 96.

For females, the maximum point of pessimism at age 50 and target age 80 is critically important for the pricing of life insurance products. If females are at the peak of pessimism when they are aged 50 and projecting to the target age 80 (which is a quite common projecting time span for products such as a life annuity), they will underestimate their survival probabilities by a lot more than life-table predictions.[15] 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.[16] This peak of pessimism among females, combined with the general pessimism among both genders we find in Table 4 and Table 7, may be part of the explanation of the annuity puzzle, in addition to the other explanations such as loadings (see, e.g., Friedman and Warshawsky, 1990 and Bernheim, 1991) default risk of the insurer (see e.g. Babbel and Merrill, 2007), illiquidity or irrevocability of annuities (see Sinclair and Smetters, 2004), mental accounting (see Hu and Scott, 2007 and Brown, 2007), and investment framing (see, e.g., Brown et al., 2008, and Gazzale and Walker, 2009). The local minimum point of pessimism is of lesser interest because it does not imply optimism among females according to Table 4 and Table 7.

Our evidence suggests that moving from younger cohorts to older cohorts and from close target ages to distant target ages shrinks subjective scaling factors. As a result, models

[14]We have also estimated a quadratic model, excluding the 3$^{\text{rd}}$ 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 year it is optimistic. For older ages, the reverse is the case.

[15]Indeed, the perceived survival probability by a female may be even much lower than the insurance industry life table on which life annuities are priced.

[16]The adverse selection will be even more serious and result in a vicious cycle.

with time-invariant subjective scaling factors are not appropriate. In addition, we find that a cubic form in *Age* and *Target Age* fits well for subjective scaling factors averaged across people of the same age, especially for females. Finally, the annuity puzzle can be partially explained by a general pessimism among people that is more pronounced for cohorts in their 50s estimating their survival prospects to ages around 80-90, which are crucial ages for annuity evaluation.

4.3 Impact of subjective beliefs in life cycle models

In this subsection we illustrate the effect subjective survival probabilities can have on optimal consumption decisions in a life cycle model. To illustrate this, 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 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. Utility parameters are set equal to the values often used in the life-cycle literature (see Gomes and Michaelides, 2005): relative risk aversion $\gamma = 5$; a time preference parameter (also referred to as subjective discount factor) $\beta = 0.96$; and $u = 0.17$ (see Yogo, 2009) as the relative utility of bequest. The real risk-free return is set at $r = 2.6\%$ (see 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:

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

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) Using the mortality probabilities from the life tables;

ii) Using the subjective mortality probabilities whose scaling factors depends on current age and target age (using columns (5) and (6) of Table 6);

iii) Using the subjective mortality probabilities whose scaling factors depends on target age only (using columns (5) and (6) of Table 6);

iv) Using the assumption of a constant scaling factor based on the subjective survival probability to age 75 (for 50 year old) or 80 (for 65 year old) (using the sample average);

v) Using the assumption of a constant scaling factor based on subjective life expectancy (using the sample average).

The consumption plan derived under method *i* is consistent with rational expectations for the population-representative individual. The consumption plan derived 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, 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. Methods *iv* and *v* are included 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 3 illustrates the effect of subjective survival probabilities on the optimal lifetime consumption level for a 50 year old (upper panel) and 65 year old (lower panel). From Figure 3 we observe that from age 65 (retired) the consumption plan based on the subjective scaling factor derived from his subjective life expectancy (method *v*) implies that an individual would consume more than is optimal (method *i*) up to age 87 and thereafter - due to a low wealth level - less than is optimal. 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*), we observe under-consumption before age 87 and over-consumption thereafter. Similar results are found using subjective mortality probabilities at age 65, which do depend on target age (method *iii*).

Interestingly, 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.

Next, considering a 50-year old (Figure 3, upper panel) we observe similar findings as for a 65 year old when using the subjective life expectancy to calibrate the optimal consumption level. Using current subjective survival probabilities (methods *iii* and *iv*) individuals would over-consume up to age 84. Interestingly, when individuals are constantly updating their mortality beliefs (method *ii*) they overconsume before age 60.[17] Hence, the subjective survival probabilities also play a role in explaining why individuals save too little for retirement, as is found in, for example, Mitchell and Moore (1998) and 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. Whereas there are existing separate explanations for both the retirement savings puzzle (such as hyperbolic discounting) and the conservative spending pattern in retirement (such as unexpected health expenditure), the empirical patter of subjective survival beliefs documented here contribute to explaining both puzzles rather than only one of them.

5 Conclusions

Many critical economic decisions depend on subjective life expectancy. Existing 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. Hamer-

[17] Considering the case of deterministic labor income, wealth before retirement can be interpreted as liquid wealth plus wealth on retirement savings account plus human capital (discounted cash flows of future income). In the case where the individual does not consume more than the decumulation of human capital (e.g., saves for retirement) his wealth minus human capital would also be positive. Therefore, the over-consumption at age 55 can be interpreted as not saving enough for retirement during the working life.

mesh, 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. Standard methods therefore treat each person's pattern of deviation from population life tables as constant.

Here we are able to use rich data on the subjective survival beliefs of 855 survey respondents to test the assumption that subjective scalings of objective population survival probabilities are constant. We use the cohort life table as our benchmark and analyze the dynamics of the subjective factors which scale objective mortality probabilities. We reject the assumption of constancy and find that a large proportion of the individual variation in subjective scaling factors can be explained by a polynomial form in current age and projecting target age.

These effects are not observable when using a dataset of point estimates on individuals' subjective expectations. Overall, subjective survival probabilities tend to pessimism, but we find evidence that pessimism decreases as the target age (forecasting horizon) increases. Furthermore, and consistent with Ludwig and Zimper (2013) and Bissonnette et al. (2012), we find an increase of optimism with cohort age. In addition, females are more pessimistic than males, which is also shown in Perozek (2008) and 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 and may be a factor in apparently irrational choices around social security. 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. Moreover, 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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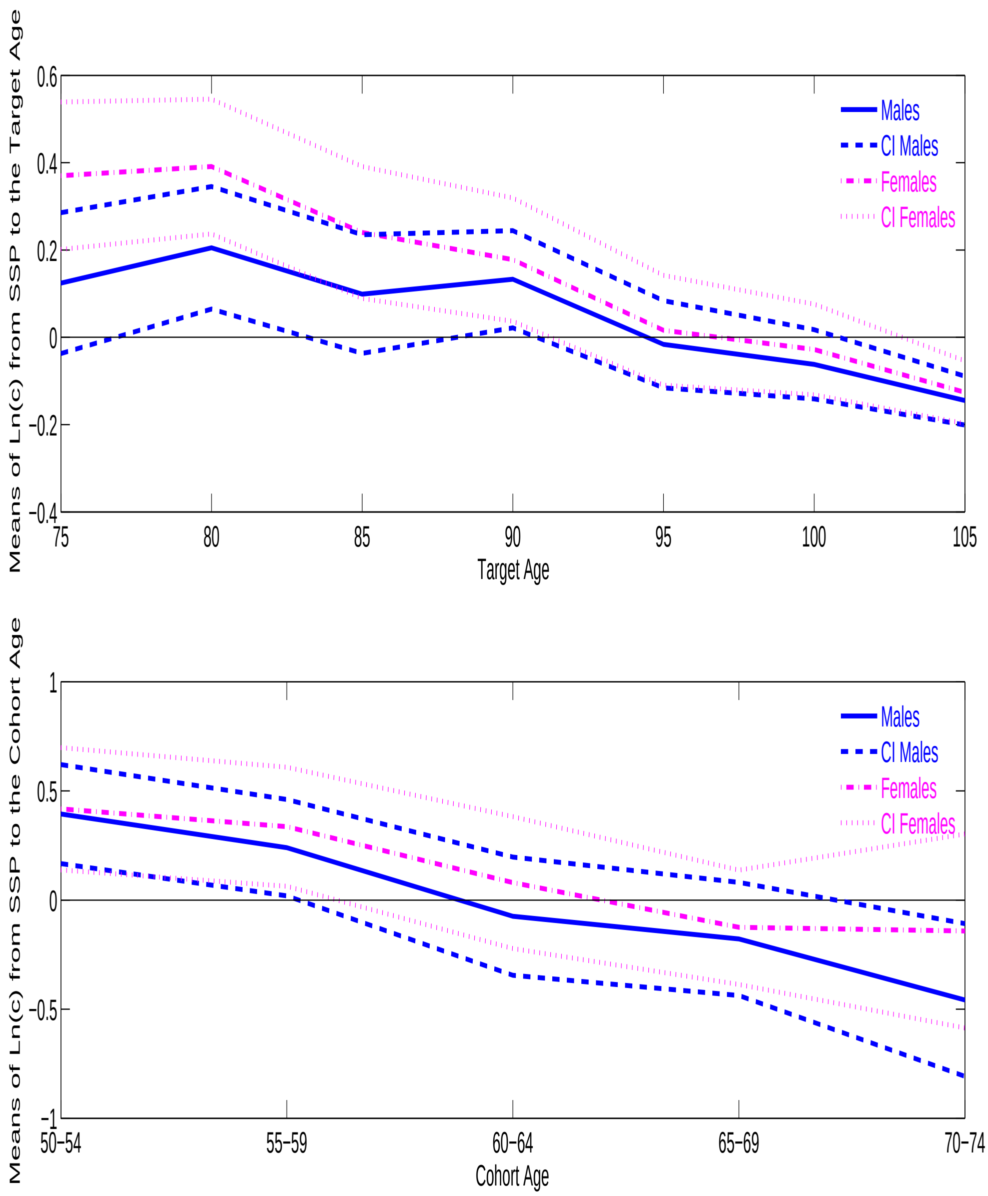
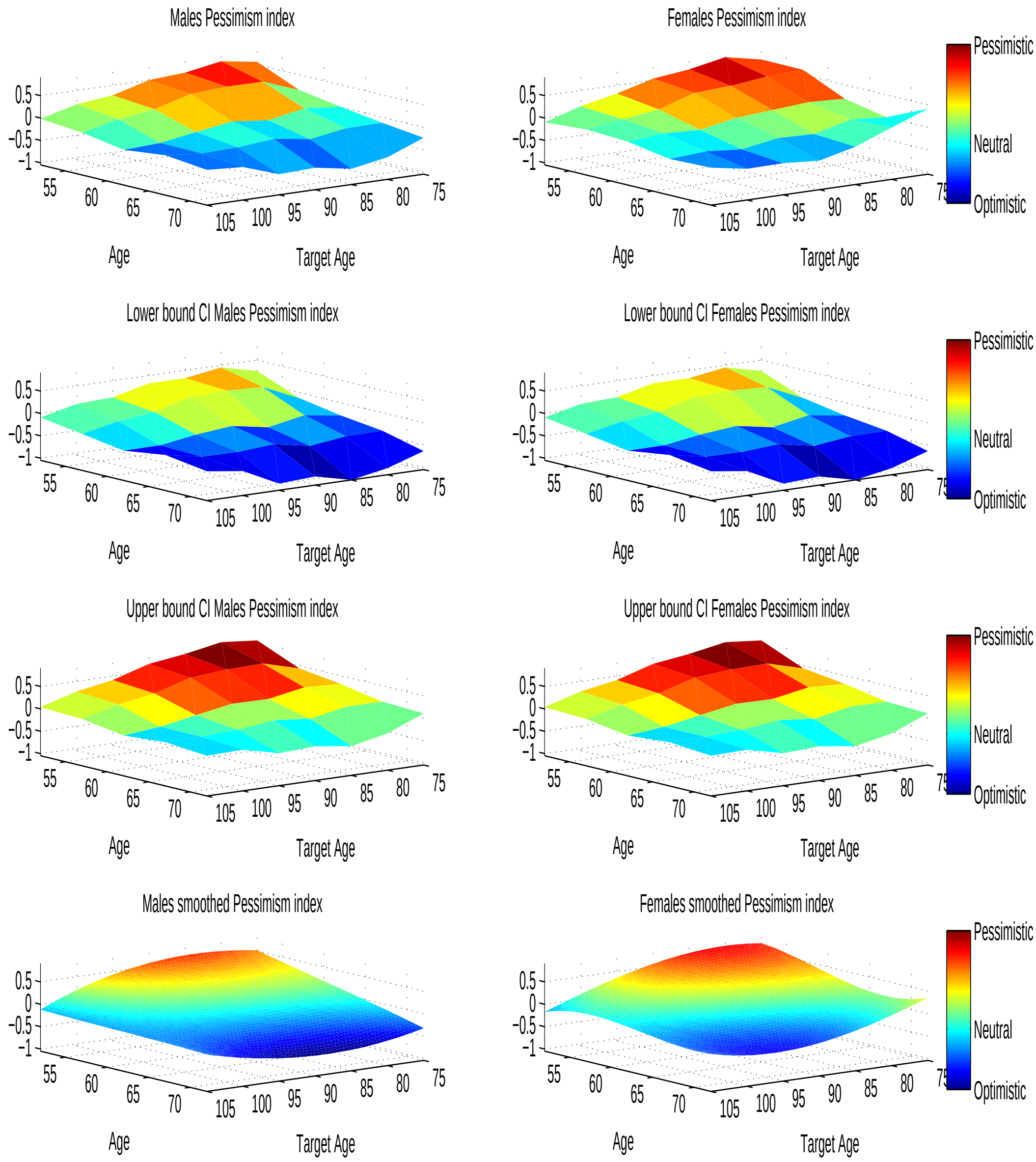
A Figures and Tables

Figure 1: Target Age and Cohort Age Effects on Pessimism



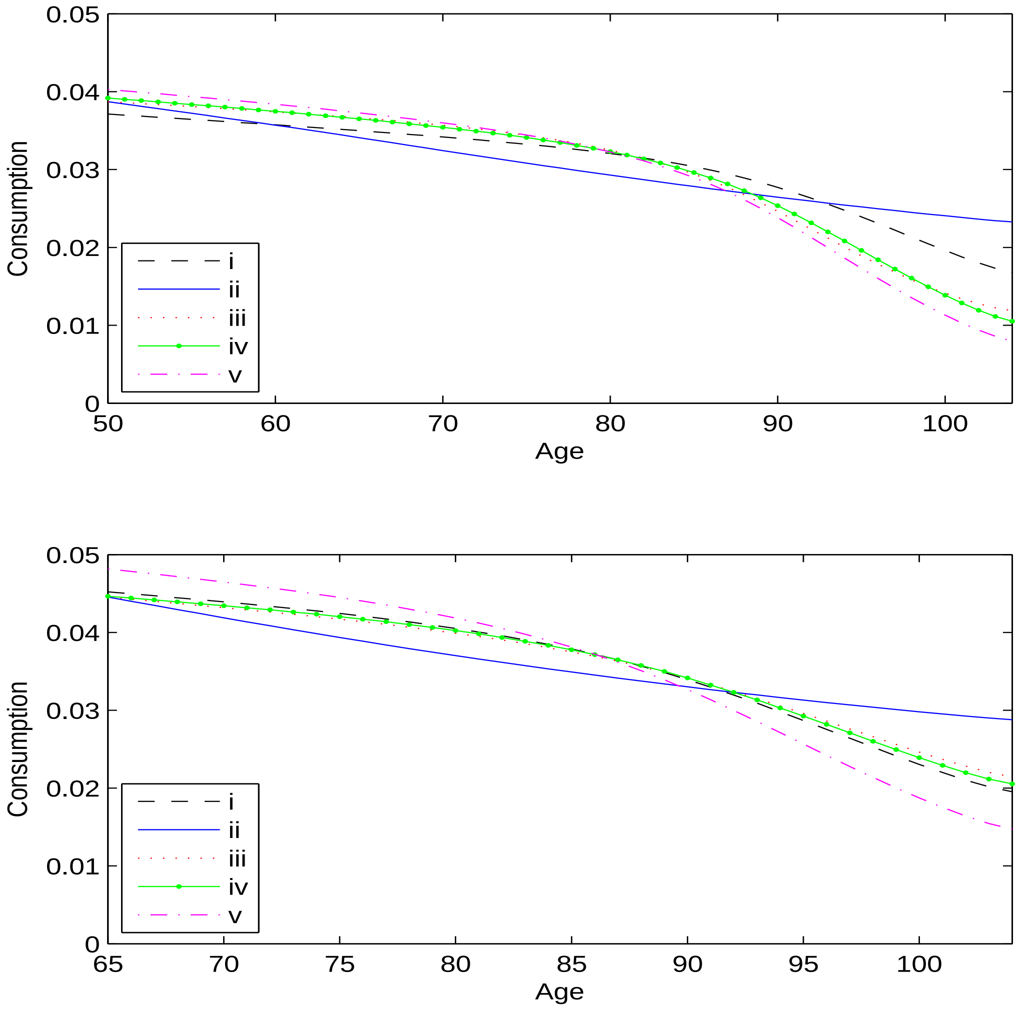
The upper panel of the figure illustrates the effect on pessimism of target ages in projecting subjective survival probabilities. The horizontal axis refers to target ages whereas the vertical axis shows percentages of the effect. The lower panel of the figure illustrates the effect on pessimism of cohort ages in projecting subjective survival probabilities. The horizontal axis refers to cohort ages whereas the vertical axis shows percentages of the effect. Estimation results are from Panel B and Panel C of Table 7. Confidence intervals are calibrated using standard error of the mean. Lines between points target ages are assumed to be linear for simplicity.

Figure 2: Pessimism Indices for Males and Females



The upper panels are the surface is derived at the cohort level where there are no factors other than the cohort age and the target age. For the upper panels, data is from the natural logarithm of subjective scaling factor for cohorts in Table 7. The color bar indicates the level of pessimism. Red refers to pessimism and blue refers to optimism. The vertical axis is measured by natural log of subjective scaling factors from Table 7 at the cohort level. Age refers to the median age of the cohort identified in Table 7. The middle panels are the lower and upper (5% and 95%) bootstrapped quantile of the subjective scaling factor. The lower panels are 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: Consumption Levels



The upper panel displays the consumption pattern for a 50 year old calibrated using the five methods described below, the lower panel displays the consumption pattern for a 65 year old. The (real) consumption level is displayed as a fraction of current wealth level. The five methods for computing optimal consumption patterns are:

i) Using the mortality probabilities from the life tables;

ii) Using the subjective mortality probabilities whose scaling factors depends on age and target age (using columns (5) and (6) of Table 6);

iii) Using the subjective mortality probabilities whose scaling factors depends on target age (using columns (5) and (6) of Table 6);

iv) Using the assumption of constant scaling factor based on subjective survival probability to age 75 (for 50 year old) or 80 (for 65 year old) (using sample average);

v) Using the assumption of constant scaling factor based on subjective life expectancy (using the sample average).

Table 1: Reference Table for Subjective Survival Probabilities

Survey respondents chose a survival probability from this list for each of seven target ages. The survey is described in Agnew et al. (2012) and was answered by 920 respondents between the ages of 50 and 74 years.

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									Pessimistic, Optimistic or Neutral	Life Expectancy Differences
Age	N	75	80	85	90	95	100	105	Mean	t-stat		
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												
Age	N	Differences in Survival Probability to Target Age: 75	80	85	90	95	100	105	Mean	t-stat	Pessimistic, Optimistic or Neutral	Life Expectancy 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												
Age	N	Differences in Survival Probability to Target Age: 75	80	85	90	95	100	105	Mean	t-stat	Pessimistic, Optimistic or Neutral	Life Expectancy 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

* Significant at 10%; ** significant at 5%; *** significant at 1%.

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 backed out from subjective life expectancy data. $\widetilde{c}_i^{(1,t_a)}$ Denotes the subjective scaling factor backed out from subjective survival probability data to target age t_a. ln Represents the natural log. t-stats are for t-tests of zero means and differences respectively.

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

* Significant at 10%; ** significant at 5%; *** significant at 1%.

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

The table reports regression results of the natural logarithm of individual subjective scaling factor from subjective survival probability on groups of independent variables. Column (1) presents OLS estimates of the following regression equation with t_a for *Target Age (TA)*:

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

Column (2) presents the Fixed Periods Effects Panel Model estimates of the above regression equation with fixed target age effects instead of $\beta_{t_a} Target\ Age$. Column (3) presents the Fixed Periods Effect with Random Cross Section Effects Panel Model estimates of the above regression equation with fixed target age effects instead of $\beta_{t_a} Target\ Age$ and random cross section 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) add terms from the cubic form of *Age* and *TA* instead of $\beta_{t_a} Fixed\ TA\ Effect$. Second order independent variables are scaled by dividing by 100 while third order independent variables are scaled by dividing 10000 to maintain the accuracy when estimates are rounded at three decimal places. 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 terms from the cubic form of *Age* and *TA*.

Female, *Marriage*, *Work*, *High School*, and *College* are binary variables that are equal to 1 if the respondent is a woman, married, employed, high school equivalent graduate, and college graduate equivalent respectively, and 0 otherwise. *Income* and *Wealth* are measured in thousands. All health variables are binary variables that that are equal to 1 if the respondent has the relevant heath problem and 0 otherwise.

t-stats are calculated from robust standard errors in parentheses. F-stats are for joint significance of *TA dummies* in columns (2) and (3), and of *Structural variables* in columns (4), (5) and (6). *Random effects* χ^2*-stats* are from Breusch and Pagan LM test for random cross-section effects. σ_ε measures the standard error of regression in columns (1), (2), (5) and (6), and measures the standard error of residuals from between-individual variation in columns (3) and (4). σ_π measures 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***	-71.047**	-61.28***	-95.81***
	(13.664)	(11.254)	(5.977)	(-2.194)	(-1.868)	(-4.160)
Demographic Characteristics						

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	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.023	0.023	0.023	0.022		
	(0.646)	(0.668)	(0.312)	(0.297)		
Marriage	0.078**	0.078**	0.078	0.078		
	(2.134)	(2.227)	(1.040)	(1.036)		
Socioeconomic Characteristics						
Work	-0.024	-0.024	-0.024	-0.026		
	(-0.613)	(-0.611)	(-0.285)	(-0.297)		
Income	-0.002***	-0.002***	-0.002	-0.002		
	(-3.021)	(-3.067)	(-1.432)	(-1.438)		
Wealth	0.000	0.000	0.000	0.000		
	(-0.505)	(-0.593)	(-0.277)	(-0.239)		
High School	0.005	0.005	0.005	0.006		
	(0.136)	(0.136)	(0.064)	(0.079)		
College	0.000	0.000	0.000	-0.003		
	(-0.001)	(-0.001)	(0.000)	(-0.044)		
Health Information						
Mobility	0.080*	0.080*	0.080	0.080		
-Problem	(1.806)	(1.744)	(0.814)	(0.812)		
Anxiety	0.400***	0.400**	0.400***	0.399***		
-/Depression	(11.195)	(11.381)	(5.300)	(5.291)		
Pain	0.068*	0.068*	0.068	0.069		
-/Discomfort	(1.818)	(1.767)	(0.825)	(0.833)		
Usual Activity	0.456***	0.456***	0.456***	0.456***		
-Problem	(9.693)	(9.871)	(4.609)	(4.590)		
Subjective Control Factors						
Age	-0.039***	-0.039***	-0.039***	0.934	0.921	2.452***
	(-13.278)	(-14.451)	(-6.747)	(0.650)	(0.834)	(3.168)
Target Age	-0.014***			1.869***	1.563**	1.698***
	(-8.175)			(4.603)	(2.330)	(3.611)
Fixed Target Age Effects						
Target Age 80		0.052	0.052			
		(0.672)	(1.367)			
Target Age 85		-0.076	-0.076**			

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Table 6 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)
		(-0.992)	(-2.018)			
Target Age 90		-0.089	-0.089**			
		(-1.212)	(-2.351)			
Target Age 95		-0.245***	-0.245***			
		(-3.445)	(-6.467)			
Target Age 100		-0.290***	-0.290***			
		(-4.280)	(-7.652)			
Target Age 105		-0.380***	-0.380***			
		(-5.699)	(-10.034)			
Structural part						
$Age \times TA/100$				-1.508***	-2.701***	-1.161**
				(-3.545)	(-3.918)	(-2.389)
$Age^2/100$				-0.569	0.303	-3.307***
				(-0.246)	(0.186)	(-2.888)
$TA^2/100$				-1.592***	-0.844	-1.538***
				(-3.941)	(-1.264)	(-3.289)
$Age^2 \times TA/10000$				-0.060**	0.026	-1.255***
				(-2.528)	(0.065)	(-4.447)
$TA^2 \times Age/10000$				0.129***	1.550***	1.535***
				(7.516)	(5.903)	(8.318)
$Age^3/10000$				0.060	-0.181	2.413***
				(0.484)	(-0.211)	(4.034)
$TA^3/10000$				0.029**	-0.048	0.224**
				(2.001)	(-0.202)	(1.335)
F-stat		14.666***	35.730***	15.187***	9.28***	18.19***
Random effects χ^2-stat			6222.910***	6318.360***		
σ_ε	1.222	1.222	0.783	0.776	0.098	0.069
σ_π			0.944	0.946		
R^2 (unweighted)	0.130	0.131	0.131	0.135	0.945	0.967
R^2 (weighted)			0.061	0.075		

* Significant at 10%; ** significant at 5%; *** significant at 1%.

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

		Means of $\ln(\widetilde{c}_i^{(1,t_a)})$ to the Target Age									Pessimistic, Optimistic or Neutral	Means of $\ln(\widetilde{c}_i^{(2)})$
Age	N	75	80	85	90	95	100	105	Mean	t-stat		
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

		Means of $\ln(\widetilde{c}_i^{(1,t_a)})$ to the Target Age									Pessimistic, Optimistic or Neutral	Means of $\ln(\widetilde{c}_i^{(2)})$
Age	N	75	80	85	90	95	100	105	Mean	t-stat		
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

* Significant at 10%; ** significant at 5%; *** significant at 1%.