Subjective Survival Beliefs and Ambiguity: The Role of Psychological and Cognitive Factors*

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December 12, 2016

Abstract

Based on data of the Health and Retirement Study (HRS), we document new facts on subjective survival beliefs by comparing them to their individual-level objective counterparts. Similar to experimental results on probability weighting in prospect theory, we show that survival beliefs can be described as objective probabilities that have undergone an inverse-S shaped transformation. With increasing age biases are driven through increased likelihood insensitivity combined with increased pessimism. Using new psychological measures in the HRS we provide further direct empirical evidence in support of these cognitive and psychological interpretations.

JEL Classification: D12, D83, I10.

Keywords: Subjective Survival Beliefs, Prelec Weighting Function, Psychosocial Explanations, Cognitive Explanations

*We thank seminar participants at LMU Munich, UC Santa Barbara, Goethe University Frankfurt, and the St. Louis FED for helpful comments.

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1 Introduction

Numerous economic decisions such as retirement, consumption and saving decisions require the formation of beliefs about the probability to survive into the future. Yet, predicting the own demise is a very difficult task which is likely prone to mistakes and biases. A growing economic literature inspired by Hamermesh (1985) documents substantial biases between subjective beliefs and their respective objective counterparts[1] and investigates the importance of such biases for economic decisions[2]. An important question that emerges from this literature is about the driving forces behind these biases. A good answer to this question would give us some guidance about how to adequately model subjective survival beliefs in economic applications.

This paper argues that increasing cognitive impairments combined with increasing pessimim for elderly people are the drivers for the age-specific patterns of survival belief biases observed in the data. We base our argument on data about psychological and cognitive variables from the Health and Retirement Study (HRS). These variables measure (dispositional) optimism, (dispositional) pessimism, and cognitive weakness. We find that optimism is decreasing and pessimism is increasing with age, on average.[3] Likewise, our measure of cognitive weakness is strongly increasing with age.

To link these direct psychological and cognitive measures to the biases in survival beliefs, we employ the celebrated prospect theory (cf. Wakker 2010 and references therein) to model and interprete subjective survival beliefs. In a first step, we determine the age-dependent patterns of biases from the HRS data on subjective survival beliefs. In the HRS interviewees are asked about their beliefs to survive from the interview age to some target age whereby this target age is several years ahead. To compare these subjective survival beliefs (SSB) with their objective counterparts, we construct for each interviewee the

[1]cf. Elder (2013), Hamermesh (1985), Ludwig and Zimper (2013), Peracchi and Perotti (2012)

[2]cf. Salm (2010), Rutledge, Wu, and Khan (2014), Gan, Hurd, and McFadden (2005), Groneck, Ludwig, and Zimper (2016b).

[3]It may seem that optimism is just the opposite of pessimism, psychologists measure both phenomena separately. We further explore the differences in Section 5.

corresponding individual level objective survival probability (OSP) by using the information on actual HRS mortality and several conditioning variables including mortality trends. Within a given age-group we find that respondents with low OSPs express overestimation whereas respondents with high OSPs express underestimation, resulting in a "flattening out" of SSB compared to the 45-degree line of OSP.[4] Across different age-groups we find that both, the average degree of underestimation and the flatness of the mapping from OSPs into SSBs, increase in age.

In a next step, we provide a structural interpretation of these biases through prospect theory (PT). One of the key insights of the experimental PT literature is that probability assessments as well as decision weights can be best described by an inverse-S-shaped transformation of additive probabilities rather than by additive probabilities themselves. As our data on SSB is consistent with an (age-dependent) inverse-S-shaped probability weighting function applied to OSP, we construct a PT model of SSB by applying the Prelec (1998) probability weighting function to OSP. The Prelec function features two parameters, one reflecting relative pessimism of respondents, the other measuring likelihood insensitivity. Likelihood insensitivity stands for a cognitive impairment according to which people tend to flatten out the 'true' likelihoods of events that are neither impossible nor certain (an extreme case of such flattening-out are 50-50 probability assessments of all uncertain events and their complements). We fit this PT model to the HRS data on SSB to trace out age-specific parameters for relative pessimism and likelihood insensitivity. We find that relative pessimism and likelihood insensitivity are both increasing with age.

Finally, we combine the HRS data on direct psychological and cognitive measures with our calibrated PT model of SSB. We analyze the extent towards which psychological and cognitive factors are associated with individuals' biases in survival assessments. To this end, we regress our structural model of SSB on the constructed OSP, several covariates as well as the psychological

[4] Our results are thus consistent with the so-called "flatness bias" documented in the previous literature Elder (2013), Hamermesh (1985), Ludwig and Zimper (2013), Peracchi and Perotti (2012): relatively young respondents (younger than age 65) express underestimation whereas relatively old respondents (older than age 70) express overestimation.

and cognitive measures. We find that OSPs do not translate one for one into SSPs, and that optimism is associated with higher SSBs and pessimism with lower SSBs. Furthermore, cognitive weakness and to a lesser extent psychological variables, covary positively with larger mistakes in survival evaluation. In counterfactuals we show that these effects are quantitatively relevant. We find an increasing importance of cognitive weakness for subjective survival belief formation over age and a rather constant impact of psychological variables.

It is unclear how additive probabilities of expected utility theory (EUT) could adequately reflect these dynamics of psychological and cognitive factors. For example, the SSBs of a standard EUT Bayesian learner would converge to the OSPs instead of exhibiting age-specific biases (cf. Ludwig and Zimper (2013)). Even if cognitive impairments are introduced in Bayesian learning models in the form of 'slow' learning, one would still obtain convergence of SBBs to OSPs. Our analysis therefore suggests that economic applications based on survival beliefs might improve their realistic appeal if they are cast within PT rather than within EUT. Such modeling choice, however, does not come cheap as PT maximization problems (typically) violate the dynamic consistency of the EUT framework.[5]

The remainder of this paper is organized as follows. Section 2 discusses our contribution to the related literature on belief formation and Section 3 presents the main stylized facts on survival belief biases. Section 4 provides a structural interpretation of these biases through prospect theory. Section 5 looks at the direct psychological measures elicited in the HRS. Section 6 presents empirical evidence on the relationship between psychological and cognitive variables, on the one hand, and biases in survival beliefs, on the other hand. Finally, Section 7 concludes. Separate appendices contain additional information on the data.

[5]We refer the interested reader to the analysis of life-cycle maximization problems under Choquet expected utility with Bayesian learning in Groneck, Ludwig, and Zimper (2016b) and under rank-dependent utility in Groneck, Ludwig, and Zimper (2016a).

2 Related Literature: Survival Belief Formation.

Our work contributes to the economic literature that seeks to understand subjective survival beliefs elicited in household surveys. This line of research starts with the pioneering work of Hamermesh (1985)[6]. This literature documents that SSBs are broadly consistent with OSPs and co-vary with direct measures of health such as health behavior (e.g., smoking) or health status in the same way as OSPs (Hurd and McGarry 1995). It has been shown that SSBs serve as predictors of actual mortality (Hurd and McGarry 2002; Smith, Taylor, and Sloan 2001) and that individuals revise their SSBs in response to new adverse (health) shocks (cf., e.g., Smith, Taylor, and Sloan (2001), building on Viscusi (1985)).[7] The latter fact has been interpreted as evidence of some form of rational Bayesian learning. However, several authors have also pointed out a systematic and age-dependent bias which contradicts typical notions of rationality. Across several data sets it has been documented that, on average, relatively young individuals underestimate whereas relatively old individuals overestimate the average probability to survive into the future. This comparison is done with respect to average cross-sectional or cohort life tables.

We extend this literature by explicitly estimating individual objective survival rates. This allows us to shed light on the bias at the individual level thereby offering a new perspective on the biases of survival beliefs. In order to estimate individual-level OSPs we adapt the methods used by Khwaja, Sloan, and Chung (2007), Khwaja, Silverman, Sloan, and Wang (2009), Winter and Wuppermann (2014). With regard to the interpretation of biases we observe our main emphasis is on psychological and cognitive factors. We thereby ex-

[6]Apart from economists, sociologist and psychologists have studied subjective life expectancy (instead of survival probabilities). Early contributions are (Handal 1969; Robbins 1988; Joubert 1992; Tolor and Murphy 1967; Denes-Raj and Ehrlichman 1991). See Mirowsky (1999, Mirowsky and Ross (2000, Ross and Mirowsky (2002) and Kastenbaum (2000), **?**) for literature reviews.

[7]See also Benitez-Silva and Dwyer (2005), Benitez-Silva and Ni (2007), Smith, Taylor, and Sloan (2001) and Hurd and McGarry (2002) who generally find that some health shocks, like newly diagnosed cancer, exert a negative influence on SSPs.

tend previous research in Economics which has mainly been concerned with objective determinants of the formation of SSPs. Since such psychometric measures are only recently available in household surveys, the literature on the impact of psychological factors on economic variables is rather scarce.[8] Some medical studies examine the link between psychosocial dispositions and health shocks (Kim, Park, and Peterson 2011) or biases in subjective body weights (Sutin 2013). Based on HRS data (Hurd, Duckworth, Rohwedder, and Weir 2012) investigate the interaction of personality traits and retirement and (Angrisani, Hurd, Meijer, Parker, and Rohwedder 2013) analyze labor market transitions. To the best of our knowledge, Mirowsky and Ross (2000) and Griffin, Loh, and Hesketh (2013) are the only studies incorporating psychological influences associated with subjective life expectancy. Griffin, Loh, and Hesketh (2013) use a sub-sample of the "45 and Up Study" of the Australian population. Mirowsky and Ross (2000) use a small sample on American adults. We extend their studies by using subjective survival probabilities and the impact of psychosocial factors once objective information is taken into account.

Finally, notice that Ludwig and Zimper (2013) and Groneck, Ludwig, and Zimper (2016b) explicitly model biased survival probabilities in a dynamic setting with age-dependent biases. The present study is the first evaluation of these models based on individual data.

3 Age Patterns of Biases in Survival Beliefs

3.1 Data

In our analyses we use the Health and Retirement Study (HRS) which is a national representative panel study. Individuals are interviewed on a biennial

[8] In the HRS, psychometric measures did not start until 2006. To circumvent this lack of data, Puri and Robinson (2007) take the difference between subjective and objective life-table survival probabilities as a measure of dispositional optimism. However, this is only a crude approximation because any deviation from average life-table estimates might also reflect private information.

basis. Interviews of the first wave were conducted in 1992. In subsequent waves, more cohorts were added in order to keep the sample representative. Interviewees are individuals older than 50 and their spouses regardless of age. An overview on the survey, its waves and interview cohorts is displayed in Appendix B.

Both for our descriptive analyses as well as our regression analyses our sample comprises waves $8-11$, i.e. years $2006-2012$. For the estimation of the individual-level objective survival probabilities (OSPs) we use waves $4-11$ of the HRS, data of the Social Security Administration (SSA), and data of the Human Mortality Index (HMI). For further details on sample selection again see Appendix B.

3.2 Subjective Survival Beliefs

In the HRS an interviewee i of age h is asked about her SSB to live to at least a certain target age m, which we denote as $SSB_{i,h,m}$. We focus on individuals in the survey of age 65 and older. This sample restriction is due to the fact that the data set does not allow us to estimate OSPs for ages less than 65 with details provided in Subsection 3.3 below. The assignment of target age $m(h)$ to interview age h for our sample is provided in Table 1.

Table 1: Interview Age h and Target Age $m(h)$

Interview age h	Target Age $m(h)$
65-69	80
70-74	85
75-79	90
80-84	95
85-89	100

Source: HRS (2015), waves 2006-2012.

3.3 Objective Survival Probabilities

To study survival misconceptions at the individual level our first objective is to assign to each individual in the sample its respective objective survival probability (OSP). Using aggregate data from (cohort) life-tables for this purpose—as, e.g., in Ludwig and Zimper (2013), Groneck, Ludwig, and Zimper (2016b), Perozek (2008) and Peracchi and Perotti (2012)—, is ill-suited because individual (objective) survival rates generally deviate from sample averages. To instead estimate the objective probability on the individual level by adapting the methods described in Winter and Wuppermann (2014, Khwaja, Silverman, Sloan, and Wang (2009, Khwaja, Sloan, and Chung (2007). We accordingly employ a duration model to estimate hazard rates conditional on several individual-level characteristics.

Among standard variables such as age, socio-economic status, health behavior, etc., the set of explanatory variables includes predicted average OSPs in order to capture time-trends of mortality hazards. We extract the time trend from a decomposition of cross-sectional survival rates into a time dependent indicator and age-specific factors following a Lee-Carter procedure.

We estimate the relationship between individual level observable variables and mortality using a hazard function given by

$$\lambda(t|\mathbf{x}_i') = \lambda_0(t)\exp(\mathbf{x}_i'\beta) \tag{1}$$

where time to failure t is the number of years to death. $\lambda_0(t)$ is the baseline hazard for which we choose the specification given by the Weibull hazard model. This allows us to model duration dependence, i.e., the fact that mortality rates are an increasing function of age. Accordingly, we impose the structure

$$\lambda_0(t) = \alpha t^{\alpha-1} \tag{2}$$

that allows for $\alpha > 1$ (capturing positive duration dependence). $\exp(\mathbf{x}'\beta)$ is the proportional hazard. In our estimation, survivors are treated as censored and we estimate function (1) by maximum likelihood.

The objective survival probabilities (OSPs) for all prediction horizons t and each individual i of interview age h are given by (cf., e.g., Cameron and Trivedi (2005)):

$$OSP_{i,h}(t) = exp\big[-\exp(\mathbf{x}_i'\beta)t^{\alpha}\big] \tag{3}$$

From this we can also construct the OSP until target age (with horizon $t = m(h) - h$), $OSP_{i,h,m(h)}$, which we assign to the respective $SSB_{i,h,m(h)}$ of individual i.

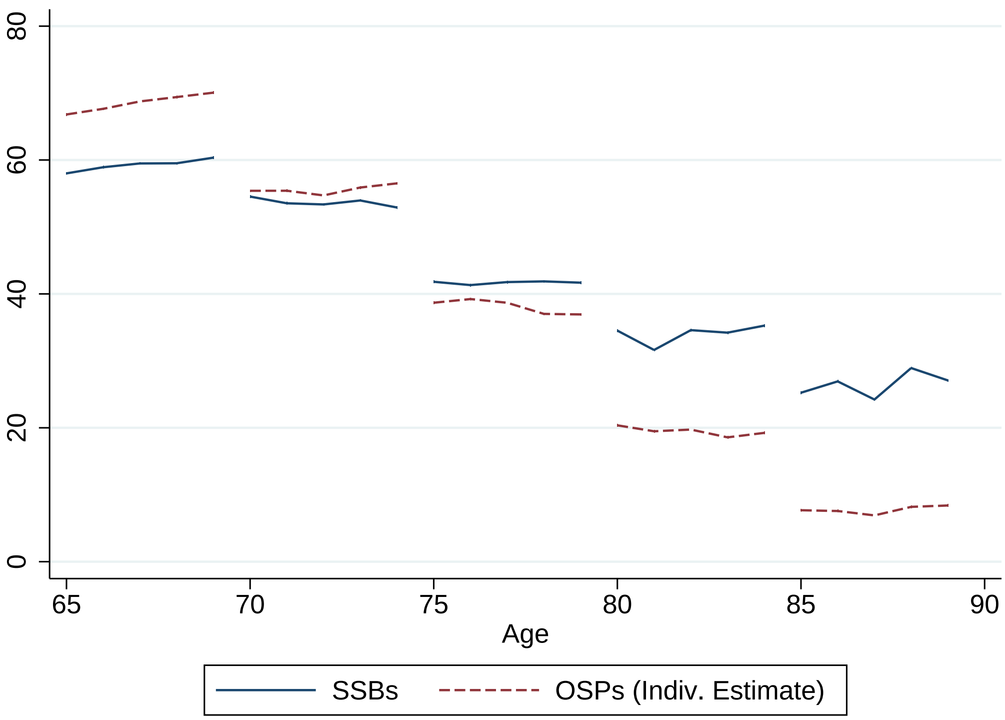
3.4 Biases in Subjective Survival Beliefs

Our following descriptive analysis compares the subjective individual survival beliefs from the survey data with our individual measures of OSPs. First, we replicate the results of previous literature—e.g., Elder (2013, Hamermesh (1985, Ludwig and Zimper (2013, Peracchi and Perotti (2012)—on the age patterns of survival beliefs in Figure 1. In contrast to that previous literature, we calculate average OSPs with our individual measures instead of average (cohort) life-tables. The step function in the figure is due to the change in assignment of interview and target age, cf. Table 1. Our findings confirm the well-established "flatness bias": At ages prior to age 70, individuals on average underestimate whereas for ages above age 75 they overestimate their probabilities to survive.

Next we take a new perspective for which individual-level data are needed. We take the same data but instead of computing averages over age we average over OSPs, i.e., for each OSP we compute the average SSB. Figure 2 shows the corresponding results by plotting average SSPs against average OSPs. If SSPs were aligned along the 45-degree line, then there would not be any biases. However, we observe a very systematic pattern of misconception: Individuals with low OSPs on average overestimate whereas those with high OSPs on average underestimate their survival chances.

The two perspectives on the data taken in the respective figures 1 and 2 are suggestive of a very simple explanation for the observed biases across age. Suppose that individuals were to always resolve any uncertainty about their

Figure 1: "Flatness Effect"



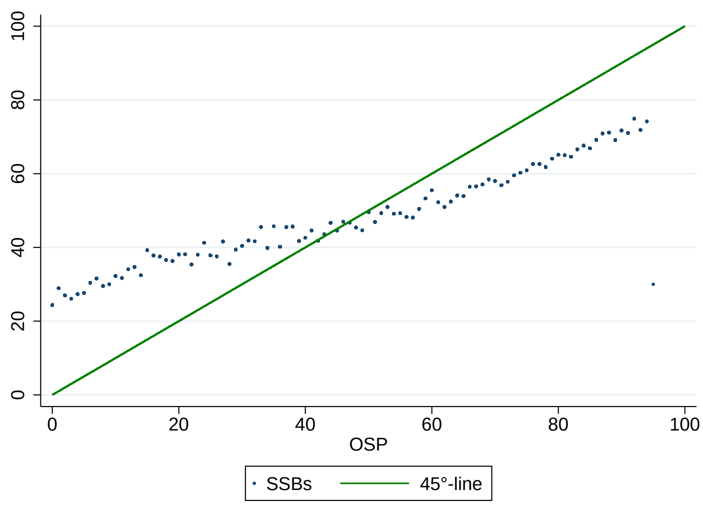
Notes: Unconditional subjective survival probabilities to survive to different target ages. The solid blue line are subjective survival beliefs, the dashed red line are the corresponding objective survival rates estimated with (1). Subjective survival beliefs are elicited in the HRS only for a combination of the age at interview of the individual (which is shown on the abscissa) and a corresponding target age, cf. Table 1. The step function follows from changes in the interview age/target age assignment.

survival chances in a 50-50 manner Bruine de Bruin, Fischhoff, and Halpern-Felsher (2000), i.e., their response would be a weighted average of a fifty percent chance of survival and the actual OSP. Observe that the intersection of the average SSB with the 45-degree line in Figure 2 is at an average OSP of about 50 percent lending support to this hypothesis.[9] Such a bias could explain the pattern of Figure 2. Furthermore, young respondents in our data have OSPs above 50 percent. If they were to apply such a simple heuristic then they would on average underestimate their chances to survive. Old re-

[9]In fact, it is slightly less than 50 percent, see below.

spondents, on the other hand, on average have OSPs less than 50 percent.[10] Under such a heuristic they would accordingly overestimate their OSPs on average. Hence, such a 50-50 bias could simultaneously explain the pattern of Figure 1.

Figure 2: Objective Survival Probabilities and Subjective Survival Beliefs



Notes: SSB over OSP. For the figure we discretize OSP in 100 points and calculate average SSB for each point such that one blue dot represents average SSB for each OSP value.

We next argue that there is more information content in the data giving rise to alternative interpretations. To this purpose we repeat the previous analysis for different age-groups. In Figure 3 we display the result of Figure 2 and additionally for each target age group, cf. Table 1. The figure suggests that the flatness of SSBs against OSPs gets stronger with increasing age—compare, e.g., age group 65-69 with age group 80-84. In addition, the intersection with the 45-degree line moves down, from about 50 percent for age group 65-69 to about 40 percent for age group 80-84. Therefore, the average tendency for underestimation increases across age groups.

Our next aim is to explain these observations—the flatness itself as well as the increasing flatness and the increasing tendency to underestimate—by

[10]Recall from Table 1 that the target age is several years ahead of the interview age.

use of age-group specific probability weighting functions from prospect theory. We subsequently show that this gives rise to cognitive and psychological interpretations of the data rather than simple 50-50 heuristics.

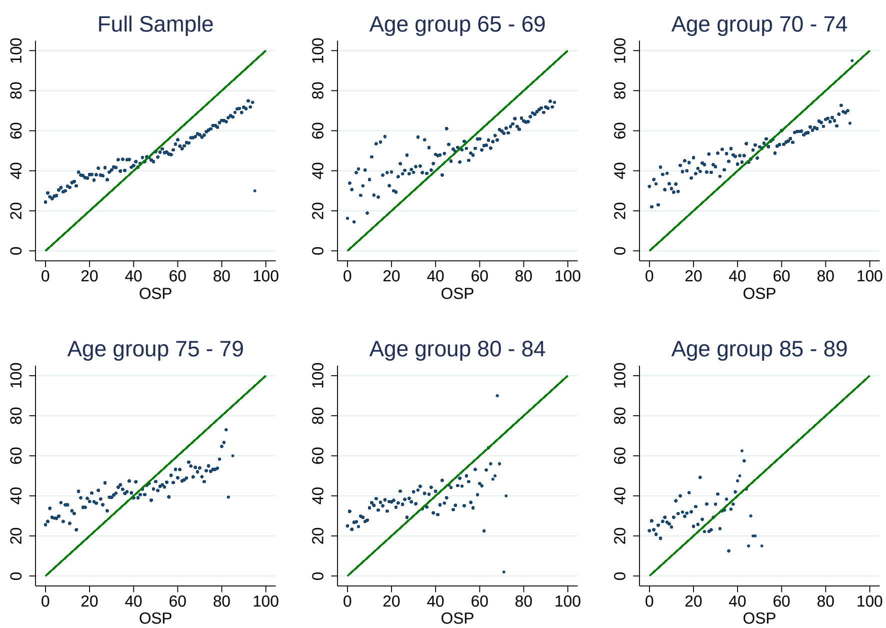
Before moving on to these theoretical foundations and the following analyses by use of psychological data, a number of cautionary remarks are in order. First, we lack data for the elderly respondents in our sample because there are no high objective survival probabilities for these age-groups. Hence, our estimates of probability weighting functions will be prone to censoring of the data. Second, survival chances are bounded from below by zero and from above by one so that respondents with very high (low) objective survival probabilities cannot overestimate (underestimate) their survival chances by much. In consequence the observed average overestimation/underestimation might be—at least in part—influenced by this truncation of the data. Importantly, our use of psychological variables in our reduced form regressions to explain the observed biases in Section 6 addresses both concerns.

4 Interpreting Biases through Prospect Theory

As a generalization of rank dependent utility theories (pioneered by Quiggin 1981, 1982), modern prospect theory (PT) has developed into a comprehensive decision theoretic framework that combines empirical insights (starting with Kahneman and Tversky 1979) with theoretical results about integration with respect to non-additive probability measures (cf. the Choquet expected utility theories of Schmeidler 1989 and of Gilboa 1987). This section models subjective survival beliefs through a probability weighting function applied to objective survival probabilities. Out of the many aspects of PT, our model of biases in survival beliefs is thus related to the experimental PT literature which shows that neither subjective probability assessments nor decision weights can be described as additive probabilities.[11]

[11]The typical finding of the so-called two stage approach is that subjective probability assessments resemble inverse S-shaped transformations of additive probabilities whereby

Figure 3: Objective Survival Probabilities and Subjective Survival Beliefs by Age Groups



Notes: SSB over OSP. For the figure we discretize OSP in 100 points and calculate average SSB for each point such that one blue dot represents average SSB for each OSP value. The age-group panel focus on different target ages according to the question in the HRS, cf. Table 1.

4.1 The Prelec Probability Weighting Function

To capture the cognitive dimension of likelihood insensitivity, on the one hand, and the psychological dispositions of optimism/pessimism, on the other hand, we adopt the non-linear probability weighting function (PWF) suggested by Prelec (1998). Thereby we allow for a flexible parametrization which allows the functional form to vary across interview age, cf. Table 1, in order to match the age-group specific bias patterns displayed in Figure 3. The objective probability of individual i to survive from interview age h to some

these assessments undergo in turn an inverse S-shaped transformation (with an emphasis on pessimism) when becoming non-additive decision weights (cf., e.g., Fox and Tversky 1998, Kilka and Weber 2001, Wakker 2004.

age $t > h$, $OSP_{i,h,t}$, is transformed by the Prelec function into the corresponding subjective survival belief, $SSB_{i,h,t}$ as follows:

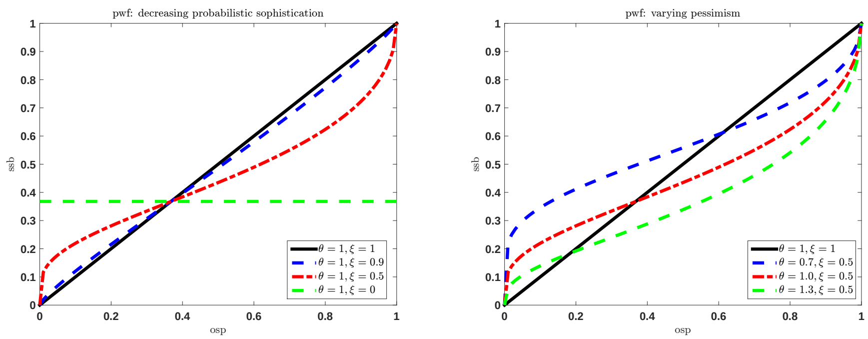
$$SSB_{i,h,t} = \left(\exp\left(-\left(-\ln\left(OSP_{i,h,t}\right)\right)^{\xi_h}\right)\right)^{\theta_h} + \epsilon_{i,h,t}. \tag{4}$$

Here, $\epsilon_{i,h,t}$ is an error term and $\theta_h \geq 0$ and $\xi_h \geq 0$ are parameters specific to the interview age. These two parameters control the elevation and the curvature of the function which can be interpreted as measures of pessimism/optimism and likelihood insensitivity, respectively.

Before using this function in the context of survival belief formation, it is instructive to illustrate the role of these parameters. To this purpose we drop subscript h for now and simply speak of ξ, θ as parameters mapping objective probabilities $o = OSP_{i,h,t}$ into subjective beliefs $s = SSB_{i,h,t}$ according to the functional form in (4). For $\xi = \theta = 1$, the function coincides with the 45-degree line. An increase of ξ above one will then lead to a S-shaped pattern, a decrease below one to an inverse-S-shape. Given the patterns in the data shown in Figure 2, $\xi \leq 1$ is the relevant parametrization in our context. Furthermore, holding θ constant at one, then for any $\xi \neq 1$ it is straightforward to show, cf. Appendix A.1, that the intersection with the 45-degree line is at objective probability $o = \exp(1)$. The lower ξ the more pronounced is the inverse-S-shape of the figure. We illustrate this in Panel (a) of Figure 4 where we decrease ξ from one to zero. In the limit where $\xi = 0$, the curve is flat. Hence, ξ can be interpreted as a measure of likelihood insensitivity and, for given θ, the closer ξ is to one, the less pronounced is this insensitivity. Next, as we illustrate in Panel (b) of Figure 4, decreasing θ leads to an upward shift of the PWF whereas increasing it to a downward shift. Accordingly, θ can be interpreted as a measure of relative pessimism whereby a higher value of θ means higher pessimism. Finally, notice that unless $\theta = 1$ (or $\xi = 1$) the two parameters interact. This can be seen in Panel (b) of Figure 4 where varying the pessimism parameter θ simultaneously affects the shape of the probability weighting function.

Figure 4: Pessimism and Probabilistic Sophistication in Stylized PWF

(a) Varying ξ (b) Varying θ



Notes: Stylized Prelec (1998) probability weighting functions. The left panel shows the impact of likelihood insensitivity, ξ, for $\theta = 1$ and $\xi \in [0, 0.5, 0.9, 1]$. The right panel shows the impact of pessimism for $\xi = 0.5$ and $\theta \in [0.7, 1, 1.3]$.

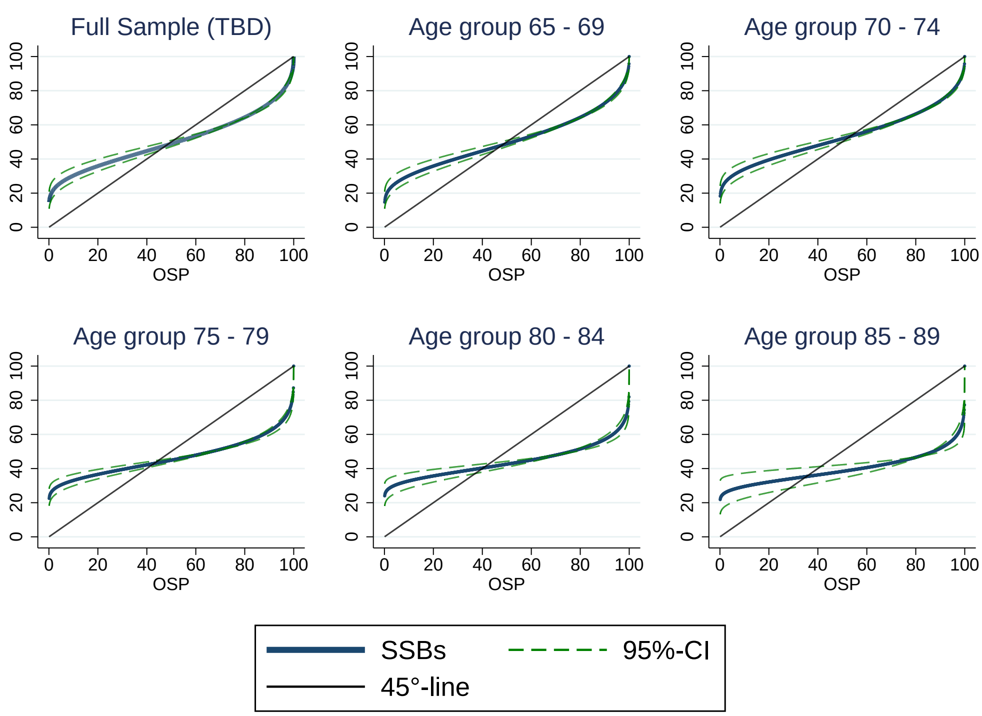
4.2 Estimated Shape of PWF: The Importance of Age

We next estimate parameters ξ_h, θ_h in the PWF 4 to match the data of Figure 4. We restrict these parameters to be the same for each interview age h assigned with a specific target age $m(h)$, i.e., we let $\xi_h = \bar{\xi}_{m(h)}$ and $\theta_h = \bar{\theta}_{m(h)}$. To identify these parameters we minimize the Euclidean distance between predicted and reported subjective survival beliefs for each individual in group $m(h)$.

Figure 5 shows predicted probability weighting functions. For the fitted values of the full sample displayed in the upper left panel we observe a quite symmetric weighting function intersecting the 45-degree line close to 0.5. As already suggested by the pattern in Figure 3, the age-specific weighting functions depicted in the other panels in Figure 5 reveal two facts: First, the functions get flatter with increasing age and second, the intersection with the 45-degree line is at lower values for older ages—it is at about 55 percent for age group 65-69 and at about 40 percent for age group 80-84.

Figure 18 depicts the parameter estimates $\xi_{m(h)}, \theta_{m(h)}$ with the corresponding 95% confidence intervals. Standard errors are bootstrapped and confidence

Figure 5: Estimated Probability Weighting Functions



Notes: Estimated Prelec probability weighting functions for the full sample (upper left panel) and for different age-groups rotating clockwise in ascending order. Parameters estimated with non-linear least squares.

intervals are computed using the percentile method.[12] [,13] According to these results, probability weighting functions get increasingly flatter with increasing age. Using the definition of Wakker (2010) such an increasing flatness may also be termed an increasing likelihood insensitivity (=lack of probabilistic sophistication) because it reflects that the information content of the objective probabilities decreases. We also observe that the intersection with the 45-degree line moves down. Again employing the terminology of Wakker (2010) this suggests that average pessimism is increasing with age.

Finally, we investigate whether a linear specification performs better than the non-linear specification a la Prelec (1998). We thereby relate to the theory of non-additive probability measures in the form of neo-additive capacities Chateauneuf, Eichberger, and Grant (2007). Assuming that there is always a positive objective probability to survive or to die, hence that $OSP_{i,h,m(h)} \in (0,1)$, the neo-additive capacity writes as

$$SSB_{i,h,m(h)} = (1-\xi^l_{m(h)})(1-\theta^l_{m(h)}) + \xi^l_{m(h)} OSP_{i,h,m(h)} \tag{5}$$

where $\xi^l_{m(h)} \in [0,1]$, $\theta^l_{m(h)} \in [0,1]$ are parameters that represent the analogues to parameters $\xi_{m(h)}$, $\theta_{m(h)}$ from the non-linear specification in (4).

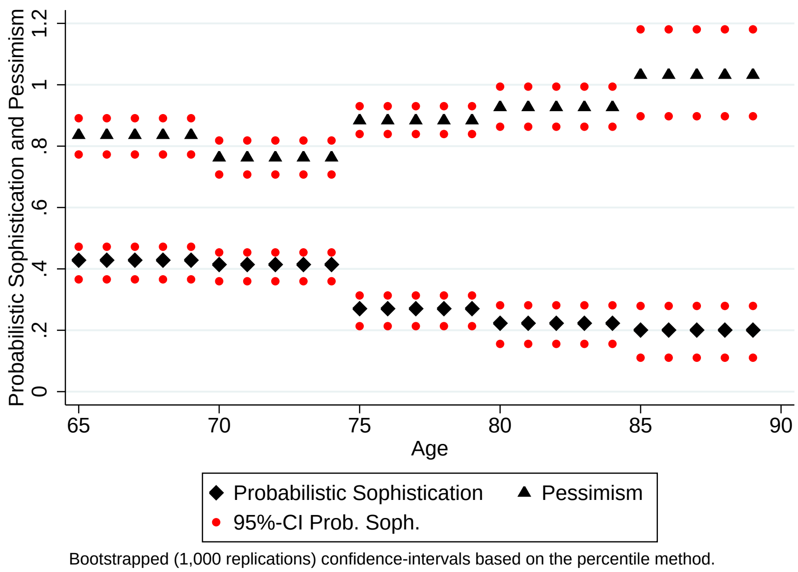
To see this observe that ξ^l controls the slope of the function whereby for $xi^l = 1$ the line in (5) corresponds with the 45-degree line. Therefore, any $\xi^l \in [0,1]$ can be interpreted as a measure of likelihood insensitivity. Likewise, $1-\theta^l \in [0,1]$ determines the intersection of (5) with the 45-degree line with the intersection moving down when θ^l increases. Accordingly, θ^l can be interpreted as a measure of pessimism. Relative to (4), the particular advantage of (5) is the parsimony in the specification which also implies that the

[12]Since our data are clustered we perform a cluster bootstrap that samples the clusters with replacement. Thus, in each bootstrap we solve

$$\min_{\bar{\xi}_{m(h)},\bar{\theta}_{m(h)}} \left\{ \sum_{i=1}^{N^{m(h)}} \left[\epsilon_{i,h,m(h)}\right]^2 \right\}.$$

[13]The percentile method uses the relevant percentiles of the empirical distribution of our bootstrap estimates of the Prelec parameters.

Figure 6: Estimated Prelec Parameters



Notes: Bootstrapped (1000 replications) 95%-confidence intervals are based on percentile method.
Source: Own Calculation based on the HRS.

measures of probabilistic specification ξ^l and pessimism θ^l are independent of each other.

We test the difference between the non-linear and the linear specifications in (4) and (5) by applying the Akaike and the Schwartz Bayesian information criteria which are the relevant criteria for comparing non-nested models, cf. Cameron and Trivedi (2005). Since both functional forms have the same number of parameters no adjustment for a difference in the degree of freedom is required. Our findings summarized in Table 2 show that the non-linear specification performs generally better than the linear one, with the exception of interview ages 75-79.[14]

We conjecture that the better fit of the non-linear model is a consequence of the natural truncation of objective survival probabilities at 0 and 1, re-

[14] We show the coefficient estimates $1 - \xi^l_{m(h)}, \theta^l_{m(h)}$ of the linear specification in analogy to Figure 18 in Appendix E.

Table 2: Information Criteria for Non-Linear and Linear Probability Weighting Functions

	AIC			SBC		
Interview age h	Linear	Prelec	Difference	Linear	Prelec	Difference
65 - 69	423.72	419.47	4.25	434.58	430.33	4.24
70 - 74	662.83	662.78	0.05	673.98	673.93	0.05
75 - 79	717.68	719.87	-2.19	728.36	730.55	-2.19
80 - 84	569.82	562.01	7.81	579.68	571.88	7.81
85 - 89	259.87	256.79	3.09	268.52	265.43	3.09

Notes: Linear: Linear PWF. Prelec: Specification of the PWF according to Prelec (1998). AIC: Akaike information criterion. SBC: Schwartz Bayesian information criterion. *Source:* Own calculations based on the HRS (2015), waves 2008-2012.

spectively. The linear model postulates that subjective beliefs discontinuously jump from a positive value for an OSP slightly above zero to zero when the OSP equals zero (respectively from a positive value below one for an OSP slightly below on to one when the OSP equals one). Our estimates suggest that this is not an appropriate model of belief formation. In particular, eyeballing of Figure 2 suggests that the SSBs bend towards zero at low values of the respective OSPs. The non-linear model better accommodates this feature of the data.

This behavior of SSBs might be driven by focal point answers at SSBs of 0, 0.5, and 1, respectively. Bunching at these focal points has been documented in the literature, cf. Ludwig and Zimper (2013) and references therein. Ideally, we would explicitly model the probability of giving such focal points answers. To investigate their importance in a simplified manner we instead adopt a simpler approach by redoing the analysis from above for a sample in which all observations with focal point answers are excluded. Results, summarized in Appendix E suggest that our findings do not hinge on focal point answers.

We can therefore summarize our quantitative findings on probability weighting functions as follows. There is a strong age dependency in non-linear inverse-S-shaped probability weighting functions in that both the implied measures of relative pessimism as well as likelihood insensitivity are increasing with age. In the next section we explore whether direct psychological measures in the HRS support this cognitive/psychological interpretation of the biases in survival beliefs.

5 Age Patterns of Psychological and Cognitive Measures

In this section we analyze the age pattern of direct cognitive and psychological variables in the HRS. Our aim is to compare these with the indirect measures derived from estimating non-linear probability weighting functions on data on subjective survival beliefs in the previous section.

5.1 Measures

From wave 8 onward the HRS contains measures on optimism and pessimism. Measures on *dispositional optimism (pessimism)* are derived from the same statements as in the well-known Life Orientation Test-Revised (LOT-R).[15,16] Respondents are given various statements regarding a specific latent variable. For most variables they were asked *"please say how much you agree or disagree with the following statements"*. Each statement is rated on a scale from one (*strongly disagree*) to six (*strongly agree*). Average scores are taken to create indices for each psychological construct. Higher values for the psychological variables imply more optimistic, respectively more pessimistic attitudes.[17]

Note that optimism and pessimism are usually measured separately, i.e., respondents are asked questions with negative connotations (pessimism) as well as with positive connotations (optimism). The reason for separate measures is

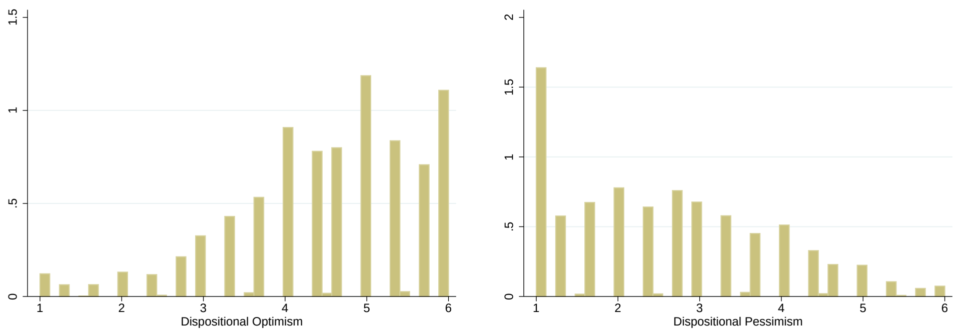
[15]Such statements are, e.g., "In uncertain times I usually expect the bes".

[16]The Life Orientation Test-Revised questionnaire (LOT-R) was developed to measure dispositional optimism, i.e., a generalized expectation of good outcomes in one's life Scheier and Carver (1987), **?**). Kaniel, Massey, and Robinson (2009) find dispositional optimism as measured with LOT-R to be related to various expectations about events in a labor market setting.

[17]The index score is set to missing if responses on more than half of the respective statements are missing.

Figure 7: Histogram of Optimism and Pessimism

(a) Optimism (b) Pessimism



Notes: Histogram of 'optimism' and 'pessimism' variable. Averages of answer pattern where 1 indicates 'strongly disagree' and 6 'strongly agree'.

that these two concepts were found to show some bi-dimensionality Herzberg, Glaesmer, and Hoyer (2006).[18] Figure 7 showing the histograms on both measures in our sample underscores this aspect. Dispositional pessimism shows a clear focal point at index value 1 (="strongly disagree") whereas dispositional optimism apparently has focal point answers at values 4, 5 and 6 whereby the peak is at 5. In our empirical analyses we therefore use separate variables for each concept although in our theoretical analysis we speak of increasing pessimism and decreasing optimism interchangeably.

For a measure corresponding to "likelihood insensitivity" our choice of a proxy variable is motivated by our cognitive interpretation of likelihood insensitivity Wakker (2010). Thus, we include a variable measuring cognitive weakness of the respondent. It is a version of a composite score taken from RAND and combines the results of several cognitive tests. For instance, respondents were asked to recall a list of random words, to count backwards and to name the (Vice) President of the United States. In total there are 35 questions and results are summarized in an ability score. We take RAND's composite score of cognitive ability as given and create our score of cognitive

[18]Some authors neglect the possibility of bi-dimensionality, cf., e.g., Liu, Tsou, and Hammitt (2007).

weakness. For this we subtract the cognitive ability score from the maximal achievable value, i.e., our measure of cognitive weakness is 35 minus cognitive ability. A higher value of the score indicates higher cognitive weakness. An overview of our three measures of psychological/cognitive variables is given in Table 3.

Table 3: Psychological and Cognitive Variables

	Min	Max	Mean	SD	α^*
Psychological Variables					
Dispositional Optimism	1	6	4.53	1.16	0.80
Dispositional Pessimism	1	6	2.60	1.30	0.77
Cognitive Variable					
Cognitive Weakness	0	35	13.50	5.19	n.a.

Notes: * Cronbrach's α. This statistic is a measure for the internal consistency of a psychometric test. As a rule of thumb the α has to be ≤ 0.7.

5.2 Age Patterns

We now display average values of the measures of psychological and cognitive weakness over age, cf. Figures 8 for optimism/pessimism and Figure 9 for cognitive weakness. Optimism decreases by 2.9% and pessimism increases by 12.2% from age 65 to 90. The fact that pessimism increases more strongly than optimism decreases supports the notion of bi-dimensionality of these two measures.[19]

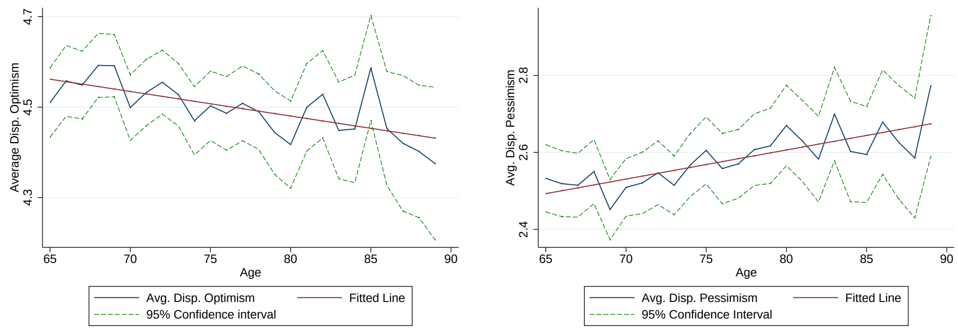
Turning to cognitive weakness the average index value is increasing from 11.8 to 17.9 between ages 65 and 89. Age-dependence is more pronounced for cognitive weakness than for the two psychological measures.

Hence, the age trends of the direct psychological measures coincide with the indirect measures we derived from estimating non-linear probability weighting

[19]Note that in both regressions $o_h = \beta_0 + \beta_1 h + \varepsilon_h$ with $\hat{\beta}_1 = -0.008$ and $p_h = \beta_0 + \beta_1 h + \varepsilon_h$ with $\hat{\beta}_1 = 0.010$ the coefficient $\hat{\beta}_1$ is significant at the 1.0% significance level.

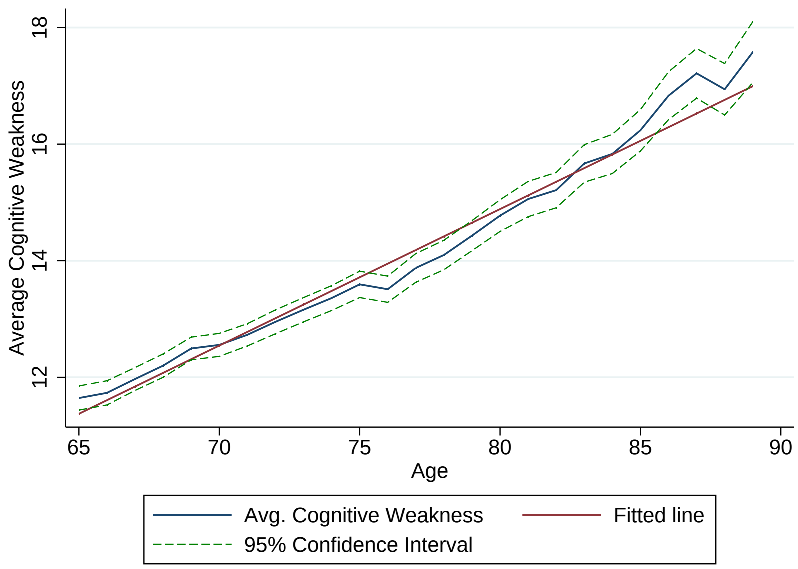
Figure 8: Average Optimism and Pessimism over Age

(a) Optimism (b) Pessimism



Source: Own calculations based on HRS.

Figure 9: Average Cognitive Weakness Score over Age



Source: Own calculations based on HRS.

functions on the data of subjective survival beliefs. These findings therefore provide support of our psychological interpretation of the biases in subjective beliefs. Our next aim is to investigate this interpretation further through regression analyses.

6 Psychological and Cognitive Factors in Survival Assessments

In this section we go beyond our previous descriptive analyses by investigating the impact of psychological, respectively cognitive, measures on the formation of subjective survival beliefs taking several control variables into account. Because psychological measures are available since 2006 we pool waves 2006-2012 of the data. Psychological variables are only available for half of the sample in each wave. We run pooled OLS regressions with fixed-effects for waves and target age (TA) groups. We consider the psychological/cognitive measures in lags so that we can treat those as weakly exogenous. As the objective survival probabilities are themselves estimates, we implement a two-sample bootstrap procedure to estimate the standard errors for our coefficient estimates, c.f. Appendix D for a detailed description of the procedure.

6.1 Psychological Dispositions, Cognitive Weakness and Subjective Survival Beliefs

We first investigate whether the psychological and cognitive variables are associated with subjective survival beliefs. As we argue in Section 4, inverse-S-shaped probability weighting functions are a reasonable model of biases in subjective survival beliefs. We now consider a parameterized variant of the Prelec (1998) function whereby we postulate that for each individual in the sample i and each age h the implicit measures of cognition and optimism/pessimism from equation (4) are linearly dependent on the cognitive, respectively psychological, variables as follows:

$$\xi_h = \xi_0 + \xi_1 c_{i,h} \tag{6}$$

$$\theta_h = \theta_0 + \theta_1 p_{i,h-2} + \theta_2 o_{i,h-2}. \tag{7}$$

In the above, $c_{i,h-2}$ is our measure of cognitive weakness and $p_{i,h-2}$ is the lag of our measure of pessimism, respectively $o_{i,h-2}$ is the lag of our measure of optimism. We include these measures with lags in order to address potential endogeneity concerns. Using (6) in (4) and adding additional control variables to capture the objective survival information (see below), we estimate the following specification on the pooled sample of HRS data:

$$SSB_{i,h,m(h)} = \left(\exp\left(-\left(-\ln\left(OSP_{i,h,m(h)}\right)\right)^{\xi_0+\xi_1 c_{i,h}}\right)\right)^{\theta_0+\theta_1 p_{i,h-2}+\theta_2 o_{i,h-2}} + \\ + \vec{\beta}_5' \vec{x}_{i,h} + \varepsilon_{i,h,m(h)}.$$

Vector $\vec{x}_{i,h}$ of control variables contains wave and 'target-age' dummies (cf. Table 1) as well as socio-economic variables, like age, gender etc., and variables on overall health conditions.[20] Since these latter controls are also used to predict OSPs, we also estimate a specification without these controls.

Recalling from our discussion in Section 4, Figure 4, lowering ξ_h leads to a flatter PWF. Therefore, under the hypothesis that the measure cognitive weakness extracted from the data is related to the theoretical construct of a flatter PWF, we expect that $\xi_1 < 0$. Figure 4 also shows that increasing θ_h leads to a lower elevation of the PWF. We therefore expect that $\theta_1 > 0$ and $\theta_2 < 0$.

Table 4 summarizes our main results. All parameter estimates are of the expected sign. Further details on estimates of $\vec{\beta}_6$, the parameter estimates on control variables, are contained in Tables **XX-YY, add soft references** in Appendix **??**. These coefficient estimates confirm standard findings. According to our preferred specification, column (4) in the table, a one percentage point increase in the OSP is associated with an increases of the SSB by only 0.512 percentage points. A one point increase of the index of optimism (pessimism) is associated to an increase (decreases) of the SSB by 1.8 (1.6) percentage points. Finally, cognitive weakness is positively associated with survival assessments and increased cognitive weakness reduces the information content respondents attach to the OSP, as expected.

[20] For a list of all variables contained in $\vec{x}_{i,h}$ cf. Appendix **??**.

Table 4: Non-linear Model: The Effects of Cognition and Psychological Measures on Subjective Survival Beliefs

	(1) SSB	(2) SSB	(3) SSB	(4) SSB
Constant	0.1694		0.0426	
	[0.1043;0.2132]		[-0.3457;0.3756]	
Lagged Cogn. Weak. (Intercept)	0.4067	0.4771	0.4065	0.4063
	[0.3423;.4691]	[0.4091;0.5237]	[0.23892;0.5196]	[0.2342;.5122]
Lagged Cogn. Weak. (Slope)	-0.0036	-0.0108	-0.0053	-0.0053
	[-0.0099;0.0018]	[-0.0149;-0.0068]	[-0.0117;.0004]	[-0.0118;0.0006]
Lagged Psycho (Intercept)	1.7655	1.0413	1.5926	1.5878
	[1.3645;2.1371]	[0.9442;1.1388]	[1.1878;3.4710]	[1.1930;3.8479]
Lagged Pessimism (Slope)	0.0417	0.0273	0.0502	0.0501
	[0.0213;0.0650]	[0.0152;0.0404]	[0.0305;0.1071]	[0.0301;0.1081]
Lagged Optimism (Slope)	-0.1055	-0.0581	-0.0822	-0.0819
	[-0.1455;-.0707]	[-0.0737;-0.0437]	[-0.2652;-0.0503]	[-0.313;-0.0519]
Intercept	yes	no	yes	no
Additional controls & Dummies	no	no	yes	yes
AIC	3002.13	3021.97	2592.97	2591.02
	[2794.04;3222.77]	[2805.78;3244.32]	[2355.52; 2749.21]	[2336.24;2751.87]
BIC	3044.68	3057.42	2848.2	2839.20
	[2836.59;3265.41]	[2841.23;3279.82]	[2610.54;3004.3914]	[2584.30;2999.60]
SSR	727.81	729.60	690.32	690.33
	[708.02;749.09]	[707.41;752.10]	[666.24;707.66]	[667.04;706.57]
No. covariates	6	5	36	35
No. observations	8875	8875	8875	8875

Notes: 95%-confidence intervals in parentheses are calculated with the percentile method (1000 replications).

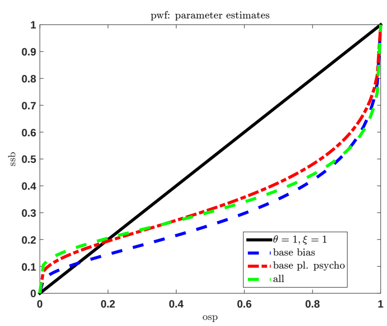
6.1.1 Sensitivity Analysis: Linear Specification

To address this we estimate the following specification:

$$\begin{aligned} SSB_{i,h,m(h)} = \beta_0 + \beta_1 OSP_{i,h,m(h)} + \beta_2 p_{i,h-2} + \beta_3 o_{i,h-2} \\ + \beta_4 c_{i,h} + \beta_5 \big(OSP_{i,h,m(h)} \times c_{i,h}\big) + \vec{\beta}_6' \vec{x}_{i,h} + \varepsilon_{i,h}. \end{aligned} \quad (8)$$

We hypothesize that $OSP_{i,h,m(h)}$ is positively related to $SSB_{i,h,m(h)}$, hence $\beta_1 > 0$. Our hypotheses on the effects of the (weakly exogenous) psychological variables are that $\beta_2 < 0$ and $\beta_3 > 0$. As to the effects of $c_{i,h}$ on subjective beliefs, the effects are ambiguous. We argue that higher cognitive weakness is associated with increased likelihood insensitivity and thus leads to less accurate estimates of survival beliefs. Thus, the sign of β_4 depends on the relative

Figure 10: Probability Weighting Functions: Parameter Estimates



Notes: Probability weighting function according to parameter estimates. "base bias": only axis coefficients of cognitive and psychological measures (ξ_0, θ_0); "base pl. cogn.": adding effects of average cognition $(\xi = \xi_0 + \xi_1 \cdot \text{avg. cogn.})$; "all": adding effects of average psychological variables $(\theta = \theta_0 + \theta_1 \cdot \text{avg. pess.} + \theta_2 \cdot \text{avg. opt.})$.
Source: Own calculations based on HRS.

composition of the sample with regard to overestimators and underestimators, cf. Figure **??**. Through the interaction term $OSP_{i,h,m(h)} \cdot c_{i,h}$ we investigate whether increasing cognitive weakness takes away predictive power from the objective survival information, i.e., whether cognitive weakness is indeed an appropriate measure of likelihood insensitivity. To summarize, our main hypotheses are that $\beta_1 > 0$, $\beta_2 < 0$, $\beta_3 > 0$, $\beta_4 \lesseqgtr 0$ and $\beta_5 < 0$.

Table 5 summarizes our main results. All parameter estimates are of the expected sign and significant at the 1 percent level. Further details on estimates of $\vec{\beta}_6$, the parameter estimates on control variables, are contained in Tables **XX-YY, add soft references** in Appendix **??**. These coefficient estimates confirm standard findings. According to our preferred specification, column (4) in the table, a one percentage point increase in the OSP is associated with an increases of the SSB by only 0.512 percentage points. A one point increase of the index of optimism (pessimism) is associated to an increase (decreases) of the SSB by 1.8 (1.6) percentage points. Finally, cognitive weakness is positively associated with survival assessments and increased cognitive weakness reduces the information content respondents attach to the OSP, as expected.

Table 5: Linear Model: The Effects of Cognition and Psychological Measures on Subjective Survival Beliefs

SSB	(1) SSB	(2) SSB	(3) SSB	(4) SSB
OSP	0.3483	0.3661	0.5011	0.4137
	[0.3077;0.3744]	[0.3230;0.3950]	[0.3402;0.5458]	[0.2469;0.5082]
Lagged Optimism	2.3352	2.2543	2.2481	1.8086
	[1.9196;2.8258]	[1.7976;2.7832]	[1.7983;2.7742]	[1.3439;2.3012]
Lagged Pessimism	-1.6924	-1.8588	-1.8320	-1.6456
	[-2.1634;-1.2690]	[-2.3425;-1.4007]	[-2.3309;-1.3855]	[-2.1102;-1.1676]
Lagged Cognitive Weakness		0.3765	0.8403	0.6744
		[0.2205;0.5071]	[0.3286;1.0181]	[0.3311;0.9041]
Lagged Cognitive Weakness			-0.0109	-0.0097
× OSP			[-0.0139;-0.0005]	[-0.0138;-0.0034]
Wave & TA-dummies	yes	yes	yes	yes
Additional controls	no	no	no	yes
AIC	95968.82	86463.56	86446.34	84330.98
	[94259.78;97609.16]	[84850.91;88132.50]	[84841.14;88127.18]	[82681.27; 85879.69]
BIC	96040.99	86541.79	86531.68	84586.26
	[94331.78;97681.47]	[84928.94;88210.93]	[84926.25;88212.75]	[82935.80;86135.63]
No. covariates	10	11	12	36
No. observations	8875	8875	8875	8875

Notes: 95%-confidence intervals in parentheses are calculated with the percentile method (1000 replications).

6.2 The Role of Psychological and Cognitive Factors for Survival Biases

Our findings so far confirm that psychological variables have predictive power beyond objective survival rates and other covariates and are of the expected sign: pessimists underestimate whereas optimists overestimate their survival probabilities. We also find that cognitive weakness takes away predictive power from the objective survival probabilities and is associated with an increasing upward bias in beliefs. These insights are consistent with our theoretical considerations of Section 3.

Yet, our previous analysis only shows that psychological and cognitive factors impact subjective survival beliefs. This does not mean that psychological variables and cognitive weaknesses are also associated with higher levels of misconception. To investigate this, we now turn to quantile regressions. We rank the data from underestimation to overestimation so that we have strong underestimators at the 10th percentile with $SSB_{i,h,m(h)} << OSP_{i,h,m(h)}$ and strong overestimators at the 90th percentile. For the two extreme percentiles and the median we next study the impact of psychological and cognitive variables on the *difference* between subjective and objective survival probabilities, i.e., on the strength of survival misconception according to the following specification:

$$SSB_{i,h,m(h)} - OSP_{i,h,m(h)} = \beta_0 + \beta_1 OSP_{i,h,m(h)} + \beta_2 p_{i,h-2} + \beta_3 o_{i,h-2} + \beta_4 c_{i,h} + \vec{\beta}_5' \vec{x}_{i,h} + \varepsilon_{i,h}. \quad (9)$$

Since the absolute value of misperception depends on the level of the objective survival probability, we include $OSP_{i,h,m(h)}$ on the right-hand side. We also include the list of control variables used in Section 6.1.[21]

If pessimism is a driver of underestimation and optimism is a driver of overestimation, then pessimism should be more pronounced for the 10th percentile, respectively optimism should be more important at the 90th percentile. We therefore hypothesize that the coefficient on optimism will increase when moving up across the percentiles and the coefficient on pessimism will decrease. As to cognitive weakness, recall from Figure 9 that cognitive weakness is increasing in age and from Figure 2 that overestimation is particularly relevant in older age, hence when cognitive weakness is also higher. Given that both cognitive weakness as well as the extent of overestimation are increasing with

[21] Observe that these quantile regressions address the concerns of biases induced by truncation and censoring, cf. our discussion at the end of Section 3.4.

age, we conjecture that cognitive weakness is increasingly positively related with biases in survival changes when we move across percentiles from strong underestimators to strong overestimators. As we control for age in the quantile regressions, we can investigate whether the increasing optimistic biases in old age are caused by age effects alone—as a simple 50-50 heuristic would imply because objective long-horizon survival probabilities are less than 50 percent, cf. our discussion in the introduction—or whether the increasing misperception is caused by the increasing average cognitive weakness of respondents in the sample.

Our results reported in Table 6 confirm our hypotheses. Our preferred specification is specification (1) which controls for the level of the objective survival probability. The coefficient of optimism is largest at the 90th percentile and small and insignificant at the 10th percentile. On the contrary, pessimism is strongest at the 10th percentile and small and insignificant at the 90th percentile. These result suggest that optimism (pessimism) is primarily important for respondents who strongly overestimate (underestimate) their survival changes. The parameter estimates on cognitive weakness increase across percentiles form negative and insignificant for the 10th percentile to positive and significant for the 90th percentile. These results imply that cognitive weakness is more strongly associated with overestimation than with underestimation of survival beliefs, just as we hypothesized.

Table 6: Drivers of Misconception: Results from Quantile Regressions

SSB-OSP	(1)	(2)
10thPercentile		
OSP	-0.7876***	
	(0.032)	
Optimism $t-2$	0.3419	0.4947*
	(0.262)	(0.364)
Pessimism $t-2$	-0.9637***	-1.6323***
	(0.166)	(0.328)
Cognitive weakness	-0.1675	0.1874***
$t-2$	(0.079)	(0.097)
Median		
OSP	-0.6834***	
	(0.076)	
Optimism $t-2$	2.3485***	2.2964***
	(0.587)	(0.399)
Pessimism $t-2$	-1.7917***	-1.9085***
	(0.400)	(0.337)
Cognitive weakness	0.1933*	0.5367***
$t-2$	(0.114)	(0.124)
90thPercentile		
OSP	-0.9987***	
	(0.097)	
Optimism $t-2$	1.4269***	1.5854***
	(0.335)	(0.409)
Pessimism $t-2$	-0.3185	-0.0003
	(0.402)	(0.315)
Cognitive weakness	0.6375***	1.0099***
$t-2$	(0.095)	(0.061)
Dummies	Yes	Yes
Add. Controls	Yes	Yes
No. observations	8875	8875

Standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

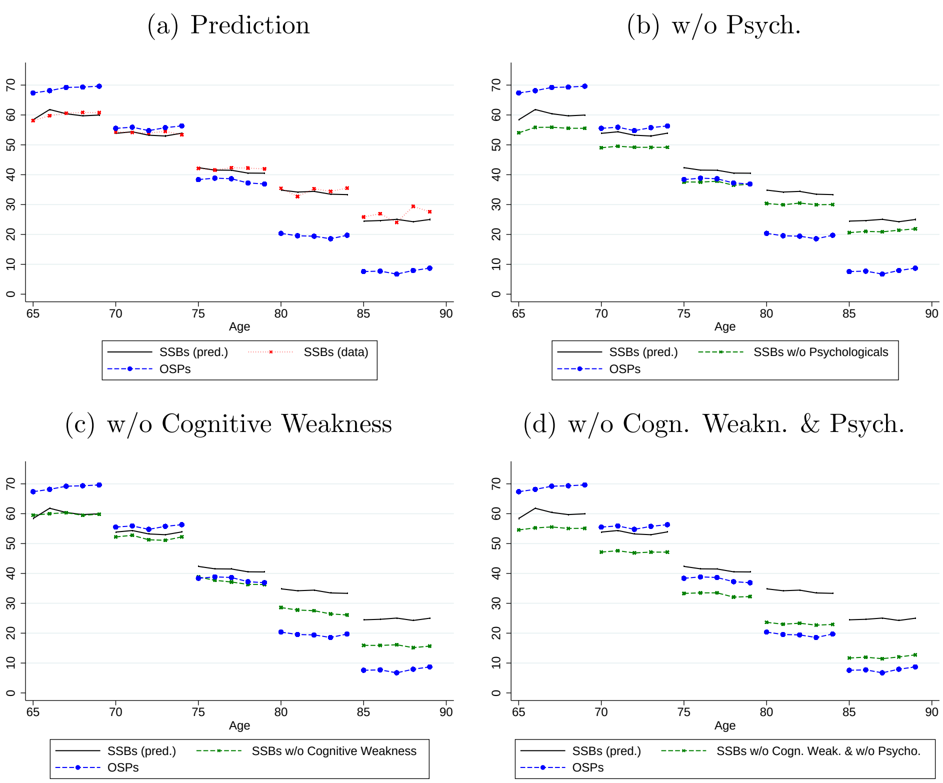
6.3 Quantifying the Impact of Pessimism and Cognitive Awareness

6.3.1 Linear Model:

We now return to our main specification in (8), specification (4), to investigate the quantitative role of the psychological and cognitive variables for survival beliefs. To this purpose we predict subjective survival rates for given coefficient estimates. Our baseline prediction includes all variables. Taking the same coefficient estimates we next form a prediction by shutting down the effects of psychological variables one at a time, i.e., we set $\hat{\beta}_2 = 0$ and $\hat{\beta}_3 = 0$. Finally, we assume that households do not suffer from any cognitive weakness, setting $c_{i,h} = 0$, in order to quantify its importance for subjective survival beliefs.

We average predicted subjective survival beliefs from all experiments across households by age and plot the predicted average survival beliefs against age, as in Figure 1. Results for the importance of psychological variables are shown in the upper part of Figure 17. Shutting down the impact of optimism, shown in Panel (a) of the figure, implies overall lower subjective survival beliefs by around 10 percentage points. Predictions for SSBs without pessimism, shown in Panel (b) of the figure, are about 3 percentage points higher. Observe that both effects are roughly constant across age.

Figure 11: Counterfactuals (Linear model): The Impact Cognition and Psychological Variables



Notes: Predicted SSBs using regression (8) without the interaction term $\beta_5(OSP_{i,h,m(h)} \times c_{i,h})$. We compare the full model (SSBs) with predictions without the effects of psychological and cognitive variables. In the upper left panel we assume $\hat{\beta}_2 = 0$, in the upper right panel we set $\hat{\beta}_3 = 0$; in the lower left panel $\hat{\beta}_4 = 0$ and finally we set $\hat{\beta}_2 = \hat{\beta}_3 = \hat{\beta}_4 = 0$ in the lower right panel.

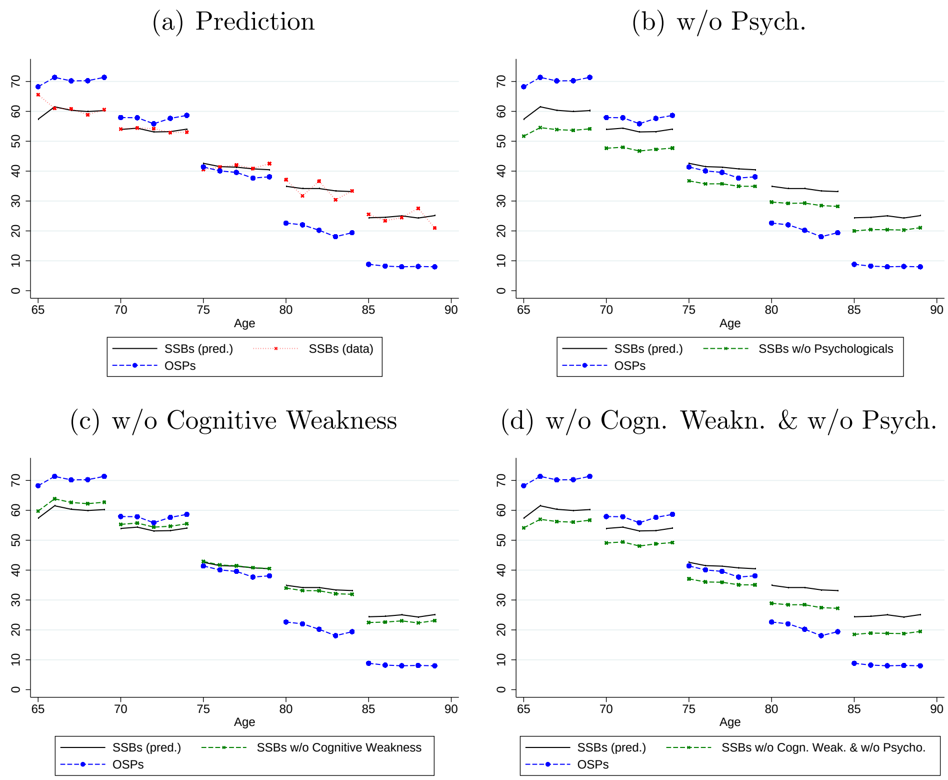
The impact of cognitive impairment is shown in Panel (c) of Figure 17. For age group 65-69, the effect of cognition is small because the average household in that age group suffers relatively little from cognition impairment. However, the effect increases significantly with age: at ages 85-89 the difference amounts to about 12 percentage points.

The combined average contribution of psychological and cognitive variables are shown in Panel (d) of the figure. For interview age group 65-69 these amount to 3 percentage points, for age group 85-89 it increases to about 15 percentage points.

Interestingly, the pattern in Panel (d) suggests that predicted survival beliefs without the effects of psychological variables and without increasing cognitive impairment converge over age from below to the average objective survival probabilities. This suggests that the process of survival belief formation based on objective data is consistent with notions of rational Bayesian learning: initial biases reflected in some prior belief vanish over age. Since we do not exploit the panel dimension of the data to estimate updating models of survival belief formation this interpretation of the data is tentative. Despite this limitation, the observation from Panel (d) of Figure 17 is consistent with the theory of biased Bayesian learning developed by Ludwig and Zimper (2013) and Groneck, Ludwig, and Zimper (2016b). This theory postulates that learning is composed of a rational Bayesian learning channel according to which subjective survival beliefs converge to the objective probabilities and a countervailing force by psychological factors that lead to persistent deviations from objective probabilities.

6.3.2 Non-Linear Model:

Figure 12: Counterfactuals (Non-Linear Model): The Impact Cognition and Psychological Variables



7 Concluding Remarks

This paper compares subjective survival beliefs (SSBs) with objective survival probabilities (OSPs) that we estimate based on individual level characteristics. We establish a two-fold and related strong regularity of survival misperceptions. First, relatively young households in our sample underestimate whereas relatively old households overestimate their chances to survive. Second, households overestimate survival chances with low objective probabilities and underestimate chances with high objective probabilities. Based on this latter finding we estimate inverse-S-shaped probability weighting functions on the data and establish a strong age dependency in the shape of these functions. Our coefficient estimates suggest that implied measures of pessimism and of cognitive weaknesses are increasing with age. We next turn to direct psychological and cognitive variables to confirm these age patterns.

Based on these descriptive findings, we turn to reduced form regressions. Our results confirm that psychological and cognitive variables have strong quantitative effects on survival beliefs. Decomposing our findings into the main driving forces, we find that the average effect of optimism leads households to overestimate their long-horizon survival chances by approximately 10 percentage points. The effect of pessimism result in an average downward bias of about 3 percentage points. Cognitive impairments cause upward biases in survival beliefs that become increasingly strong with age. For the oldest age group in our sample (age group 85-89) the average effect of cognitive weakness results in an overestimation of survival chances by about 15 percentage points.

Our decomposition analysis also suggests that our findings are consistent with theories of rational learning with psychological biases developed in Ludwig and Zimper (2013) and Groneck, Ludwig, and Zimper (2016b). Specifically we show that over age predicted subjective survival beliefs converge to the respective objective survival probabilities when we shut down the effects of psychological variables and the lack of cognition. This is consistent with rational Bayesian learning. The psychological and cognitive factors then superimpose the aforementioned biases. However, with respect to learning dynamics, our findings are only suggestive because we do not develop econometric specifications of learning models and accordingly do not directly test their implications with dynamic panel methods.

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A Analytical Appendix

A.1 The Probability Weighting Function

To simplify notation, we suppress subscripts. We show that for $\theta = 1$, $\xi \neq$, the Prelec (1998) probability weighting function implies that the intersection with the 45-degree line (where the OSP and the SSB coincide) is given at $OSP = SSB = \exp(1)$. For $\theta = 1$, equation (4) writes as

$$\begin{aligned} & SSB = \exp\left(-\left(-\ln\left(OSP\right)\right)^{\xi}\right) \\ \Leftrightarrow \qquad & -\ln(SSB) = \left(-\ln\left(OSP\right)\right)^{\xi} \end{aligned}$$

t For $\xi = 1$ the above equation implies that $SSB = OSP$. For $\xi \neq 1$ the equation only holds if $\ln(SSB) = \ln(OSP) = 1$, hence $SSB = OSP = \exp(1)$.

B Data Sets and Samples

In this paper we use three data sets: The Health and Retirement Study (HRS), the Human Mortality Database (HMD), and data of the Social Security Administration (SSA). Two different samples of the HRS are used for estimating individual-level OSPs out of the panel mortality and for our main cross-sectional analyses, respectively. The HMD and the data of the SSA are used for estimating *Average Objective Survival Probabilities* (AOSPs).

B.1 Health and Retirement Study (HRS)

The Health and Retirement Study (HRS) is a national representative panel study on biennial basis. The survey is administered by the Institute for Social Research (ISR) at the University of Michigan and is mainly funded by the National Institute of Aging (NIA). Interviews of the first cohort (HRS) started in 1992 and consisted of more than 12,000 individuals at baseline **Juster-Suzman1995**. In subsequent waves, more cohorts were included to keep the sample representative. By 2012 (wave 11) the HRS includes six cohorts. Interviewees are individuals older than 50 and their spouses regardless of age. The main goal of the HRS is to contribute a rich panel data set to the research of retirement, health insurance, saving, and economic well-being. Initially, the HRS focused on eliciting information about demographics, income, assets, health, cognition, family structure, health care utilizations and costs, housing, job status and history, expectations and insurance.

Information on psychological variables was very limited. Since 2006 (wave 8) the HRS is complemented with a rich set of psychosocial information. These data are collected in each biennial wave from an alternating (at random) 50% of all core panel participants who were visited for an enhanced face-to-face interview (EFTF).[22] Thus, longitudinal data are available in four-year intervals and the first panel with psychosocial variables is provided in 2010. A general overview of the samples in the HRS data set is provided in Figure **??**.

B.1.1 Hazard Model

The hazard model is used to predict individual level objective survival probabilities (OSPs). The prediction coefficients of the hazard model are calculated using information about panel mortality within the HRS. As the time horizons of the OSPs have to match the SSBs, c.f. Table **??**, our sample has to cover between 11 and 15 years[23].

The sample for the hazard model includes waves 4-11. We exclude waves < 4

[22] In 2006 (wave 8) respondents were sent an additional questionnaire in case they were part of the random 50% subsample that was selected for the EFTF interview – provided they were alive and either they or a proxy completed at least part of the interview in person (subsample A). In 2008 (wave 9), respondents who were not selected for the EFTF interview in 2006 were automatically selected in 2008 (random 50% subsample B). As in 2006 they were sent a questionnaire in case they were alive or a proxy completed at least part of the interview in person. In 2010 (wave 10) respondents who had completed the EFTF interview in 2006 again were chosen to participate in this mode of data collection. As a result the first panel set is available in 2010 (subsample A).

[23] Note that if individuals are younger than 65 years they were asked about their belief to survive another $20 - 35$ years. As the HRS data set does not cover this large time horizon, we restrict our sample to individuals aged between 65 and 89. The lower bound of the age interval is chosen due to technical considerations and the upper bound is chosen as people older than 89 are not asked about their SSB. Since we want our hazard model to fit this age group well, we restrict the sample with respect to age in the same way.

due to consistency problems in how some variables were measured. Due to the panel design of the survey we observe many individuals multiple times. We are interested in relatively long time spans. Therefore, if we have more than one observation of an individual we only use the observation where the difference between interview date and last interview date is maximized.

B.1.2 Cross-Sectional Analysis

The HRS contains variables about psychosocial factors from wave 8 onwards. In our analyses we use lagged variables of the psychological variables. Hence, the main cross-sectional analysis of the paper is restricted to waves 9,10 and 11. Those who died between waves 9 and 11 (2008-2012) automatically dropped out of the sample after their death. Since partners and spouses are interviewed as well, some interviewees are younger than 50, some of them more than 10 years. As outlined above we do not have individual-level OSPs for individuals younger than 65. Thus, we exclude all respondents aged below 65. Individuals, who did not report their respective SSB were naturally dropped from the sample. By survey design these include proxy interviews as well as interviewees aged above 89.

B.1.3 Health and Retirement Study (HRS): Overview

B.2 Human Mortality Base (HMD) and Social Security Administration (SSA)

Section C requires the use of cohort life tables. These are not publicly available and need to be constructed, c.f. Appendix C. For this we need a sequence of (period) life tables which are publicly available. t-period life tables for the years $t = 1993 - t = 2013$ are obtained from the Human Mortality Database (HMD)[24]. For earlier years ($t = 1900, ..., 1932$) t-period life tables are taken

[24]The Human Mortality Database (HMD) is a cooperation of the Department of Demography at the University of California and the Max Planck Institute for Demographic Research and includes detailed data on U.S. mortality and provides detailed population and mortality data for 38 countries (2016).

Table 7: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
TA 65	0.245	0.43	0	1	31312
TA 70	0.285	0.451	0	1	31312
TA 75	0.223	0.417	0	1	31312
TA 80	0.15	0.357	0	1	31312
Wave 9	0.345	0.475	0	1	31312
Wave 10	0.331	0.471	0	1	31312
Age	74.771	6.398	65	89	31312
Male	0.427	0.495	0	1	31312
Black	0.14	0.347	0	1	31303
Married	0.594	0.491	0	1	31307
Widowed	0.264	0.441	0	1	31307
Mom alive	0.056	0.229	0	1	30678
Dad alive	0.01	0.1	0	1	30908
College	0.195	0.396	0	1	31305
Subjective Health (Excellent/Very Good)	0.361	0.48	0	1	31284
ADL-Index	0.28	0.696	0	3	31312
Mobility-Index	1.432	1.622	0	5	28580
Muscle-Index	1.483	1.339	0	4	29459
Obese	0.292	0.455	0	1	30949
Smoke (now)	0.092	0.289	0	1	31100
Smoke (ever)	0.576	0.494	0	1	31104
Drink (ever)	0.463	0.499	0	1	31306
Ever have condition					
High Blood Pressure	0.684	0.465	0	1	31236
Diabetes	0.26	0.439	0	1	31241
Cancer	0.202	0.402	0	1	31209
Lung Disease	0.126	0.332	0	1	31254
Heart Disease	0.326	0.469	0	1	31244
Stroke	0.122	0.327	0	1	31266
Psychiatric	0.174	0.379	0	1	31257
Arthritis	0.702	0.457	0	1	31264
OSP	46.746	28.682	0	94.708	24715
Lag Optimism	4.547	1.139	1	6	12792
Lag Pessimism	2.548	1.276	1	6	12782
Lag Cognitive Weakness	13.14	4.97	0	35	25892

from the Social Security Administration (SSA).

C Estimation of Objective Survival Probabilities (OSP)

Our goal is to forecast individual-level objective survival probabilities (OSPs) using individual level information. We use the panel dimension to link panel mortality to individual level characteristics. Additionally, we take into account that overall mortality trends are decreasing. In order to account for both effects, we proceed in a two-step manner. First, we adopt an method proposed by **Lee and Carter, 1992** to predict Average Objective Survival Probabilities (AOSP) – basically extrapolating the trend-effect from previous years. In a second step, we use individual information in order to model individual-level OSPs as deviations from our trend-adjusted AOSPs in a Weibull hazard model. Our implicit assumption is that even though there is a time trend in how average OSPs evolve, the individual information that leads to a deviations from AOSPs is sufficiently constant – at least for the time period under study. In the first subsection we will describe how AOSPs are forecasted. In the second subsection we will illustrate how – given average OSPs – individual level OSPs are predicted as deviations from its average counterparts. Then we go on presenting some descriptive statistics for our measure of individual-level survival probabilities. In the last subsection we empirically test our measure of indidividual level OSPs against actual mortality exploiting the panel structure of our data.

C.1 Average OSPs: Lee-Carter

Most papers that compare SSBs to objective measures use period life tables, and thus, refrain from directly including trend-effects (e.g. **Hamermesch (2004)**). Only a few use cohort life tables (**LZ (2013), Groneck et al. (2016), Peracchi and Perotti (2012)**). As noted before, for the purpose

of our analysis we need cohort life tables for the cohorts $\omega \in \{???\}\}$. We construct ω-cohort life tables based on a sequence of t-period life tables.
A t-period life table provides information of the mortality rate of individuals aged $j = 0, 1, 2, ..., J$ in year t. Thus, $\delta_{j,t}$ denotes the probability of an individual aged j who was born in $\omega = t - j$ of dying in year t.
ω-cohort life tables give the mortality rates of people of a given cohort and in principle are obtained by simple rearrangements of period life tables. However, given an individual is of some birth cohort ω and period life tables are available from t_{min} until t_{max} the ω-cohort life table is restricted to the interval $\max(t_{min} - \omega; 0)$ to $t_{max} - \omega$. If one wants to deduct the objective survival probability to an age larger than $t_{max} - \omega$ (as in our paper) one has to make a statement on how future survival rates (1 - $\delta_{j,t}$), and thus, how mortality rates evolve.[25] Hence, we have to predict future period life-tables.

C.1.1 Idea

We employ the method proposed by **Lee-Carter, 1992**. Unlike theoretical models (e.g. **Carnes and Olshansky (2007)**) which take into account expert opinions and changes in the pattern of deaths by different causes, the Lee-Carter approach is completely extrapolative in its nature. The underlying assumption is that the drivers that were effective in the experience period in changing mortality trends are also going to be effective in the future. This trend is identified and used to predict future period life-tables.

C.1.2 Model

We use period life tables from years 1950 (**double check that. In this case we do actually not need the SSA data**) up to 2013 in order to identify the trend. In line with **LC (1992)** mortality rates are expressed in log-linear

[25] For instance, in the paper period life tables are available from $t_{min} = 1900$ until $t_{max} = 2013$. Given a cohort $\omega = 1960$ (e.g. age 50 in 2010), the ($\omega = 1960$)-cohort life table obtained via simple rearrangement is restricted to the interval 0 to 53 because we only have t-period-life tables up to year $t = 2013$. Thus, one does not get 1960-cohort data for ages larger than 53.

form:

$$\log(\delta_{j,t}) = \alpha_j + \beta_j \cdot k_t + \varepsilon_{j,t} \tag{10}$$

The procedure comprises the age specific vectors α_j and β_j and a single index k_t which captures the time dimension of mortality affecting all age groups in the same manner. k_t is assumed to follow a unit-root process with drift and an error term $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$[26] :

$$k_t = \phi \cdot k_{t-1} + \epsilon_t \tag{11}$$

The estimated drift terms are $\hat{\phi} = -1.4460$ and $\hat{\phi} = -1.8114$ for men and women respectively. Subsequently, mortality rates are predicted until 2090 holding $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\phi}$ constant. After transforming log mortality rates into survival rates, these data are used to complete missing data in respective ω-cohort tables of which objective survival rates to the target ages are calculated.

[27]

C.2 Individual OSPs: Hazard Model

In Table 8 we display the variables used in our hazard model.

Note that we only included variables that were significant at a significance level of below 10%. The reason is that we want to minimize the estimation variance. Additionally, we checked whether our measures of optimism and pessimism helped at explaining short-term panel mortality. We could not find any statistical evidence for that hypothesis.

[26]**Li et al.** on the effect of structural breaks and how to cope with this when determining k_t.

[27]Note that all parameters on the right-hand-side are unobserved. Thus, cannot simpl fit the model by OLS. Thus, use alternative solution method, singular value decomposition (SVD) (originally used by **Lee-Carter (1992)**) and maximum likelihood estimation (used by **Brouhns et al. (2002)**). To ensure parameter uniqueness, we rescale the initial estimates of b_x and k_t so that the parameter constraints $\sum b_x = 1$ and $\sum k_t = 0$ are satisfied.

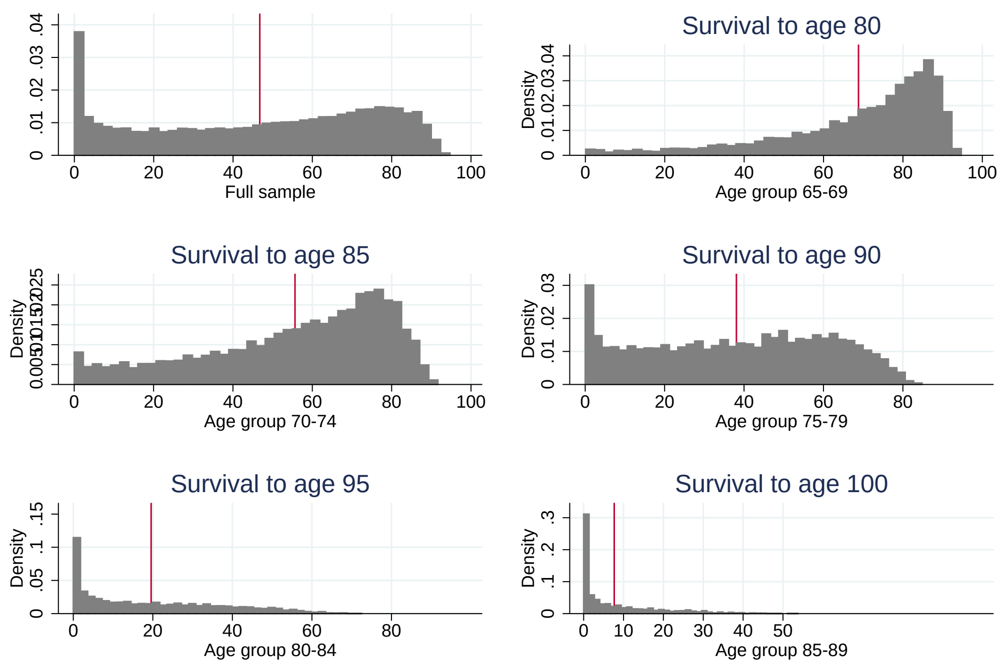
Table 8: Variables Used in Hazard Model

Variable	Description
Age	In years
Male	1 if male, 0 otherwise
Black	1 if black, 0 if otherwise
Married	1 if married, 0 if otherwise
Subjective Health Status (Excellent)	1 if true, 0 if otherwise
Subjective Health Status (Very Good)	1 if true, 0 if otherwise
Subjective Health Status (Good)	1 if true, 0 if otherwise
Subjective Health Status (Poor)	1 if true, 0 if otherwise
Smoke (ever)	1 if true, 0 if otherwise
Smoke (now)	1 if true, 0 if otherwise
Drink (ever)	1 if true, 0 if otherwise
ADL Index	Index between 0 and 3
Mobility Index	Index between 0 and 5
Muscle Index	Index between 0 and 4
Cognitive Weakness	Index between 0 and 35
Ever have conditions	
High blood pressure	1 if true, 0 if otherwise
Diabetes	1 if true, 0 if otherwise
Cancer	1 if true, 0 if otherwise
Lung Disease	1 if true, 0 if otherwise
Heart Diseases	1 if true, 0 if otherwise
Stroke	1 if true, 0 if otherwise
AOSP (12 years)	Avg. OSP to survive another 12 years

C.3 Descriptive Statistics and Validity Check of Individual-level OSPs

In Figure 13 we depict the distribution of our measure for the individual survival probability for each age group and the overall sample. Additionally, each subfigure includes a red vertical line which indicates the average objective survival probability for respective age group. The histograms reveal that there is a significant dispersion of objective survival probabilities. Note that taking life table data one would only have a maximum of five different survival probabilities for each target age group.

Figure 13: ”Histograms of OSP”



Notes: The red vertical line indicates the average objective survival probability.

Validity test to be re-done wit more recent data.

D Bootstrap

Standard errors of the parameters of our Regressions in Section 6 have to be corrected in order to account for the estimation variance in the OSPs. Thus, we implement a two-sample bootstrap procedure with $1,000$ replications to estimate the standard errors for our coefficient estimates. In the two-sample procedure we correct for the estimation variance in objective survival probabilities as follows[28]. The procedure works as follows: In each of the bootstrap replications

- Draw a sample with replacement from the HRS sample used to estimate OSPs.
- Estimate the OSPs for the sample of cross-sectional analysis
- Draw a sample with replacement from the cross-sectional sample
- Perform regression analysis

We redo these steps $1,000$ times. In each iteration the coefficients are saved and percentiles are calculated based on the percentile-method.

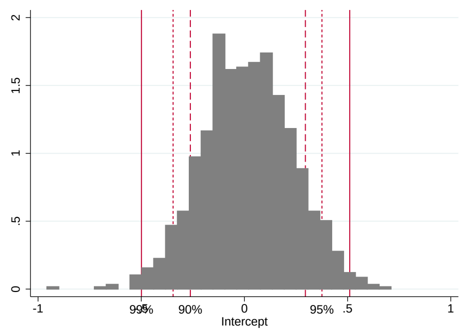
[28]Note, that our two samples are both based on the HRS dataset. The first sample is based on the sample used to estimate the OSPs and the second sample is used in the overall analysis, e.g. regression analysis.

D.1 Bootstrap Distributions and Statistics

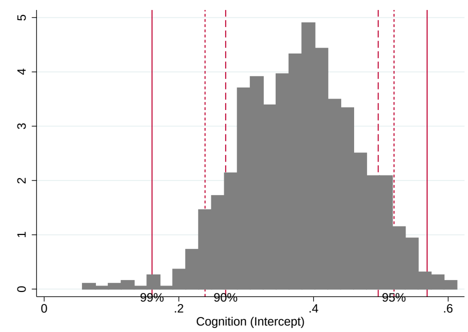
D.1.1 Distributions

Figure 14: Bootstrap Distributions: Coefficients

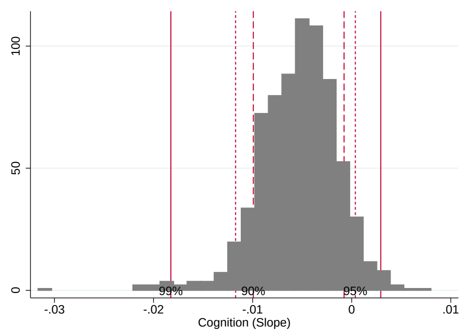
(a) Intercept



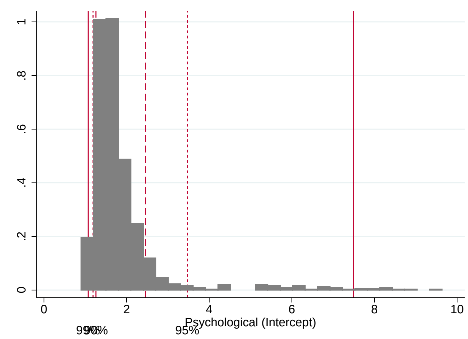
(b) Cognition (Intercept)



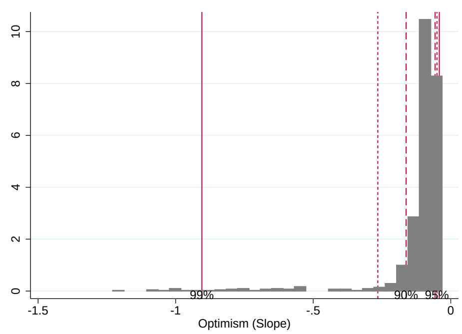
(c) Cognition (Slope)



(d) Psychological (Intercept)



(e) Optimism (Slope)



(f) Pessimism (Slope)

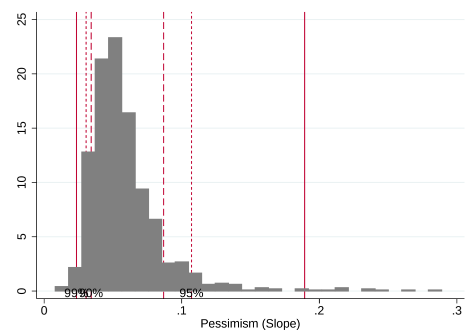
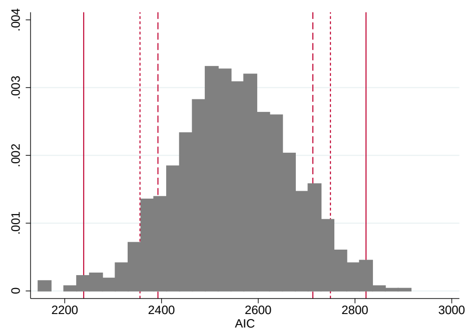
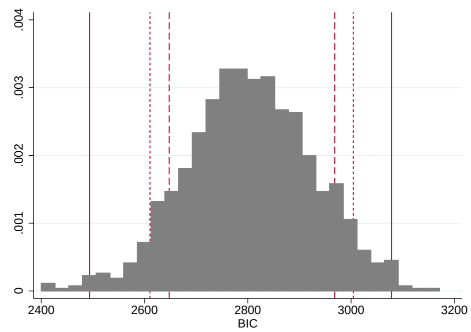


Figure 15: Bootstrap Distributions: Statistics

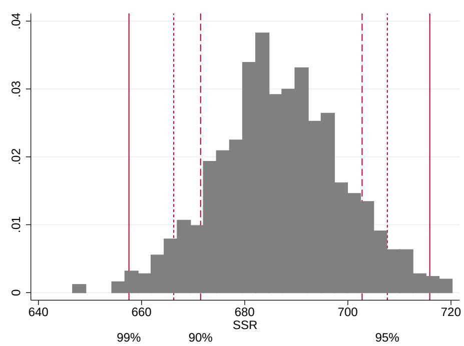
(a) AIC



(b) BIC



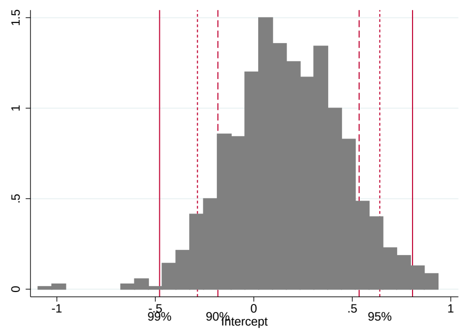
(c) SSR



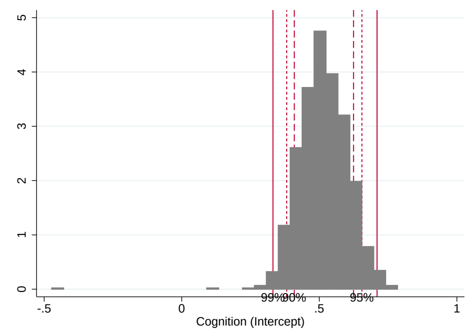
D.1.2 Distributions: Robustness Check Excluding Focal Point Answers 0,50, and 100

Figure 16: Bootstrap Distributions: Coefficients

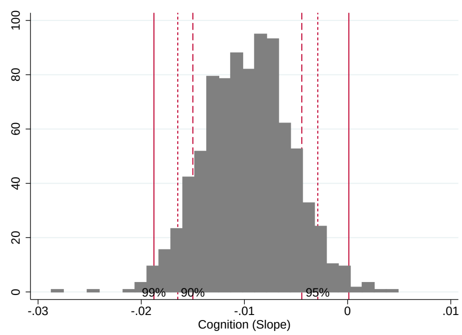
(a) Intercept



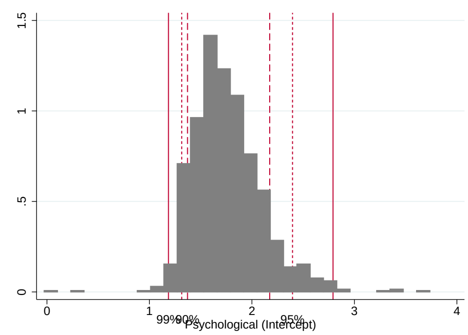
(b) Cognition (Intercept)



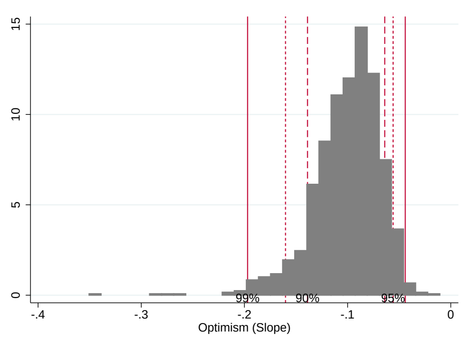
(c) Cognition (Slope)



(d) Psychological (Intercept)



(e) Optimism (Slope)



(f) Pessimism (Slope)

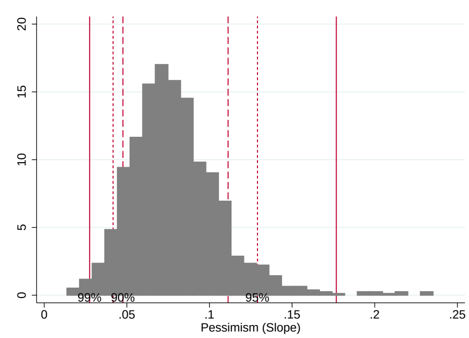
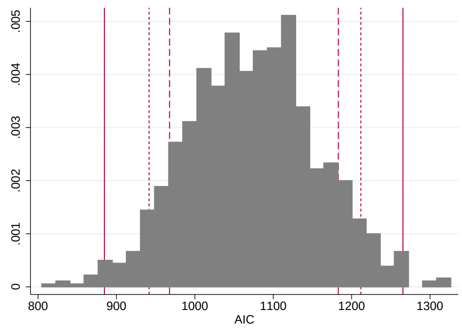
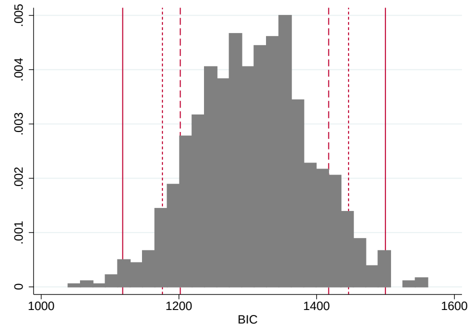


Figure 17: Bootstrap Distributions: Statistics

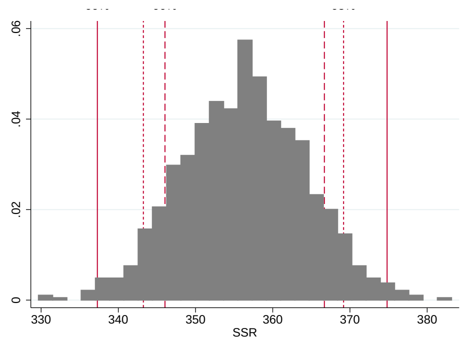
(a) AIC



(b) BIC



(c) SSR



E Additional Results

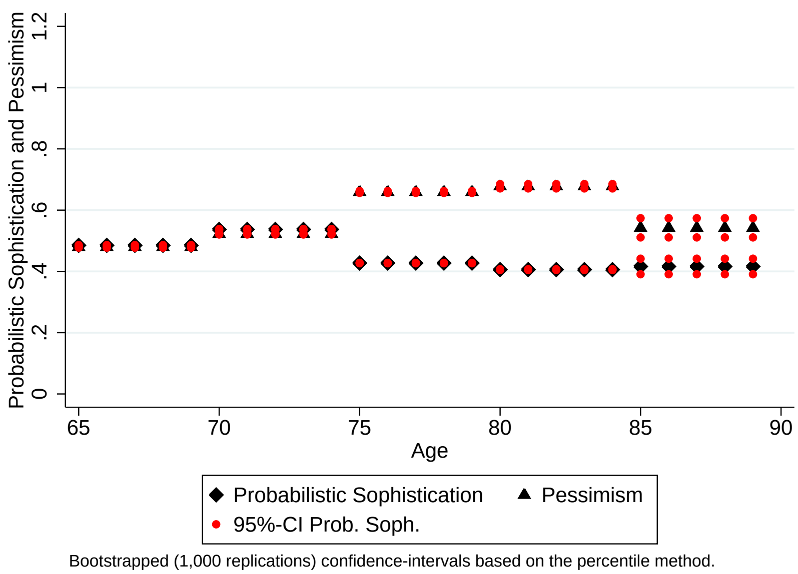
E.1 Parameters of Linear PWF

Figure 18 displays $\xi^l_{m(h)}$ and $\theta^l_{m(h)}$ from the linear specification (5).

E.2 Focal Point Answers

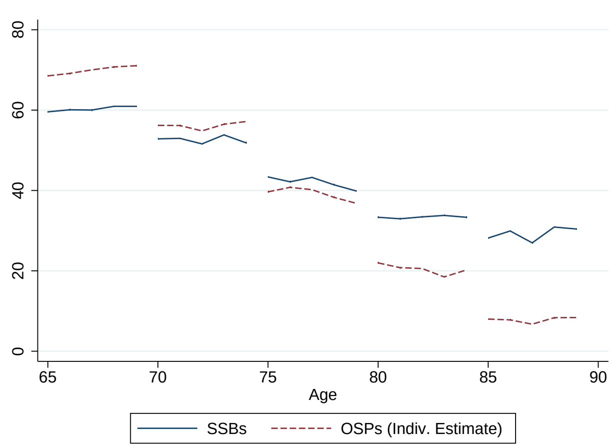
We redo the analysis in Section 3 and 4 by excluding focal point answers at $0, 0.5, 1$, respectively. Results are summarized in Figures 20 to 23 and Table 9.

Figure 18: Estimated Linear PWF Parameters



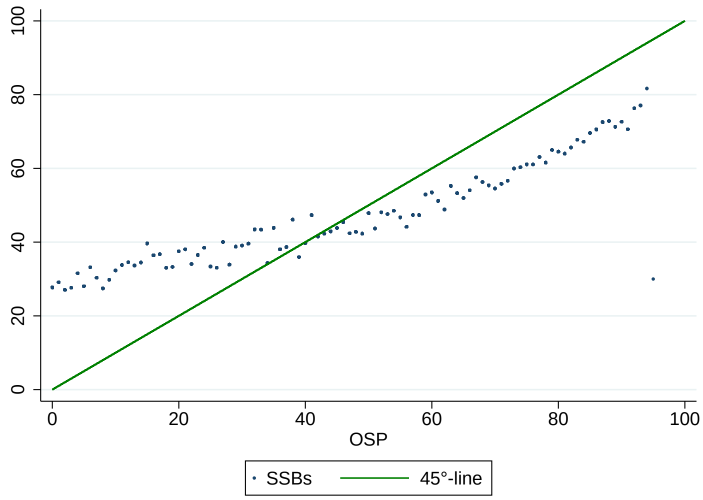
Bootstrapped (1,000 replications) 95%-confidence intervals calculated under normality assumption.
Source: HRS and Own Calculation

Figure 19: "Flatness Effect": The Role of Focal Point Answers



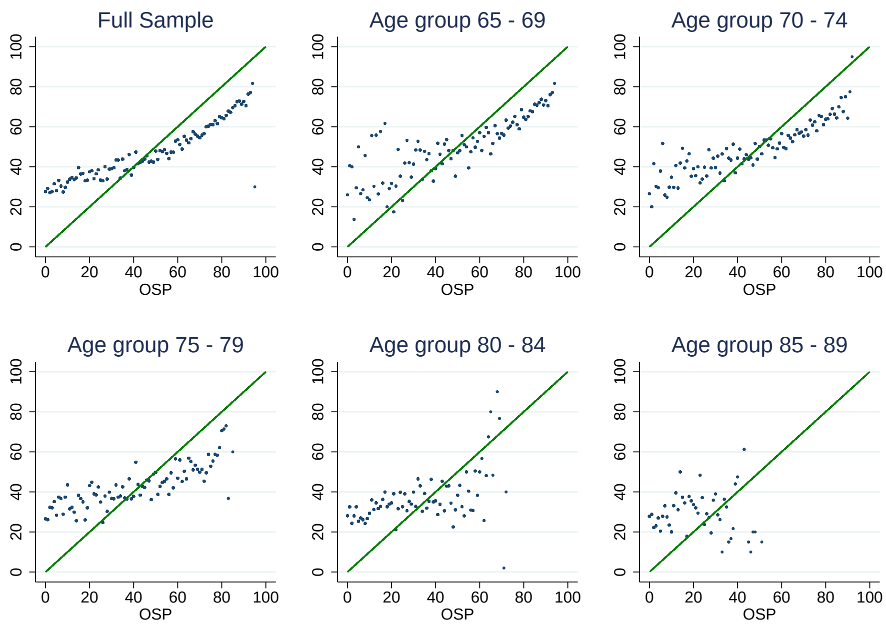
Notes: Unconditional subjective survival probabilities to survive to different target ages. The solid blue line are subjective survival beliefs, the dashed red line are the corresponding objective survival rates estimated with (**??**). Subjective survival beliefs are elicited in the HRS only for a combination of the age at interview of the individual (which is shown on the abscissa) and a corresponding target age, cf. Table 1. The step function follows from changes in the interview age/target age assignment. Observations with SSBs at $0, 0.5, 1$, respectively, are excluded.

Figure 20: Objective Survival Probabilities and Subjective Survival Beliefs: The Role of Focal Point Answers



Notes: SSB over OSP. For the figure we discretize OSP in 100 points and calculate average SSB for each point such that one blue dot represents average SSB for each OSP value. Observations with SSBs at $0, 0.5, 1$, respectively, are excluded.

Figure 21: Objective Survival Probabilities and Subjective Survival Beliefs by Age Groups: The Role of Focal Point Answers



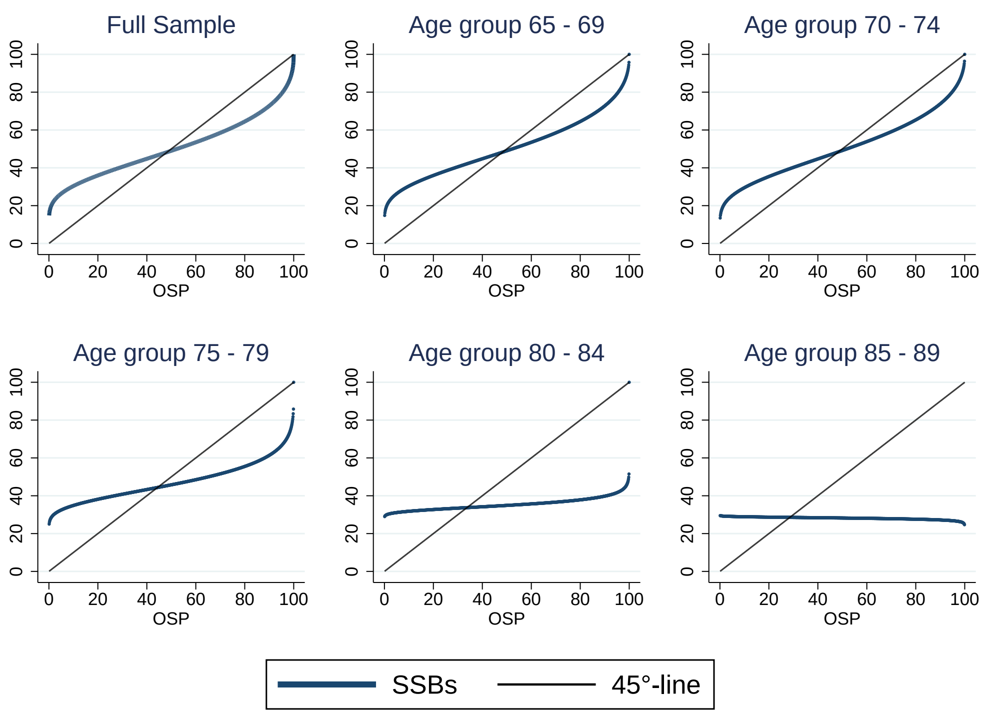
Notes: SSB over OSP. For the figure we discretize OSP in 100 points and calculate average SSB for each point such that one blue dot represents average SSB for each OSP value. The age-group panel focus on different target ages according to the question in the HRS, cf. Table 1. Observations with SSBs at $0, 0.5, 1$, respectively, are excluded.

Table 9: Information Criteria for Non-Linear and Linear Probability Weighting Functions: The Role of Focal Point Answers

	AIC			SBC		
Interview age h	Linear	Prelec	Difference	Linear	Prelec	Difference
65 - 69	166.80	163.10	3,70	176.61	172.91	3.70
70 - 74	288.47	287.70	0,77	298.41	297.65	0.77
75 - 79	356.07	358.48	-2,47	365.51	367.92	-2.41
80 - 84	186.72	185.12	1,60	195.29	193.69	1.60
85 - 89	99.87	99.85	0,02	107.04	107.02	0.02

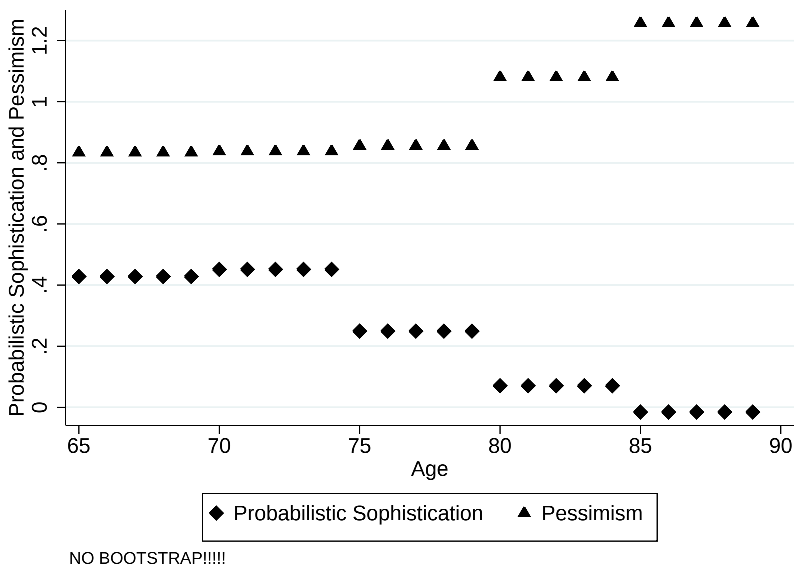
Notes: Linear: Linear PWF. Prelec: Specification of the PWF according to **?**). Observations with SSBs at $0, 0.5, 1$, respectively, are excluded. AIC: Akaike information criterion. SBC: Schwartz Bayesian information criterion. *Source:* Own calculations based on the HRS (2015), waves 2008-2012.

Figure 22: Estimated Probability Weighting Functions: The Role of Focal Point Answers



Notes: Estimated Prelec probability weighting functions for the full sample (upper left panel) and for different age-groups rotating clockwise in ascending order. Parameters estimated with non-linear least squares. Observations with SSBs at $0, 0.5, 1$, respectively, are excluded.

Figure 23: Estimated Prelec Parameters: The Role of Focal Point Answers



Notes: Bootstrapped (1000 replications) 95%-confidence intervals are based on percentile method. Observations with SSBs at $0, 0.5, 1$, respectively, are excluded.
Source: Own Calculation based on the HRS.