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Cognition, Optimism and the Formation of Age-Dependent Survival Beliefs*

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Abstract

This paper investigates the roles psychological biases play in deviations between subjective survival beliefs (SSBs) and objective survival probabilities (OSPs). We model deviations between SSBs and OSPs through age-dependent inverse S-shaped probability weighting functions. Our estimates suggest that implied measures for cognitive weakness increase and relative optimism decrease with age. We document that direct measures of cognitive weakness and optimism share these trends. Our regression analyses confirm that these factors play strong quantitative roles in the formation of subjective survival beliefs. Our main finding is that cognitive weakness rather than optimism is an increasingly important contributor to the well-documented overestimation of survival chances in old age.

JEL Classification: D83, D91, I10.

Keywords: Subjective Survival Beliefs, Probability Weighting Function, Confirmatory Bias, Cognition, Optimism, Pessimism

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1 Introduction

Important economic problems, such as the decision about when to retire, how much to save for retirement and whether to purchase life-insurance, depend on the formation of survival beliefs over an individual's life-cycle. A rational individual would be modeled as a statistician whose survival beliefs are given as data-based estimates. For this benchmark, any differences between subjective survival beliefs (SSBs) and their objective counterparts can only result from an insufficient amount of data, and biases will decrease when the individual collects more data with age. Empirical studies, however, do not support this notion of convergence of perceived survival chances to objective survival probabilities (OSPs). Instead, the literature robustly documents a *flatness bias*, i.e., respondents of age 50-70 express underestimation, whereas older respondents (older than age 75) express overestimation of survival chances on average by non-negligible amounts.[1] In this paper we provide a *structural interpretation* of these biases through transformations of objective probabilities known from experimental prospect theory (PT).[2] Accordingly, when plotting SSBs against OSPs, SSBs do not lie along the 45-degree line but rather exhibit an inverse S-shape. We document that *psychological factors* such as optimism and cognitive weakness are important quantitative drivers of this transformation. Our findings suggest that age-increasing overestimation of OSPs is not due to increasing optimism as one may expect. It is rather a consequence of age-increasing insensitivity to objective likelihood leading to inverse S-shaped transformations of OSPs. When OSPs decrease with age individuals therefore overestimate those more strongly.

As our first step, we compare SSBs to OSPs using data from the Health and Retirement Study (HRS). In the HRS, interviewees are asked about their beliefs to survive from the interview age to some target age. To construct objective counterparts, we estimate for each interviewee the corresponding individual-level OSP by using the information on actual HRS mortality and several conditioning variables. Plotting SSBs against OSPs over age, we document the *flatness bias* in the form of an average underestimation of survival chances by respondents of age 70 and younger, and an overestimation of survival chances by respondents of age 75 and older. *Within* a given age group, we find that respondents with low OSPs express overestimation, whereas respondents with high OSPs express underestimation.

For our structural interpretation of these biases we model SSBs as age-dependent inverse S-shaped Prelec (1998) probability weighting functions (PWFs). In line with the usual interpretation of the parameters of the Prelec function, cf. Wakker (2010), we assume that

[1] Inspired by Hamermesh (1985), a growing body of economic literature documents such a *flatness bias*, cf., e.g., Elder (2013), Ludwig and Zimper (2013), Peracchi and Perotti (2014), Heimer et al. (2019), Groneck et al. (2016), and Bissonnette et al. (2017).

[2] See Kahneman and Tversky (1979), Tversky and Kahneman (1992), and Wakker (2010).

the motivational factor *relative optimism* is expressed through the *elevation* of the Prelec function and that the cognitive factor of *likelihood insensitivity* corresponds to its *flatness*. Likelihood insensitivity refers to a cognitive weakness according to which people cannot distinguish well among respective likelihoods of events. An extreme case of flattening-out are fifty-fifty probability judgments, which are well-documented in the psychological literature (Bruine de Bruin et al. 2000).[3] Estimating age-specific Prelec PWFs on our data of SSBs, we find that the *elevation* of the Prelec function weakly decreases with age, whereas its *flatness* increases. Thus, the implicit measure of relative optimism weakly decreases and the implicit measure of likelihood insensitivity increases with age.

We next analyze directly observable counterparts of these implicit cognitive and motivational factors. We use HRS data on *dispositional optimism* derived from the same statements as in the well-known Life Orientation Test-Revised (LOT-R). As a proxy for likelihood insensitivity, we consider HRS measures on the *cognitive weakness* of the respondent, which is motivated by a cognitive interpretation of likelihood insensitivity (Wakker 2010). We show that these direct measures exhibit the same age trends as our indirect measures.

To quantify the impact of these direct measures on subjective survival beliefs we finally specify both parameters of the Prelec function—*relative pessimism* and *likelihood insensitivity*—as linearly dependent on dispositional optimism and cognitive weakness. Our according estimates give rise to a decomposition analysis with the following main findings. We identify a strong *base bias* in the form of a baseline inverse S-shaped transformation of OSPs, which captures the survival belief of the most pessimistic person with the lowest cognitive weakness. Thus, individuals apparently only partially use the information on their individual-level OSPs when forming SSBs to the effect that they express likelihood insensitivity with respect to the OSPs. This may reflect an initial degree of cognitive weakness, incomplete statistical learning, (rational) inattention with respect to OSPs, rounding[4], or a statistical artifact from truncation of the data[5]. Since the baseline inverse S-shaped transformation of OSPs is constant over age, changes in differences between SSBs and OSPs attributable to the base bias are caused by movements of the OSPs. Because OSPs are relatively high at age 65, the base effect induces an underestimation of long-horizon survival chances of approximately 6%p.

[3] Gonzalez and Wu (1999) refer to these concepts as *attractiveness* and *diminishing sensitivity*, respectively.

[4] There exists a growing literature on rounding of subjective probability questions, including questions on perceived survival chances, and how to correct for potential rounding or focal point answers, cf., e.g., Hurd (2009), Manski and Molinari (2010), Hudomiet and Willis (2014), Kleinjans and van Soest (2014), Ruud et al. (2014), Bissonnette et al. (2017), and Drerup et al. (2017). Kleinjans and van Soest (2014) conclude that reporting behavior—i.e., rounding, focal point answers and item nonresponse—does not have a large effect on estimated subjective probability distributions.

[5] Underestimators cannot report SSBs less than zero and overestimators cannot report SSBs above one. Such truncation may induce overestimation, on average, for OSPs close to zero and underestimation for OSPs close to one, which leads to a natural flatness of the PWF relative to the 45-degree line.

At age 85, however, OSPs are relatively low and the base bias induces an overestimation of approximately 15%p. *Cognitive weakness* leads to a further age-increasing flatness of the probability weighting function, which induces an additional underestimation of subjective survival beliefs at age 65 by about -5%p, and to an additional overestimation at age 85 also by 5%p. In contrast to these dynamic effects of cognition, the impact of the motivational factor *relative optimism* is constant in age leading to an upward bias by about 10%p. Thus, the age-increasing overestimation of survival probabilities can (partially) be explained by cognitive weakness and not by increasing optimism as one may expect.

The remainder of this paper is organized as follows. Section 2 reviews related literature, Section 3 presents the main stylized facts on survival belief biases, Section 4 provides our structural interpretation of these biases, Section 5 looks at direct psychological measures elicited in the HRS, and presents our results on their quantitative roles for subjective survival beliefs. Finally, Section 6 concludes with a discussion on the economic implications of our findings. Separate appendices contain further information on the data and additional results.

2 Literature

We contribute to the literature on subjective expectations (Manski 2004), particularly on subjective survival beliefs, inspired by Hamermesh (1985). On the one hand, this literature documents that SSBs are broadly consistent with OSPs and co-vary with health behavior, e.g., smoking, or health status, in the same way as OSPs (Hurd and McGarry 1995; Gan et al. 2005), that SSBs serve as predictors of actual mortality (Hurd and McGarry 2002; Smith et al. 2001), and that individuals revise their SSBs in response to new adverse (health) shocks (Smith et al. 2001). On the other hand, several authors document important biases in subjective survival beliefs when comparing sample average beliefs to objective survival probabilities (Elder 2013; Ludwig and Zimper 2013; Peracchi and Perotti 2014; Groneck et al. 2016; Bissonnette et al. 2017). We emphasize that motivational and cognitive factors are important contributors to these biases.

In this respect, our work relates to medical studies examining the link between psychosocial dispositions and health shocks (Kim et al. 2011) or subjective body weight (Sutin 2013). Mirowsky and Ross (2000) and Griffin et al. (2013) study how incorporating motivational factors influences subjective life expectancy. We extend their work by controlling for OSPs.

Manifestations of biases driven by motivational factors have also been discussed in the behavioral learning literature in form of *confirmatory* biases (Rabin and Schrag 1999), *myside* biases (Zimper and Ludwig 2009), *partisan* biases (Jern et al. 2014; Weeks 2015), and *irrational belief persistence* (Baron 2008) and in the literature on motivated beliefs (Bénabou and Tirole 2016). People biased by motivational factors 'only see/learn what they want to see/learn' so that any new information tends to confirm already existing beliefs. One would expect that motivational biases play an important role in the formation of survival beliefs, since "most of us prefer to minimize even our cognitive encounters with death" (Kastenbaum 2000). Elderly people might express more *optimistic* attitudes towards their likelihood of surviving and an age-increasing motivational (confirmatory) bias in the form of optimism could accordingly explain the observed age increasing overestimation of survival chances. Although our analysis suggests that a confirmatory bias (optimism) is important for the formation of survival beliefs at all ages, we find that it leads to a roughly constant bias across age. Our findings instead suggest that cognitive weakness is an increasingly important quantitative contributor to the overestimation of survival chances over an individual's life-cycle.[6] In this respect, our findings caution against using survival expectations to proxy optimism as, e.g., in Puri and Robinson (2007) and Angelini et al. (2019), as overestimated survival beliefs may additionally reflect lack of cognition.

To model age-dependent survival beliefs, we employ a Prelec probability weighting function applied to objective survival probabilities, which is a prominent approach in *prospect theory* (PT). As a generalization of *rank-dependent utility theories*, pioneered by Quiggin (1981, 1982), modern 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. Schmeidler (1989) and Gilboa (1987). Our model of age-dependent biases in survival beliefs is related to the experimental PT literature, which shows that subjective probability judgments cannot be described as additive probabilities. According to experimental findings, inverse S-shaped beliefs are prevalent in decision situations under *risk*, but are even more pronounced in situations under *uncertainty*, cf. Wakker (2004). We contribute to this literature using survey instead of experimental data, where only few papers document evidence of inverse S-shaped probability judgments, e.g., Polkovnichenko and Zhao (2013) and Andrikogiannopoulou and Papakonstantinou (2016). Since it is plausible to assume that assessments of long-run survival chances involve ample uncertainty, the strong quantitative role of the base bias we uncover can be interpreted as a confirmation that inverse-S-shaped probability weighting is indeed very pronounced under uncertainty. It speaks to the robustness of the experimental PT findings that we confirm the typical inverse S-shape for survival beliefs, and our regression analyses supports the typical psychological interpretations of this shape.

With this emphasis on the role of uncertainty our work relates to d'Uva et al. (2017) who analyze the accuracy of longevity expectations. They find that with higher cognitive

[6]Our finding of increasing likelihood insensitivity with age is also consistent with Booij et al. (2010).

weakness of respondents in the HRS the accuracy of SSBs to predict OSPs decreases. Likewise, through this perspective we relate to Hill et al. (2004) who show that uncertainty with respect to survival beliefs increases in cognitive weakness. Our work complements these by asking how individuals with a given noisy signal on OSPs assess SSBs. Also, these findings are fully consistent with our notion of cognitive weakness as a proxy for likelihood insensitivity leading to a flatter probability weighting function in light of uncertainty.

3 Age Patterns of Biases in Survival Beliefs

Our data on subjective survival beliefs (SSBs) and our corresponding estimates of objective survival probabilities (OSPs) are both based on the Health and Retirement Study (HRS). The HRS is a national representative panel study of the elderly US population. Individuals are interviewed on a biennial basis. Interviews of the first wave were conducted in 1992. The interviewees are individuals older than 50 and their spouses regardless of age. An overview of the survey, its waves and the interview cohorts is contained in Appendix A.

3.1 Subjective Survival Beliefs

In the HRS, an interviewee is asked the following question in the Expectations section of the HRS Core questionnaire:

> [On a scale from 0 to 100, where "0" means that you think there is absolutely no chance, and "100" means that you think the event is absolutely sure to happen,] What is the percent chance that you will live to be $[X]$ or more?,

where $X \in \{80; 85; 90; 95; 100\}$ is the target age, equal to the age of the respondent at the time of the survey plus an horizon ranging between 11 to 15 years for respondents aged 65-89. We denote this belief as $SSB_{i,h,m(h)}$ for interviewee i of age h and target age $m(h) > h$. We focus on individuals in the survey who are age 65 and older. This sample restriction is used because the data set does not allow us to estimate OSPs for ages less than 65, with details provided in Subsection 3.2 below. The assignment of target age $m(h)$ to interview age h for our sample is summarized in Table 1.

3.2 Objective Survival Probabilities

Comparing individual level SSBs to survival probabilities extracted from aggregate cohort life-tables as, e.g., in Perozek (2008), Ludwig and Zimper (2013), Peracchi and Perotti (2014), and Groneck et al. (2016) is ill-suited because individual level OSPs generally deviate from

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: Health and Retirement Study (HRS).

sample averages. To estimate individual-level OSPs, we instead follow Khwaja et al. (2007), Khwaja et al. (2009), Winter and Wuppermann (2014), Kutlu-Koc and Kalwij (2017), Perozek (2008), Bissonnette et al. (2017) and Siegel et al. (2003) by adapting a mixed-proportional hazard (MPH) model, see van den Berg (2001). This allows us to estimate hazard rates conditional on a broad set of individual-level characteristics.

Let T be a nonnegative random variable denoting the time to failure event, i.e., the number of years to death. Further, let $f(t_i)$ be the density of $F(t_i) = P(T \leq t_i)$, where t_i is a realization of T. The survivor function defined as the probability of surviving beyond time t_i is given by $S(t_i) = 1 - F(t_i) = P(T > t_i)$ and the hazard function $\mathrm{h}(t_i) = \frac{f(t_i)}{S(t_i)}$ is the conditional, or age-specific, failure rate (force of mortality). The hazard rate is duration dependent if it changes with t_i. We assume that mortality of individual i conditional on covariates x_i and unobserved heterogeneity η_i is given by the hazard function

$$\mathrm{h}(t_i|\mathbf{x_i}, \eta_i; \alpha, \beta) = \lambda_0(t_i; \alpha) \cdot \exp(\mathbf{x}_i'\beta) \cdot \eta_i,$$

where $\lambda_0(\cdot)$ is the baseline hazard, and $\exp(\mathbf{x}_i'\beta)$ is the proportional hazard with coefficient vector β. The individual specific proportional hazard thus scales the common baseline hazard function with the underlying assumption that conditional on the baseline characteristics the duration to death is given by the same baseline hazard function for all individuals (Cleves et al. 2008). For the baseline hazard function $\lambda_0(t)$ we assume a Weibull distribution[7]

$$\lambda_0(t_i) = \alpha t_i^{\alpha-1}$$

which allows for $\alpha > 1$ capturing positive duration dependence. The unobserved heterogeneity η_i accounts for random differences of individuals not captured by observed variables and

[7] According to Perozek (2008) the Weibull and the Gompertz model are most widely used when estimating human mortality. Significant differences mainly occur at advanced ages past 85.

dynamic selection effects, i.e., a potentially selected sample with rising age, see Kalwij et al. (2013) and van den Berg et al. (2006). As common in the literature since (Lancaster 1979), it is assumed to obey a Gamma distribution with mean one (for reasons of identification) while the variance σ is estimated from the data.

The response variable in our data is the duration until death. However, some respondents do not die until the end of the observation time. These individuals are *right-censored*, i.e., we only know the probability that they did not die before a certain period. To take right-censoring into account, denote by d_i an indicator variable which is one if individual i is uncensored. Note that $S(t_i)$ is also the probability that t_i is right-censored. Hence, we can write the log-likelihood as

$$\ln L\left\{\beta|((t_t,x_t),...(t_n,x_n)\right\} = \sum_{i=1}^{n} d_i \cdot \log\left[S(t_i|\mathbf{x_i}\beta)\mathrm{h}(t_i|\mathbf{x_i}\beta)\right] + (1-d_i)\log\left[S(t_i|\mathbf{x_i}\beta)\right] \quad (1)$$

which we minimize with respect to β, α and σ. Using the estimated parameters we predict OSPs at all horizons t for each individual i of interview age h by averaging over the distribution of unobserved heterogeneity as

$$OSP_{i,h,h+t} = \exp\big[-\exp(\mathbf{x}_i'\beta)t^{\alpha}\big]. \quad (2)$$

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.

We restrict our sample to individuals aged $65-98$. We choose all observations when respondents enter the HRS (which can be at different waves) within our observed time period. This sample at initial state consists of $21,435$ respondents. The average age is 70.7 and 42% of individuals die within the observed time interval of at most 17 years. As covariates we use demographic variables (age, gender, marital status), a set of objective and subjective health variables, as well as a measure for the average age-specific survival probability that we estimate using the Lee and Carter (1992) procedure employing the life-tables from the Human mortality database in order to account for the time-trend in life-expectancy, cf. Table 5 in Appendix A.1. In addition, we allow a non linear relation between age and time to death by employing a third order polynomial. Control variables are held constant at their respective values when individuals enter the sample.

The parameter estimate of the Weibull hazard function is $\alpha = 1.64$ significantly above one thus indicating positive duration dependence, i.e., the probability of death increases the longer the individual was observed in the sample. The estimated variance of the Gamma distribution is significant at $\sigma = 0.06$, thus our sample features unobserved heterogeneity of small size. This implies that our coefficient estimates are very similar to a model without unobserved heterogeneity. Both estimates are in line with the literature (e.g. Kalwij (2014), Bissonnette et al. (2017) and Kalwij et al. (2013)).

The signs of the coefficient estimates on the control variables reported in Table 6 of Appendix A.1 are broadly in line with prior expectations and what has been found in the literature, cf. Khwaja et al. (2007), Khwaja et al. (2009), Kutlu-Koc and Kalwij (2017). E.g., most measures of health limitations are positively associated with the hazard of dying.[8] We also include cognitive weakness (see Section 5 for the variable's construction) as a control in our estimation of objective survival probabilities, which we find to be significant. However, we cannot include the motivational variable optimism in the hazard model because this would reduce the sample size to only $2,108$ observations.[9] If optimists were more likely to survive, then any deviation from SSBs caused by this motivational attitude would (at least partially) reflect additional information of respondents on their objective mortality risk rather than psychological biases. We address this concern in a smaller sub-sample by re-estimating the hazard model with the inclusion of the motivational variable, using HRS data from waves 8-12, with results shown in Table 7 in Appendix A.1. We do not find that optimism has a significant effect on mortality. The coefficient estimates of other control variables are not much affected either. This supports our interpretation of the effects of optimism on SSBs as reflecting psychological biases that do not directly affect mortality.

Descriptive statistics of the distributions of OSPs and SSBs are given in Appendix A.2. There we also show that our model of OSPs fits actual sample mortality well.

3.3 Biases

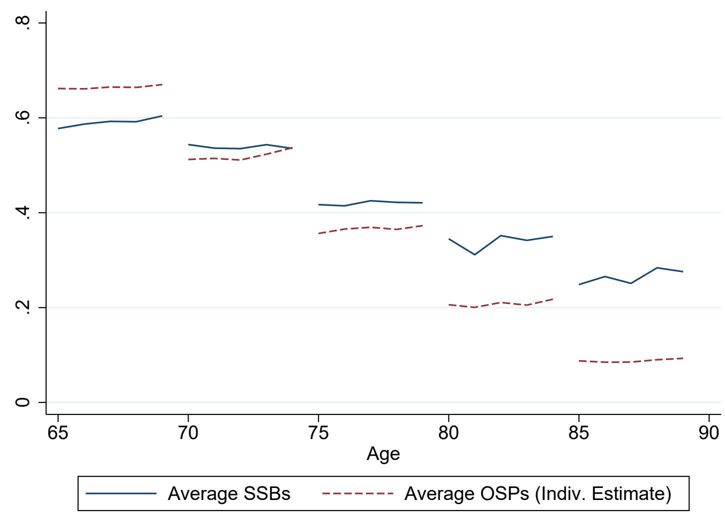
As a first step of comparing individual-specific SSBs and OSPs, we replicate results of previous literature (e.g., Hamermesh (1985), Elder (2013), Ludwig and Zimper (2013), Peracchi and Perotti (2014)) on the age patterns of survival beliefs in Figure 1. As a crucial difference from this literature, we calculate average OSPs from our individual measures instead of using average (cohort) life-tables. The step function in the figure is due to the change in assignment of interview and target ages, cf. Table 1. Our findings confirm the well-established *flatness bias* with individual level data: At ages prior to 70, individuals, on average, underestimate their probabilities to survive, whereas for ages above 75, they overestimate it.

Next, we take a new perspective for which individual-level data are needed. Instead of computing averages over age, we average over OSPs, i.e., for each OSP, we compute

[8]Exceptions are the muscle index and the variable ever drinking, which is likely due to collinearity with ADLs.

[9]We only observe motivational variables from wage 8 onward, additionally containing many missing values.

Figure 1: Flatness Bias

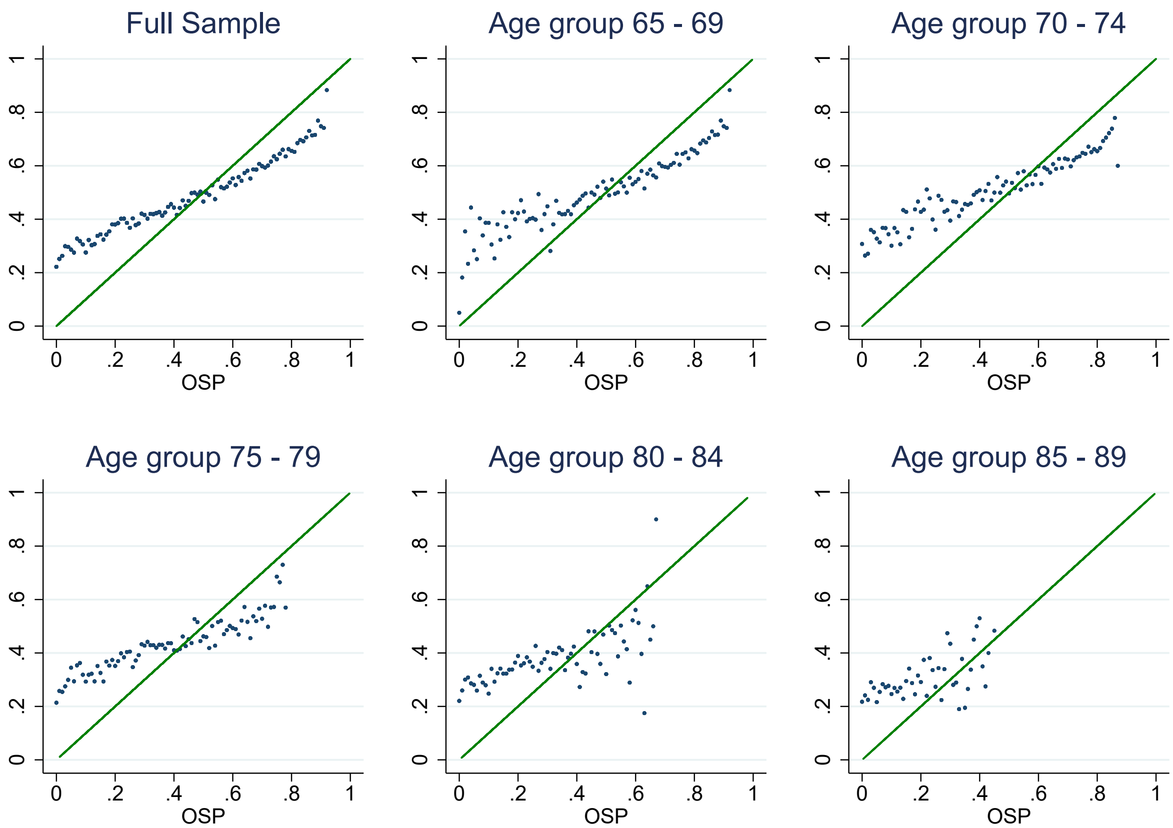


Notes: Average subjective survival beliefs (SSBs, solid line) and corresponding average objective survival probabilities (OSPs, dashed line), cf. equation (2). SSBs are elicited in the HRS for a combination of the age at interview of the individual (which is shown on the abscissa) and a corresponding target age, cf. Table 1. The step function follows from changes in the interview age/target age assignment. *Source*: Own calculations, Health and Retirement Study (HRS).

the average SSB. In the upper left panel of Figure 2, we show the corresponding results by plotting average SSBs against average OSPs. If SSBs are aligned along the 45-degree line, then there is no bias on average. However, we observe a very systematic pattern of misconception: Individuals with low OSPs, on average, overestimate their survival chance, whereas those with high OSPs underestimate it.

The two perspectives on the data taken in Figure 1 and the upper left panel of Figure 2 suggest a very simple explanation for the observed biases across age. Suppose that, irrespective of any cognitive notion on likelihood sensitivity, individuals were to always resolve any uncertainty about their survival chances in a 50-50 manner, i.e., their response were a weighted average of a fifty percent chance of survival and the actual OSP, then such a 50-50 heuristic could obviously explain the pattern in the upper left panel 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 respondents, on the other hand, have long-run OSPs less than 50 percent, on average, and would accordingly overestimate their OSPs, on average. Hence, such a 50-50 bias could simultaneously explain the patterns in these graphs.

Figure 2: Objective Survival Probabilities and Subjective Survival Beliefs by Age Group



Notes: SSB over OSP by age group. The upper left panel is for all ages. The remaining age group panels focus on different target ages according to Table 1. *Source*: Own calculations, Health and Retirement Study (HRS).

However, there is more information content in the data, giving rise to alternative interpretations.[10] This can be illustrated by repeating the previous analysis for different target age groups in the remaining panels of Figure 2, which suggests that the flatness of SSBs against OSPs grows 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 downward, from approximately 50 percent for age groups 65-69 and 70-74 to approximately 40 percent for age group 80-84. Therefore, the average tendency for underestimation a given OSP increases

[10]The general notion of more information content beyond a mere 50-50 bias is also shared in the earlier work by Hurd and McGarry (1995), Hurd et al. (1999), Smith et al. (2001), Smith et al. (2001), Hurd and McGarry (2002) and Gan et al. (2005). We add to this literature by emphasizing the roles of cognitive and motivational factors.

across age groups. Figure 11 in Appendix B further supports this view by showing that average SSBs by bins of OSPs weakly decrease over age.

4 Modeling Subjective Survival Beliefs

We interpret these biases in survival beliefs through the lens of prospect theory (PT) by adopting age dependent inverse S-shaped probability weighting functions (PWF) to map OSPs into SSBs. This enables us to model the observed (age increasing) flatness of SSBs relative to OSPs. We use a parsimonious parametrization of PWFs, which, employing the terminology of Wakker (2010), gives rise to two psychological interpretations. First, the increasing flatness of SSBs relative to the 45-degree line reflects, along a *cognitive* dimension, an increasing insensitivity to the objective likelihood of the decision maker (likelihood insensitivity). Second, the decreasing intersection of SSBs with the 45-degree line reflects decreasing optimism, and hence a *motivational* interpretation of the data.

4.1 The Prelec Probability Weighting Function

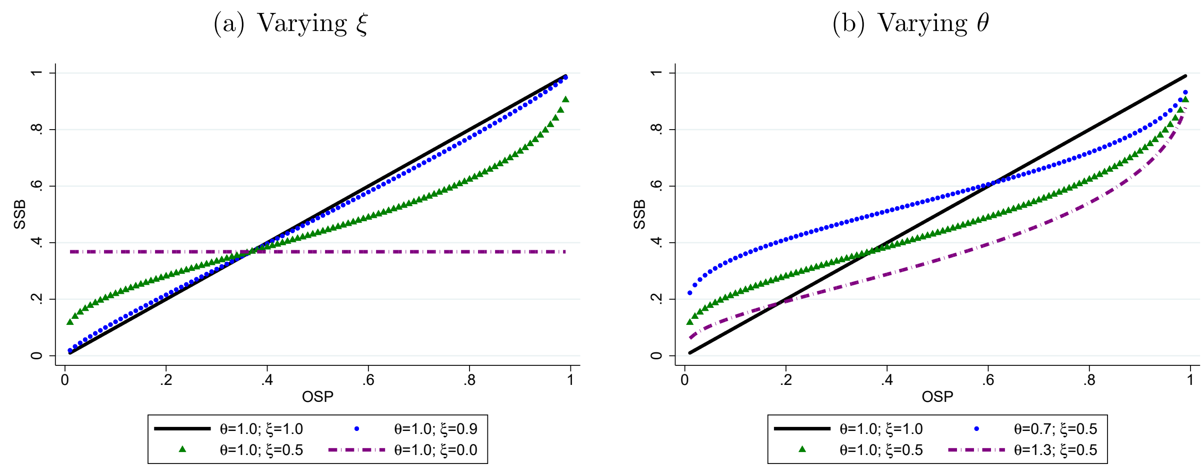
Specifically, we employ the probability weighting function suggested by Prelec (1998) and accordingly map OSPs into SSBs by

$$SSB = \left(\exp\left(-\left(-\ln\left(OSP\right)\right)^{\xi}\right)\right)^{\theta} \tag{3}$$

for parameters $\xi \geq 0, \theta \geq 0$. These two parameters control the elevation and the curvature of the function, which can be interpreted as measures of optimism and likelihood insensitivity, respectively. To see this, observe that for $\xi = \theta = 1$, function (3) coincides with the 45-degree line. Holding θ constant at one, an increase of ξ above one leads to a S-shaped pattern and a decrease below one leads to an inverse S-shape, where the intersection with the 45-degree line is at the objective probability of $OSP = \exp(-1) \approx 0.37$. This dependency on ξ is illustrated in Panel (a) of Figure 3, where we decrease ξ from one towards zero giving rise to an inverse S as in the data of Figure 2. In the limit where $\xi = 0$, the curve is flat. Hence, ξ can be interpreted as a measure of likelihood insensitivity. In Panel (b) we show that decreasing θ leads to an upward shift of the PWF, whereas increasing θ leads to a downward shift. Accordingly, θ can be interpreted as a measure of optimism/pessimism.

It is instructive to emphasize three different effects by use of Figure 3. Suppose that with age relative pessimism θ increases. For all OSPs, this induces stronger underestimation (Panel (b)). At the same time, however, OSPs decrease with age to the effect that the mass of the population lives to the left of the intersection of the PWF with the 45-degree line. This

Figure 3: Pessimism and Likelihood Sensitivity in Stylized PWF



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 $\theta \in [0.7, 1, 1.3]$.

movement of OSPs induces overestimation in old age. If with age also likelihood sensitivity, ξ, decreases, the corresponding flattening of the PWF leads to additional overestimation of OSPs at low OSP levels (Panel (a)).

4.2 Age-Dependent Probability Weighting Functions

Due to the age pattern in the data, cf. Figure 2, we proceed by specifying an age-dependent probability weighting function and accordingly model the subjective belief of individual i to survive from age h to some future age $h + t$ as

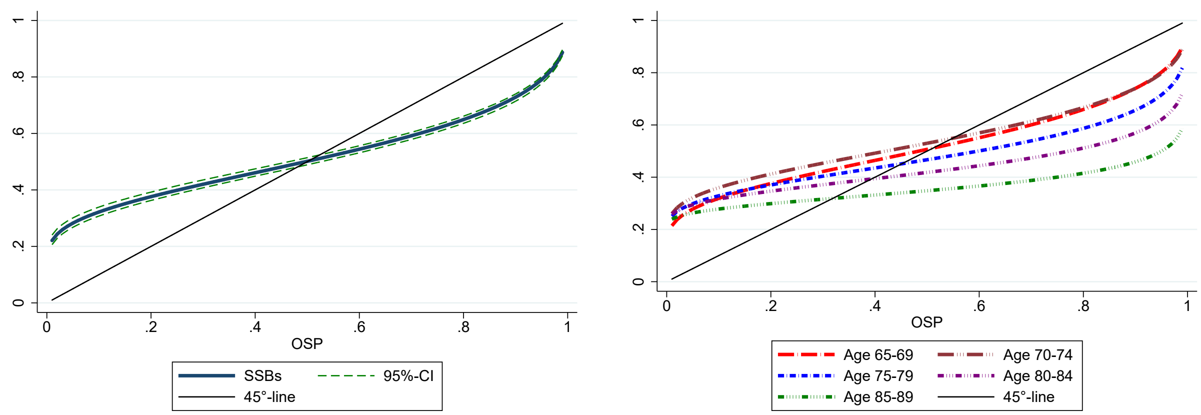
$$SSB_{i,h,h+t} = \left(\exp\left(-\left(-\ln\left(OSP_{i,h,h+t}\right)\right)^{\xi_h}\right)\right)^{\theta_h}. \tag{4}$$

for a given $OSP_{i,h,h+t}$ with age specific parameters θ_h, ξ_h. At the estimation we restrict parameters ξ_h, θ_h 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 $\theta_h = \bar{\theta}_{m(h)}$. We identify these parameters by estimating (4) for $h + t = m(h)$, adding an additive error term $\epsilon_{i,h,m(h)}$ to the equation and minimizing the Euclidean distance between the predicted and reported SSBs for each individual in group $m(h)$. Figure 4 shows the predicted average PWF with corresponding bootstrapped 95% confidence intervals in Panel (a) and predicted target age group specific

PWFs in Panel (b).[11] For the full sample we observe a quite symmetric PWF intersecting the 45-degree line close to 0.5. The age-specific PWFs in turn become flatter with increasing age, and, with the exception of interview age group 70-74, their intersection with the 45-degree line is at lower values for older ages—it is at approximately 55 percent for age group 65-69 and at approximately 40 percent for age group 80-84.

Figure 4: Estimated Non-linear Probability Weighting Functions

(a) PWF with full sample (b) Age-specific PWF



Notes: Estimated Prelec PWFs for the full sample in Panel (a)—including 95%-confidence intervals—and for different age groups in Panel (b).

Figure 5 depicts the corresponding parameter estimates $\xi_h = \bar{\xi}_{m(h)}, \theta_h = \bar{\theta}_{m(h)}$ with bootstrapped 95% confidence intervals. The coefficient estimates $\xi_h = \bar{\xi}_{m(h)}$, shown in Panel (a), are decreasing in h, reflecting increasing likelihood insensitivity. Similarly, estimates $\theta_h = \bar{\theta}_{m(h)}$, shown in Panel (b), are increasing between interview age groups 70-74 and 85-89, while there is a non-monotonicity before. We can thus conclude that pessimism (or, the opposite of optimism) increases for ages above 70.

These findings suggest that the overestimation of SSBs at ages 75 and older documented in Figure 1 cannot be explained by increasing optimism, as one may suspect. It is rather due to the flatness of the PWF and the reduction of OSPs, with age-increasing likelihood insensitivity further increasing the flatness of the PWF and thus additionally adding to

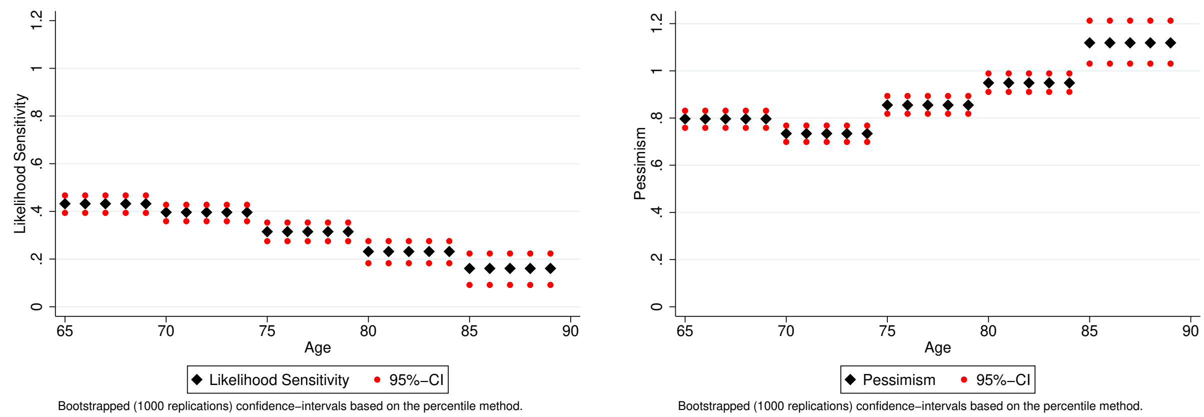
[11] Since our data are clustered, we perform a cluster bootstrap that samples the clusters with replacement. Thus, in each bootstrap, we solve

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

Standard errors are computed using the percentile method.

Figure 5: Estimated Prelec Parameters: Likelihood Sensitivity and Pessimism

(a) Likelihood Sensitivity ξ_h (b) Pessimism θ_h



Notes: This figure shows estimates of $\xi_h = \bar{\xi}_{m(h)}$ in Panel (a), estimates of $\theta_h = \bar{\theta}_{m(h)}$ in Panel (b), and the bootstrapped (1,000 replications) 95% confidence intervals, which are based on the percentile method. *Source*: Own calculations, Health and Retirement Study (HRS).

the overestimation at low OSP levels. Thus, likelihood insensitivity is an (increasingly) important contributor to the overestimation of survival chances in old age.

However, our estimates may be biased by two features of the data. First, for the oldest two age groups our data is censored, because the long-run objective survival chances do not exceed 70%, respectively 50%, cf. Figure 2. This implies that our estimates of the PWFs extrapolate outside the sample for these age groups. Second, survival chances are naturally 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, whereas the respective other side is less limited. This may induce a flatness of the PWFs. We address these concerns in our subsequent regression analyses on the relationship between direct psychological measures and SSBs.

5 Psychological Measures and Survival Beliefs

Since our preceding structural interpretation of biased survival beliefs suggests that cognitive and motivational factors are important determinants for the formation of SSBs, we proceed by quantitatively evaluating the relationship between direct cognitive and motivational measures and SSBs. To this purpose we specify both parameters of the Prelec function—*relative optimism* and *likelihood insensitivity*—as linearly dependent on dispositional optimism and cognitive weakness and use proxies from the HRS for both variables.

On the basis of our estimates we then decompose the quantitative impact of these variables on subjective survival beliefs.

5.1 The Measures

From wave 8 onward, the HRS contains measures on *dispositional optimism* derived from the same statements[12] as in the Life Orientation Test-Revised (LOT-R).[13] This psychosocial information is obtained in each biennial wave from a rotating (random) 50% of the core panel of participants who complete the enhanced face-to-face interview (EFTF). Respondents are given various statements regarding a specific latent variable, and answers to questions of the form *"please say how much you agree or disagree with the following statements"* are rated on a scale from one (*strongly disagree*) to six (*strongly agree*). We take average scores for each question normalized to the $[0, 1]$ interval to construct an index for relative optimism, so that higher values mean more optimistic attitudes.[14]

Based on our cognitive interpretation of *likelihood insensitivity* (Wakker 2010), our proxy variable for it measures the cognitive weakness of the respondent. It is a version of a composite score taken from RAND and combines the results of several cognitive tests, such as the ability to recall a list of random words and to count backwards. In total, 35 questions are summarized in an ability score. We use it to create our index of cognitive weakness by subtracting the cognitive ability score from the maximal achievable value of 35—so that a higher score indicates higher cognitive weakness—and normalize it to the $[0, 1]$ interval.

Details on both measures of cognitive and motivational variables are provided in Appendix A. We subsequently use lagged variables as controls, denoting by $c_{i,h-2}$ the lag of cognitive weakness, and by $o_{i,h-2}$ the lag of optimism, respectively. Using lags allows us to treat these measures as weakly exogenous to avoid spurious correlation[15], and to interpret our findings on the relationship between cognitive and motivational measures and SSBs tentatively as causal.[16] We use the pooled HRS data from waves 8-12, i.e., years 2008-2014 which consists of $11,952$ observations. Table 2 shows the coefficients of simple regressions of standardized cognitive weakness and dispositional optimism on age. Interestingly, the age

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

[13]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; Scheier et al. 1994).

[14]We construct the uniform optimism score on the basis of questions regarding optimistic as well as pessimistic personality traits.

[15]E.g., health shocks may affect cognition and motivational attitudes directly and lead to adjustments of subjective survival beliefs.

[16]While the approach of using lags for causal identification is widespread in social sciences, this approach is not without criticism, cf. Bellemare et al. (2017). We therefore speak of a "tentative" causal interpretation.

trends coincide with those of the implicit measures we backed out from the estimated PWFs in Section 4 and they are much stronger for cognitive weakness than for optimism.

Table 2: Regressing Cognitive and Motivational Variables on Age

	Cognitive Weakness	Dispositional Optimism
Age	0.045***	-.0071***
Constant	-3.36***	0.532***
Observations	48,081	21,182

Notes: This table reports coefficients for simple regressions using *standardized* cognitive weakness and *standardized* optimism as dependent variable and age as the independent variable.

5.2 Parameterizing the Non-linear PWF

As our parameterized variant of the Prelec (1998) function we postulate that for each individual in the sample i and each age h, the implicit measures of cognition, $\xi_{i,h}$, and optimism, $\theta_{i,h}$, from equation (4) are linearly dependent respective psychosocial variable:

$$\xi_{i,h} = \xi_0 + \xi_1 c_{i,h-2} \tag{5a}$$

$$\theta_{i,h} = \theta_0 + \theta_1 o_{i,h-2} \tag{5b}$$

Replacing in (4) the age-specific parameters ξ_h and θ_h with the individual and age-specific parameters $\xi_{i,h}, \theta_{i,h}$ and using (5), our specification of survival beliefs is

$$SSB_{i,h,m(h)} = \left(\exp\left(-\left(-\ln\left(OSP_{i,h,m(h)}\right)\right)^{\xi_0+\xi_1 c_{i,h-2}}\right)\right)^{\theta_0+\theta_1 o_{i,h-2}}, \tag{6}$$

We add error term $\epsilon_{i,j,m(h)}$ and estimate equation (6) by nonlinear least squares.

Turning to the parameters of interest in specification (6), we refer back to our analysis of Section 4, in particular to the illustration in Figure 3. In light of our discussion there, parameters ξ_0 and θ_0 capture a *base effect* in subjective beliefs. With regard to the base effect in cognition, ξ_0, we conjecture that this base effect exists in form of an inverse S, and we therefore expect $\xi_0 \in (0, 1)$. This may reflect an initial degree of cognitive weakness (with measured cognitive weakness index at zero), incomplete statistical learning, (rational) inattention with respect to objective survival probabilities, rounding, or a statistical artifact from truncation of the data. With regard to optimism recall that $\theta_0 < 1$ reflects rather optimistic beliefs, whereas $\theta_0 > 1$ reflects rather pessimistic beliefs. Since our measure of optimism is normalized to 0 for the least optimistic persons in the sample, we expect that $\theta_0 > 1$. Also, recall that a lower likelihood sensitivity leads to a flatter PWF. Therefore, if changes in cognitive weakness are relevant for the formation of subjective beliefs, we would find its coefficient to be negative, $\xi_1 < 0$. Finally, since increasing relative optimism reduces θ_h leading to a higher elevation of the PWF, we expect that $\theta_1 < 0$.

5.3 Quantitative Roles of Motivational and Cognitive Measures

Our baseline estimates summarized in Table 3 show that there is indeed a significant baseline inverse S-shaped transformation of objective survival probabilities, $\xi_0 = 0.54 < 1$, and the estimated probability weighting function is downward shifted, $\theta_0 > 1$. Our estimates also show that increasing lack of cognition leads to increasing likelihood insensitivity, $\xi_1 = -0.39$, flattening the non-linear PWF, and that increasing relative optimism leads to a significant upwards shift, $\theta_1 = -0.43$, of the non-linear PWF. Thus, cognitive and motivational factors have significant effects on the formation of subjective survival beliefs of the expected sign.

Table 3: The Effects of Cognition and Motivational Measures on Subjective Survival Beliefs

Cognitive Weakness Intercept (ξ_0)	0.540
	[0.477; 0.603]
Cognitive Weakness Slope (ξ_1)	-0.399
	[-0.566;-0.250]
Optimism Intercept (θ_0)	1.140
	[1.075; 1.214]
Optimism Slope (θ_1)	-0.433
	[-0.515; -0.358]
OSP_0	0.3678
	[0.3677;0.3685]
SSB_0	0.3197
	[0.2971; 0.3413]
AIC	4,125
Observations	11,954

Notes: Column 2 shows the point estimates. Bootstrapped 95% confidence intervals in brackets (1000 replications, computed with percentile method). AIC: Akaike (1973) information criterion. *Source:* Own calculations, Health and Retirement Study (HRS).

To separately quantify the impact of the respective variables of interest, we further decompose the probability weighting function as

$$\text{base bias:} \quad SSB^b_{i,h,m(h)} = \Big(\exp\Big(-\big(-\ln\big(OSP_{i,h,m(h)}\big)\big)^{\xi_0}\Big)\Big)^{\theta_0} \tag{7a}$$

$$\text{base + cogn. weakn.:} \quad SSB^{bc}_{i,h,m(h)} = \Big(\exp\Big(-\big(-\ln\big(OSP_{i,h,m(h)}\big)\big)^{\xi_0+\xi_1 c_{i,h-2}}\Big)\Big)^{\theta_0} \tag{7b}$$

and thus we define as the *base bias*, the $SSB^b_{i,h,m(h)}$ for individuals with optimism and cognitive weakness indices at zero. The SSB for the *base bias plus cognitive weakness* $SSB^{bc}_{i,h,m(h)}$ additionally takes into account the effects of increasing cognitive weakness. We accordingly define the contribution of the respective factors on the SSB by the differences

$$\text{cogn. weakn.:} \quad \Delta SSB^c = SSB^{bc}_{i,h,m(h)} - SSB^b_{i,h,m(h)} \tag{8a}$$

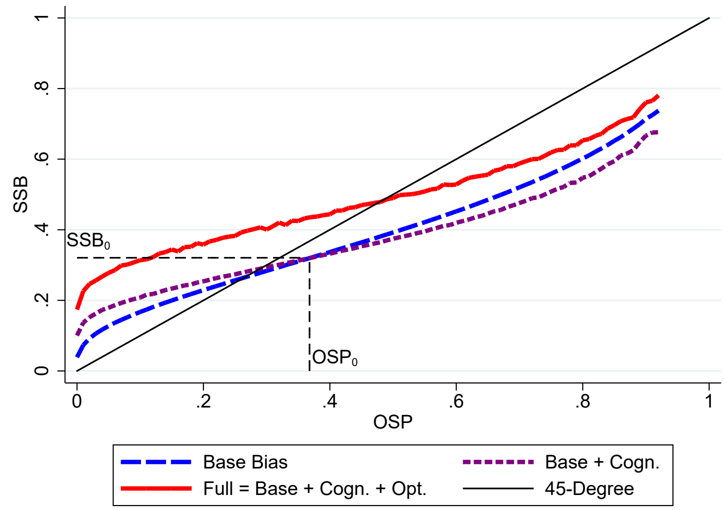
$$\text{optimism:} \quad \Delta SSB^o = SSB_{i,h,m(h)} - SSB^{bc}_{i,h,m(h)} \tag{8b}$$

In our decomposition analyses we first predict models (7) and the respective contributions (8) for each individual in the sample and then compute sample averages. We further define by OSP_0 the level of the objective survival probability at which the base bias $SSB^b_{i,h,m(h)}$ intersects with the base bias plus cognition $SSB^{bc}_{i,h,m(h)}$ and the associated SSB is denoted by SSB_0—i.e., to quantify the effects of cognition we pivot the probability weighting function around point (OSP_0, SSB_0), with respective estimates as sample averages of the individual specific intersections reported in Table 3.

Results on the predictions for the full model and its decomposition are displayed in Figure 6. The predicted base bias $\widehat{SSB}^b$ displays a pronounced inverse S reflecting the underlying misperception of survival chances mentioned above. Predictions for the base bias plus changes in cognitive weakness $\widehat{SSB}^{bc}$ lead to a clockwise rotation of the PWF around $(\widehat{OSP}_0, \widehat{SSB}_0)$. The additional effect of optimism shifts the PWF upward by more than 10%p. As a consequence of both mechanisms, the PWF in the full model is both flatter and shifted upwards relative to the base PWF.

Figure 7 provides the corresponding decomposition over age. Panel (a) shows the data on SSBs and OSPs—i.e., the data points of Figure 1—, as well as the predicted values for the full model—displaying a very close match to the average SSBs by age—and for the base bias. Consistent with our findings in Figure 6, the base bias features an age increasing underestimation relative to the full model. Panel (b) displays the sample average (conditional on age) contributions to the formation of SSBs of changes in cognitive weakness, optimism and of both according to our respective definitions in equation (8). Due to the age increasing cognitive weakness, individuals, on average, overestimate their survival chances increasingly

Figure 6: Decomposition of Non-linear PWFs



Notes: Sample averages of predicted non-linear probability weighting functions according to equations (6) and (7); “base bias”: $\widehat{SSB}^b$; “base + cogn. weakn.”: $\widehat{SSB}^{bc}$; “full”: $\widehat{SSB}$.

more as they grow older: relative to the base bias, cognitive weakness initially leads to a downward bias of almost -5%p because relatively young individuals have relatively higher objective survival chances on average and thus the clockwise tilting of the PWF leads to underestimation. Since with age objective survival rates decrease this initial underestimation turns into an overestimation of about +5%p for the oldest age group. Furthermore, over the life-cycle optimism leads individuals to overestimate their survival chances by roughly 10%p.

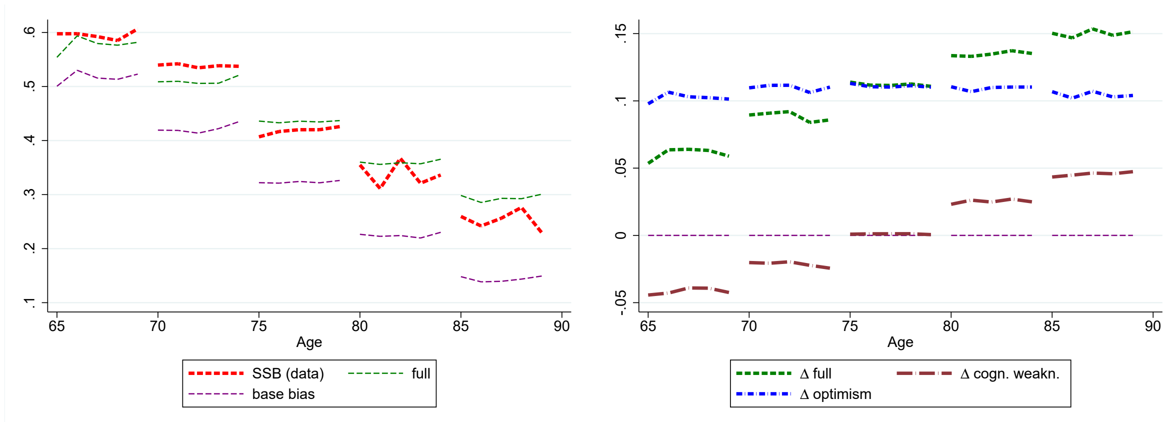
Overall, the effects of cognitive and motivational variables on subjective survival beliefs are therefore quite strong. Importantly, the effects of cognitive weakness is changing with age, whereas the effect of optimism is constant. Therefore lack of cognition rather than optimism plays an increasingly important role for the observed overestimation of SSBs.

5.4 From Structural to Reduced Form Approaches

Our identification of these mechanisms partially rests on our structural interpretation of the data combined with the non-linear functional form assumption on the PWF. As sensitivity analyses we relax these assumptions in a stepwise manner, by considering a linear functional form and by subsequently moving towards reduced form approaches. As a linear model we consider a neo-additive PWF (Chateauneuf et al. 2007), which is linear for interior survival

Figure 7: Non-Linear PWF: Decomposition over Age

(a) Full model and Base Bias (b) Additional Effects against Base Bias



Notes: Sample averages of predicted subjective survival beliefs according to equations (6) and (7) by age; Panel (a): "full": $\widehat{SSB}$; "base bias": $\widehat{SSB}^b$; Panel (b): "Δ full": $\widehat{SSB} - \widehat{SSB}^b$; "Δ cogn. weakn.": $\widehat{SSB}^{bc} - \widehat{SSB}^b$; "Δ optimism": $\widehat{SSB} - \widehat{SSB}^{bc}$.

probabilities $OSP_{i,h,h+t} \in (0, 1)$, thereby approximating the non-linear model as

$$SSB_{i,h,h+t} = (1 - \theta_h^l)(1 - \xi_h^l) + \xi_h^l OSP_{i,h,h+t} \tag{9}$$

where $\xi_h^l \in [0, 1]$, $\theta_h^l \in [0, 1]$ are parameters that are the analogues to parameters ξ_h and θ_h of the non-linear specification in (4). To see this observe that ξ_h^l controls the slope of the function, whereby for $\xi_h^l = 1$ the line in (9) corresponds with the 45-degree line; it can thus be interpreted as a measure of likelihood insensitivity. Likewise, $1 - \theta_h^l \in [0, 1]$ determines the intersection of (9) with the 45-degree line, whereby the intersection moves down when θ_h^l increases; it can thus be interpreted as a measure of relative pessimism.

Next, as for the non-linear model let $m(h) = h + t$ and use (5) in (9) to get

$$SSB_{i,h,m(h)} = ((1 - \theta_0) - \theta_1 \cdot o_{h-2}) ((1 - \xi_0) - \xi_1 \cdot c_{h-2}) + (\xi_0 + \xi_1 \cdot c_{h-2}) \cdot OSP_{i,h,m(h)}. \tag{10}$$

Now let $OSP_0 = 1 - \theta_0$ and observe that the decomposition analogous to (7) is

$$SSB^b_{i,h,m(h)} = OSP_0 \cdot (1 - \xi_0) + \xi_0 \cdot OSP_{i,h,m(h)} \tag{11a}$$

$$SSB^{bc}_{i,h,m(h)} = SSB^b_{i,h,m(h)} + \xi_1 \cdot c_{h-2} \cdot \left(OSP_{i,h,m(h)} - OSP_0\right), \tag{11b}$$

$$SSB_{i,h,m(h)} = SSB^{bc}_{i,h,m(h)} - \theta_1 \cdot (1 - \xi_0) \cdot o_{h-2} + \theta_1 \cdot \xi_1 \cdot (c_{h-2} \cdot o_{h-2}) \tag{11c}$$

and notice from (11a) and (11b) that—unlike in the non-linear model—the intersection of SSB^b with SSB^{bc} is exactly on the 45-degree line at $OSP_0 = 1-\theta_0 = SSB_0$. Also observe from (11b) that the "pure" (i.e., ignoring interactions with the motivational variable optimism) marginal effect of an increase of cognitive weakness at a given OSP is $\xi_1 (OSP - OSP_0)$. For $\xi_1 < 0$ we find that increasing cognitive weakness gives rise to stronger underestimation for $OSP > OSP_0$, and to stronger overestimation for $OSP < OSP_0$, just as in the non-linear model. Likewise, from (11c) the marginal effect of an increase of optimism is given by $\theta_1 (1 - \xi_0)$, and we hence expect that $\theta_1 (1 - \xi_0) > 0$.

The reduced form specification follows from rewriting (10) as

$$SSB_{i,h,m(h)} = \beta_0 + \beta_1 \cdot OSP_{i,h,m(h)} + \beta_2 \cdot \left(c_{h-2} \cdot OSP_{i,h,m(h)}\right) + \\ \beta_3 c_{h-2} + \gamma_1 o_{h-2} + \gamma_2 \cdot (o_{h-2} \cdot c_{h-2}), \quad (12)$$

where the structural model parameters map into the regression coefficients by

$$\beta_0 = OSP_0 (1 - \xi_0), \beta_1 = \xi_0, \beta_2 = \xi_1, \beta_3 = -OSP_0\xi_1, \gamma_1 = -\theta_1(1 - \xi_0), \gamma_2 = \theta_1\xi_1. \quad (13)$$

Since the reduced form does not exactly identify all parameters of the structural model—there are 6 parameters in the reduced form and 4 parameters in the structural model—we impose at the estimation the additional restrictions implied by (13) of

$$\beta_3 = -\frac{\beta_0 \cdot \beta_2}{1 - \beta_1} \text{ and } \gamma_2 = -\frac{\beta_2}{1 - \beta_1}\gamma_1. \quad (14)$$

The results from estimating (12) subject to the restrictions (14) are summarized as Model 1 in Table 4. All coefficient estimates are of the expected sign and significantly different from zero. The decomposition shows very similar patterns to Figure 7. Relative to those results the effects of cognitive weakness are slightly downward shifted—initially there is still a downward bias of about -5%p, but in the oldest age group there is an upward bias of only 3%p—and the effect of optimism is upward shifted—now leading to a constant overestimation by roughly 13%p, cf. Figure 12 in Appendix B.

We next interpret (12) as a reduced form specification and correspondingly estimate it without imposing the additional restrictions in (14). Apart from the constant this mainly affects our estimate of the effects of cognitive weakness and of OSP_0, which we again identify as the intersection point of SSB^c with SSB^{bc}. As we show in the decomposition in Figure 12 in Appendix B not imposing the restrictions in (14) mainly implies that we lose an anchor of the base bias so that the additional effects of cognitive weakness are now significantly

Table 4: Linear Models: The Effects of Cognition and Motivational Measures on Subjective Survival Beliefs

	(1) Restricted model	(2) Simple OLS model	(3)
Constant (β_0)	0.090	-0.007	-20.194
	[0.068; 0.115]	[-0.082; 0.068]	[-37.429;-3.370]
OSP (β_1)	0.624	0.607	0.537
	[0.552; 0.691]	[0.535; 0.677]	[0.426;0.637]
OSP $\times$ Cog. Weak. (β_2)	-0.384	-0.302	-0.359
	[-0.574; -0.202]	[-0.509; -0.114]	[-0.552;-0.174]
Cognitive Weakness (β_3)	0.092	0.319	0.205
	[0.047; 0.141]	[0.139; 0.509]	[0.032;0.379]
Optimism (γ_1)	0.131	0.234	0.162
	[0.099; 0.169]	[0.139; 0.325]	[0.071;0.241]
Optimism $\times$ Cog. Weak. (γ_2)	0.134	-0.118	0.041
	[0.070; 0.203]	[-0.349; 0.156]	[-0.184;0.299]
OSP_0	0.242	0.923	0.589
	[0.195; 0.291]	[0.405;1.250]	[0.156;1.065]
Additional Controls	No	No	Yes
AIC	4102	4087	3522
Observations	11,954	11,954	11,898

Notes: Column 2 shows estimates of the linear model, column 3 shows estimates of the linear model without restriction (14), column 4 adds control variables. Bootstrapped 95% confidence intervals in brackets (1000 replications, computed with percentile method). AIC: Akaike (1973) information criterion. OSP_0 defined as the intersection between SSB^b and SSB^bc

upward shifted, ranging from $+4\%p$ to $+13\%p$. While thus the level of the cognitive weakness effect is shifted, the overall differential effect over the life-cycle of about 9%p is unchanged relative to the baseline specification so that increasing cognitive weakness leads to increasing overestimation. We also again find that relative optimism induces to a relatively constant upward shift, now of about 14%p.

Finally, we add control variables to the RHS of (12). The relevance of control variables can be motivated by the notion that in a decision situation under uncertainty individuals may only be imperfectly informed by the respective OSP and instead condition their assessment of their SSB also on other variables. A related interpretation is based on formal statistical learning models according to which individuals learn their individual OSP by obtaining more information. This suggests that they base their survival beliefs on the OSP and additional variables as well as cognitive and motivational factors. Thus adding control variables can be interpreted as a *snapshot* of a reduced form learning model, as in Viscusi (1985) and Smith et al. (2001), and for biased beliefs in Ludwig and Zimper (2013) and Groneck et al. (2016). We include the same set of control variables we use for the estimation of the objective survival beliefs. Results are reported as Model 3 in Table 4 and estimates for the control variables are contained in Table 9 of Appendix B (which are of the expected sign and are in line with findings in the literature). As the main effect, the estimate on the objective survival rate decreases, which reflects that now the additional controls soak up objective survival information. All other coefficient estimates are close to those from the structural Model 1, respectively the confidence intervals overlap. With the additional control variables, we now fit average subjective beliefs by age in the full model quite well. Otherwise, the decomposition in Figure 12 is similar to what we have seen for the structural Model 1 and our baseline results in Figure 7. The effects of cognitive weakness range from -2% to 7% thus a similar range as before and the effect of optimism is roughly constant at 12%p.

Additional robustness analyses (i) with ad hoc reduced form specifications, (ii) for quantile regressions, (iii) with respect to focal point answers, and (iv) for an extension of the non-linear model are presented in our Online Appendix. These findings confirm our main results in a sense that the quantitative contribution of cognition is monotonically increasing over the life-cycle with a differential effect of about 9%p and a roughly constant overestimation through optimism. If anything we find that the effect of optimism is decreasing with age (in robustness analysis (iv)).

6 Concluding Discussion on Economic Implications

This paper analyzes the effects of cognitive weakness and optimism on the formation of subjective survival beliefs in the HRS through the lens of inverse S-shaped probability weighting functions. Our main finding suggests that the age patterns of biases in survival beliefs documented in many studies are driven by increasing cognitive weakness inducing a monotonically increasing bias in survival misconception from an underestimation of survival beliefs by -5%p at age 65-69 to an overestimation by 5%p at age 85-89. On the contrary, the quantitative effect of optimism is roughly constant leading to an overestimation by about 10%p for all age groups. Thus, cognitive weakness rather than optimism is an increasingly important contributor to overestimation of survival chances in old age.

What are the economic implications of our findings? If we were to use our parameter estimates in a life-cycle model of consumption and savings in order to calibrate subjective survival beliefs we would conclude with similar findings as in Groneck et al. (2016) and accordingly report that life-cycle models with biased survival beliefs substantially improve the model fit to data on life-cycle asset holdings, relative to a rational expectations benchmark. The key mechanism is that the overestimation of survival beliefs in old age leads households to hold on to their assets and thus partially resolves the old-age dissaving puzzle. However, psychological attitudes may also bias other beliefs—e.g., income expectations (Dominitz and Manski 1997; Rozsypal and Schlafmann 2017)—and may directly affect pure time discounting through cognitive processes (Binswanger and Salm 2017; Gabaix and Laibson 2017). If cognitive weakness leads to an increase of presence bias as in the theoretical work by Gabaix and Laibson (2017) then this constitutes an opposing force on effective time discounting to the one induced by increasing overestimation of survival beliefs. Related, optimism may induce households to overestimate their retirement incomes leading to lower savings, which is again a countervailing force to the effect of optimism on effective time discounting through the overestimation of survival beliefs. We therefore caution against the use of subjective survival beliefs in life-cycle models of consumption and savings to study their implications for savings behavior in a ceteris paribus manner. Our results rather suggest that an important avenue of future research is to apply our methods to other expectations data, to study the empirical relationship between cognition and pure time discounting and to explore simultaneously the consequences of various psychological mechanisms in calibrated life-cycle models.

Appendix

A Data Appendix

The main data used in this paper is the Health and Retirement Study (HRS). The HRS is a national representative panel study on a biennial basis, see Juster and Suzman (1995) for an overview.[17] The main purpose of the HRS is to contribute a rich panel data set to the research of retirement, health insurance, saving, and economic well-being. Since 2006 (wave 8) the HRS is complemented by 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).[18] Thus, longitudinal data are available in four-year intervals and therefore the first panel with psychosocial variables is provided in 2010.

A.1 Estimation of Objective Survival Probabilities (OSP)

We estimate the objective survival probability (OSP) as a counterpart for the subjective belief to survive (SSB) to a certain target age. We use the HRS to estimate conditional hazard rates for mortality. These hazards are estimated conditional on various characteristics of the individual and on a trend-adjusted average objective survival probability. The hazard rates are used to compute individual specific objective survival probabilities (OSPs).

We use nine waves of the HRS (years 1998−2014).[19] We restrict our sample to individuals older than 64 and younger than 99. We choose all observations when respondents enter the HRS (which can be at different waves) within our observed time period. This sample at initial state consists of $21,435$ respondents. The average age is 70.7 and 43% of them are males. 42% of individuals die within the observed time interval of at most 17 years. The covariates used for the estimation are summarized in Table 5. We use demographic variables (age, gender, and marital status), and a wide set of health variables. We choose four sets of health variables. First, we use self-reported health, a measure where the individual can rate its

[17] The survey is administered by the Institute for Social Research (ISR) at the University of Michigan and mainly funded by the National Institute of Aging (NIA).

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

[19] We exclude earlier waves due to consistency problems in how some variables were measured.

general health on a scale of one (=”excellent”) to five (=”poor”). We use indicator variables for each value where the reference group are individuals with a value of one (=”excellent”). Second, we construct three indices measuring functional limitations. The activities of daily living (ADL) index collects information whether the individual is able to bath, dress and eat alone. The Mobility index counts limitations with certain kinds of mobility (walking across a room, walking several/one blocks, climbing several/one flights of stairs). The limitation in muscle index counts whether the individual is able to sit for two hours, get up from a chair, being able to stoop, and/or push/pull large objects. All categorial variables are scaled such they can be interpreted as a higher number representing more limitations. Lastly, we take cognitive limitations into account (see further below for a detailed definition of this variable). Third, we take drug consumption variables into account (ever smoke, smoke now, ever drink). Fourth, we take a set of variables indicating the incidence whether the respondent ever had a certain (chronic) disease. In addition to demographic- and health variables, we include estimated average survival probability by gender and year of birth, in order to account for the time trend in life-expectancy. This probability is estimated using the Lee and Carter (1992) procedure employing the life-tables from the Human mortality database.[20] For all control variables, we take the first observation when the individual enters the sample. Hence, we treat the covariates as constant over time. The final number of observations used in the estimation reduces to $15,370$ due to many missing values for the health variables, see Table 5.

In Table 7 in Appendix we use the optimism variable in the current wave (not lagged) which decreases the sample size to $2,108$. The coefficient of optimism is showing the expected sign, -0.591, but is insignificant with a p-value of 0.19. Significance of optimism with the lagged variable and a smaller sample size is, naturally, even worse.

A.2 Descriptive Statistics on OSPs and SSBs

Figure 8 compares various average predicted survival probabilities from our model with the fraction of survivors in the data, ranging from 4 to 14 year survival probabilities. Note, that in our main analysis, we are mainly concerned with 10 to 15 year survival probabilities. The model fits the data well indicated by the points being close to the 45-degree line. It is important to note, though, that our model accounts for right-censoring and is therefore not meant to perfectly match the (right-censored) data.

[20]The Lee-Carter procedure decomposes mortality into a vector of age-specific constants and age-specific drift terms. These trends are then used to predict future survival probabilities until age 2090 to complete life tables on the basis of these estimates.

Table 5: Control Variables for the Hazard Model

	Mean	Std.Dev.	Obs.	Min	Max
Average Survival Probability					
Average 12yr survival probability (Lee-Carter)	58.89	23.93	21435	0	83
Demographic Variables					
Age	70.68	7.07	21435	65	98
Age^2	5046	1066	21435	4225	9604
Age^3	364193	121798	21435	274625	941192
Male	0.43	0.50	21435	0	1
Married/Partnered	0.64	0.48	21421	0	1
Health Variables					
Self-rated health (excellent)	0.10	0.30	21424	0	1
Self-rated health (very good)	0.26	0.44	21424	0	1
Self-rated health (good)	0.32	0.47	21424	0	1
Self-rated health (fair)	0.22	0.41	21424	0	1
Smoke (ever)	0.58	0.49	21251	0	1
Smoke (now)	0.13	0.33	21375	0	1
Drink (ever)	0.46	0.50	21432	0	1
Limitations: ADL Index	0.24	0.65	21435	0	3
Limitations: Mobility Index	1.19	1.56	18644	0	5
Limitations: Muscle Index	1.29	1.34	19434	0	4
Cognitive weakness (normalized)	0.36	0.15	19113	0	1
Ever had high blood pressure	0.53	0.50	21405	0	1
Ever had diabetes	0.19	0.39	21406	0	1
Ever had cancer	0.13	0.34	21390	0	1
Ever had lung disease	0.09	0.29	21411	0	1
Ever had heart disease	0.25	0.43	21408	0	1
Ever had stroke	0.09	0.29	21415	0	1

Notes: Average survival probability in percent, estimated with the Lee-Carter procedure using data from the HMD and SSA life-tables. Category health variables (ADL, Mobily and Muscle index) scaled such that higher values imply worse health conditions. *Ever had*-variables indicate diagnosed cases.

Table 6: Mixed Proportional Hazard Model

Average Survival Probability		
Average 12yr survival probability (Lee-Carter)	-0.0206***	(-2.75)
Demographic Variables		
Age	2.792***	(3.14)
Age^2	-0.0359***	(-3.02)
Age^3	0.000155***	(2.99)
Male	0.125	(1.50)
Married/Partnered	-0.0685**	(-2.12)
Health Variables		
Self-rated health (excellent)	-0.489***	(-6.57)
Self-rated health (very good)	-0.449***	(-7.29)
Self-rated health (good)	-0.307***	(-5.61)
Self-rated health (fair)	-0.186***	(-3.67)
Smoke (ever)	0.291***	(8.72)
Smoke (now)	0.584***	(13.50)
Drink (ever)	-0.160***	(-5.21)
Limitations: ADL Index	0.0267	(0.94)
Limitations: Mobility Index	0.150***	(10.58)
Limitations: Muscle Index	-0.0609***	(-4.13)
Cognitive weakness	0.978***	(9.17)
Ever had high blood pressure	0.126***	(4.24)
Ever had diabetes	0.378***	(10.16)
Ever had cancer	0.322***	(8.23)
Ever had lung disease	0.530***	(11.33)
Ever had heart disease	0.311***	(9.56)
Ever had stroke	0.173***	(3.61)
Constant	-76.52***	(-3.60)
Observations	15,373	
Log Likelihood	-10,172	
Duration dependence parameter α	1.644**	
Variance of Unobserved Heterog.	0.064**	

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The duration dependence parameter α refers to the baseline hazard $\lambda_0(t) = \alpha t_i^{\alpha-1}$. The unobserved heterogneneity estimate refers to the variance of the Gamma distribution of unobserved heterogneity. Limitations variables are defined such that higher values imply higher limitations. Positive (negative) signs of the coefficients imply a positive (negative) impact on the hazard of dying.

Table 7: Impact of Psychological Variables in the Hazard Model

Psycho and Cognitive Variables				
Optimism			-0.591	(-1.30)
Cognitive weakness	1.300*	(1.83)	1.107*	(1.69)
Average Survival Probability				
Average 12yr survival probability (Lee-Carter)	-0.181	(-1.12)	-0.174	(-1.11)
Demographic Variables				
Age	25.32	(1.33)	23.66	(1.29)
Age^2	-0.342	(-1.33)	-0.319	(-1.29)
Age^3	0.00150	(1.35)	0.00140	(1.30)
Male	-0.770	(-0.57)	-0.726	(-0.55)
Married/Partnered	-0.0745	(-0.36)	-0.0812	(-0.43)
Health Variables				
Self-rated health (excellent)	-1.355***	(-2.66)	-1.281***	(-2.59)
Self-rated health (very good)	-1.658***	(-4.57)	-1.614***	(-4.77)
Self-rated health (good)	-1.056***	(-3.75)	-1.022***	(-3.89)
Self-rated health (fair)	-0.568**	(-2.50)	-0.570**	(-2.55)
Smoke (ever)	0.571**	(2.46)	0.553**	(2.41)
Smoke (now)	0.486*	(1.92)	0.466**	(2.46)
Limitations: ADL Index	0.400***	(2.69)	0.388***	(2.69)
Drink (ever)	-0.311*	(-1.70)	-0.298	(-1.64)
Limitations: Mobility Index	0.147*	(1.68)	0.140*	(1.83)
Limitations: Muscle Index	-0.160*	(-1.68)	-0.155*	(-1.83)
Ever had high blood pressure	-0.149	(-0.80)	-0.145	(-0.79)
Ever had diabetes	0.484***	(2.64)	0.465***	(2.58)
Ever had cancer	1.086***	(4.35)	1.080***	(6.13)
Ever had lung disease	0.828***	(3.78)	0.835***	(4.17)
Ever had heart disease	0.380**	(2.10)	0.380**	(2.14)
Ever had stroke	0.240	(0.95)	0.214	(0.87)
Constant	-604.4	(-1.34)	-564.7	(-1.30)
Observations	2,108		2,108	
Log Likelihood	−485.9		−485.1	
Duration dependence parameter (α)	1.459		1.457	
Variance of Unobserved Heterog.	0.029		0.000	

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Comparison of model (1) without optimism and model (2) including optimism on a smaller subsample of individuals where optimism is available.

Figure 9 shows the distribution of OSPs for the full sample and each interview age group. Each subfigure also contains a red vertical line indicating the average objective survival probability for the respective age group. The histograms reveal that there is a significant dispersion of objective survival probabilities.

Figure 10 shows the corresponding distributions of SSBs. Average SSBs decrease as we move up across target age groups, as with OSPs. However, the movement is not as pronounced as for the OSPs and the difference in the averages depicted by the red lines in both figures just reflects the facts shown in Figure 1 of the main text. Second, there are focal point answers at SSBs of 0, 0.5 and 1. Observe that the fraction of individuals providing a focal point answer at 1 decreases whereas the fraction giving answer 0 increases when the target age increases. This indicates that focal point answers do have information content that goes beyond simple heuristics that individuals may apply when being confronted with such complicated questions about survival prospects.

A.3 Psychological Measures

From wave 8 onward, the HRS contains measures on optimism and pessimism, in section LB, the leave-behind questionnaires. Measures on *dispositional optimism* are derived from the same statements as in the well-known Life Orientation Test-Revised (LOT-R).

The following six questions are asked to the responded.

> Please say how much you agree or disagree with the following statements
>
> 1. If something can go wrong for me it will.
> 2. I'm always optimistic about my future.
> 3. In uncertain times, I usually expect the best.
> 4. Overall, I expect more good things to happen to me than bad.
> 5. I hardly ever expect things to go my way.
> 6. I rarely count on good things happening to me.

The answer scale is given by: 1 = Strongly disagree, 2 = Somewhat disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Somewhat agree, and 6 = Strongly agree.

We follow the documentation report, cf. Smith et al. (2017) to construct a measure of optimism from these questions. To this end, we recode question 1, 5, and 6 by reversing the answer pattern. Then we build a 6-item optimism score by averaging the scores across all questions. We set the score to missing if there is more than half of the answers missing.

In some studies, *optimism* and *pessimism* are measured separately, i.e., respondents are asked questions with negative connotations (pessimism) or positive connotations (optimism). The reason for separate measures is that these two concepts tend to display bi-dimensionality (Herzberg et al. 2006). In our sample, the two distinct measures (optimism consisting of question 1,5,6 and pessimism consisting of questions 2,3,4) have their peak at 1 (pessimism) and 5 and 6 (optimism) implying no strong bi-polarity. Hence, for the sake of simplicity, we follow the literature and treat optimism and pessimism as one dimension, cf. Carver and Scheier (2014).

We take the cognitive functioning total score ('RxACOGTOT') from RAND which summarizes a set of cognitive functioning measures into one index. One set of questions include immediate and delayed word recall (20 questions in total), asking to recall a number of words (e.g. a 10 or 20 word list) that were recalled correctly either immediately, or after a delay of 5 minutes. The second set of questions is a so-called mental status summary. This measure includes the serial 7s test, counting backwards, and naming tasks. The serial 7 test asks the individual to subtract 7 from the prior number, beginning with 100 for five trials. Counting backwards asks the respondent to count backwards for 10 continuous numbers from 20 and 86, respectively. The naming tasks comprise of correctly stating today's date, the name of the President and Vice-President, as well as naming certain objects (a cactus and scissors), and to give definitions of five given words (e.g. repair, fabric, domestic, remorse, plagiarize). The total cognition score sums all correctly answered questions on total word recall and the mental status summary scores, resulting in a range of 0-35. We reverse the RAND score of cognitive weakness by subtracting the cognitive ability score from the maximal achievable value 35. As a result, a higher score indicates higher cognitive weakness.

Table 8: Cognitive and Motivational Variables

	Min	Max	Mean	SD	N
Cognitive Variable					
Cognitive Weakness, normalized	0	1	0.387	0.149	48,081
Lagged Cognitive Weakness, normalized	0	1	0.377	0.142	42,445
Motivational Variables					
Dispositional Optimism, normalized	0	1	0.695	0.188	21,182
Lagged Dispositional Optimism, normalized	0	1	0.700	0.188	16,532

Notes: This table summarizes the sample moments our measure of cognitive weakness and the two motivational variables, dispositional optimism and pessimism. *Source:* Own calculations, Health and Retirement Study (HRS).

A.4 Bootstrap

Standard errors of the parameters of our regressions have to be corrected in order to account for the estimation variance of OSPs. We accommodate this by implementing a two-sample bootstrap procedure with 1000 replications to estimate the standard errors of our coefficient estimates.[21] In this procedure we correct for the estimation variance in objective survival probabilities as follows.[22] In each bootstrap replication we (i) draw a sample with replacement from the HRS sample used to estimate OSPs, (ii) estimate the OSPs, (iii) draw a sample with replacement from the cross-sectional sample used for regression analysis, (iv) perform regression analysis. Based on the resulting estimates we compute standard errors with the percentile method.

B Additional Results

B.1 Subjective Beliefs by Objective Survival Probability

Figure 11 shows SSBs by bins of OSPs over age. It shows that SSBs for given OSPs are decreasing in age from interview age group 70-74 on.

B.2 Decomposition of Linear Model

Figure 12 shows the decomposition of the linear model (12). Panels (a) and (b) are for the structural interpretation of the linear model additionally imposing the restrictions (14). Panels (c) and (d) are the respective results where we give equation (12) a full reduced form interpretation by accordingly not imposing these restrictions. Finally, Panels (e) and (f) show the results of that reduced form model with additional control variables.

B.3 Control Variables in Linear Model

Table 9 shows the results of our estimation for the control variables.

[21] We discard 8.5% of the bootstrap iterations that did not converge.

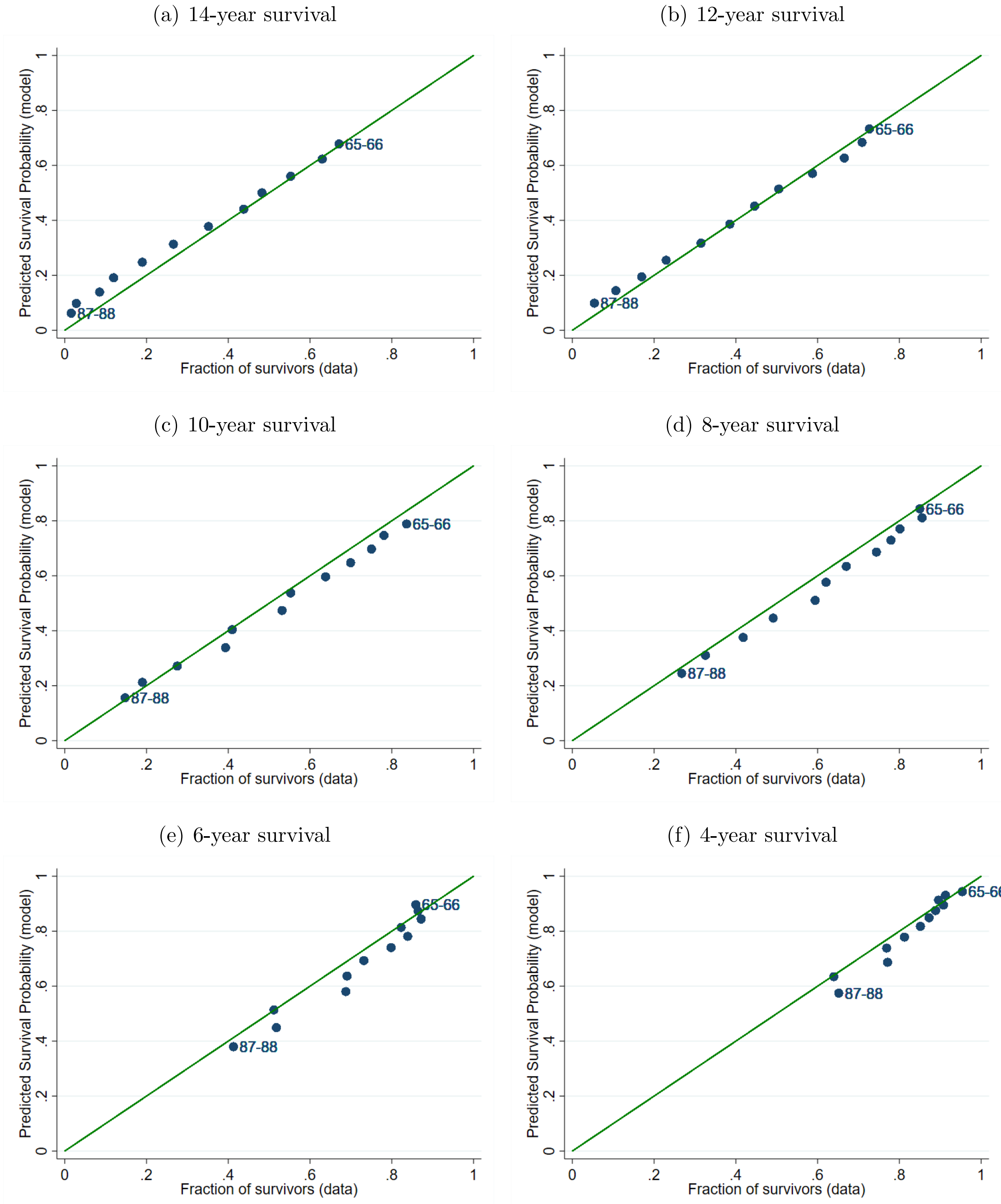
[22] Note, that our two samples are both based on the HRS dataset. The first sample is based on the sample used to estimate the OSPs and the second sample is used in the overall regression analyses.

Table 9: Linear Model: The Effects of Cognition and Motivational Measures on Subjective Survival Beliefs: Parameter Estimates on Control Variables

	coefficient	CI-	CI+
Average Survival Probability			
Average 12yr survival probability (Lee-Carter)	-0.003	-0.008	0.002
Demographic Variables			
Age	0.817	0.128	1.514
Age^2	-0.011	-0.020	-0.002
Age^3	0.000	0.000	0.000
Male	-0.020	-0.070	0.029
Married/Partnered	-0.020	-0.033	-0.005
Health Variables			
Self-rated health (excellent)	0.216	0.179	0.252
Self-rated health (very good)	0.154	0.123	0.185
Self-rated health (good)	0.108	0.082	0.138
Self-rated health (fair)	0.052	0.026	0.080
Smoke (ever)	0.035	0.019	0.052
Smoke (now)	0.011	-0.016	0.036
Drink (ever)	0.004	-0.011	0.018
Limitations: ADL Index	-0.004	-0.018	0.010
Limitations: Mobility Index	0.007	0.000	0.014
Limitations: Muscle Index	-0.005	-0.012	0.001
Cognitive weakness	0.105	0.038	0.164
Ever had high blood pressure	-0.004	-0.018	0.010
Ever had diabetes	0.028	0.009	0.046
Ever had cancer	0.002	-0.016	0.019
Ever had lung disease	0.035	0.011	0.057
Ever had heart disease	0.007	-0.008	0.023
Ever had stroke	0.033	0.009	0.054
Constant	-20.194	-37.429	-3.370
Observations	11,898		

Notes: Column 2 shows the point estimates, columns 3 and 4 the respective bounds of 95%-confidence intervals (CI- and CI+), which are calculated with the percentile method (1,000 replications).

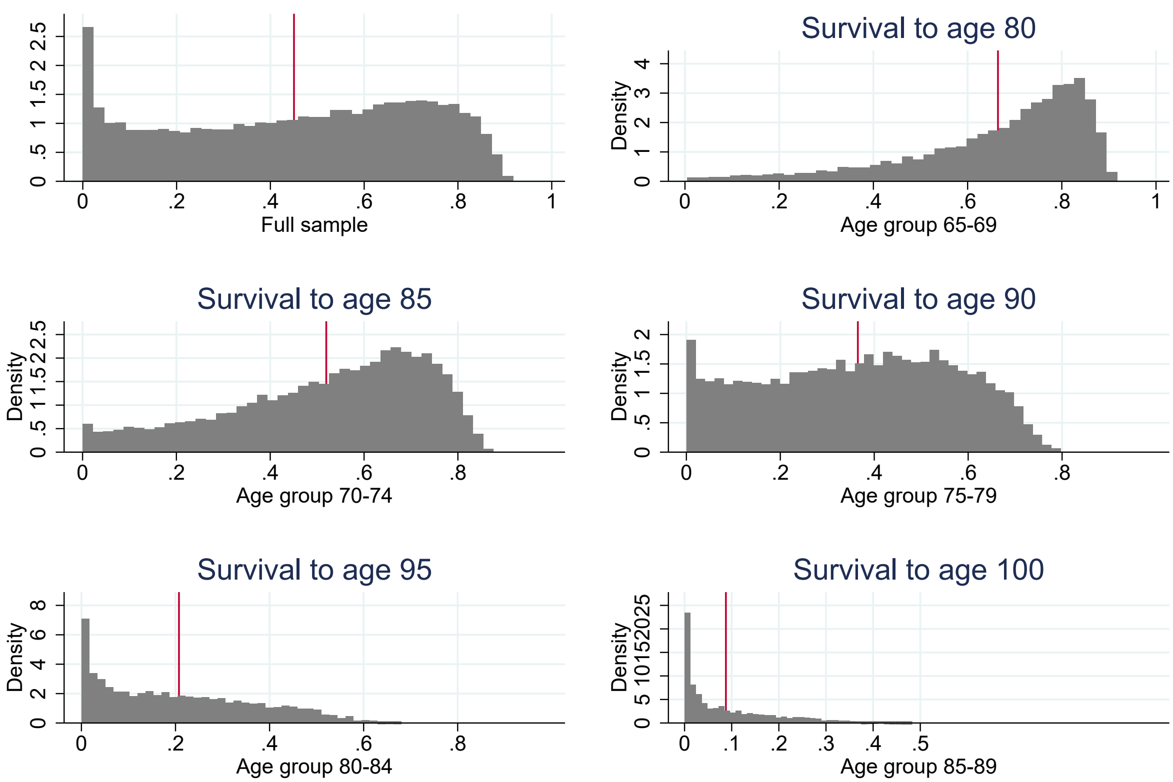
Figure 8: Objective survival probabilities: Model vs. Data



(a) 14-year survival (b) 12-year survival (c) 10-year survival (d) 8-year survival (e) 6-year survival (f) 4-year survival

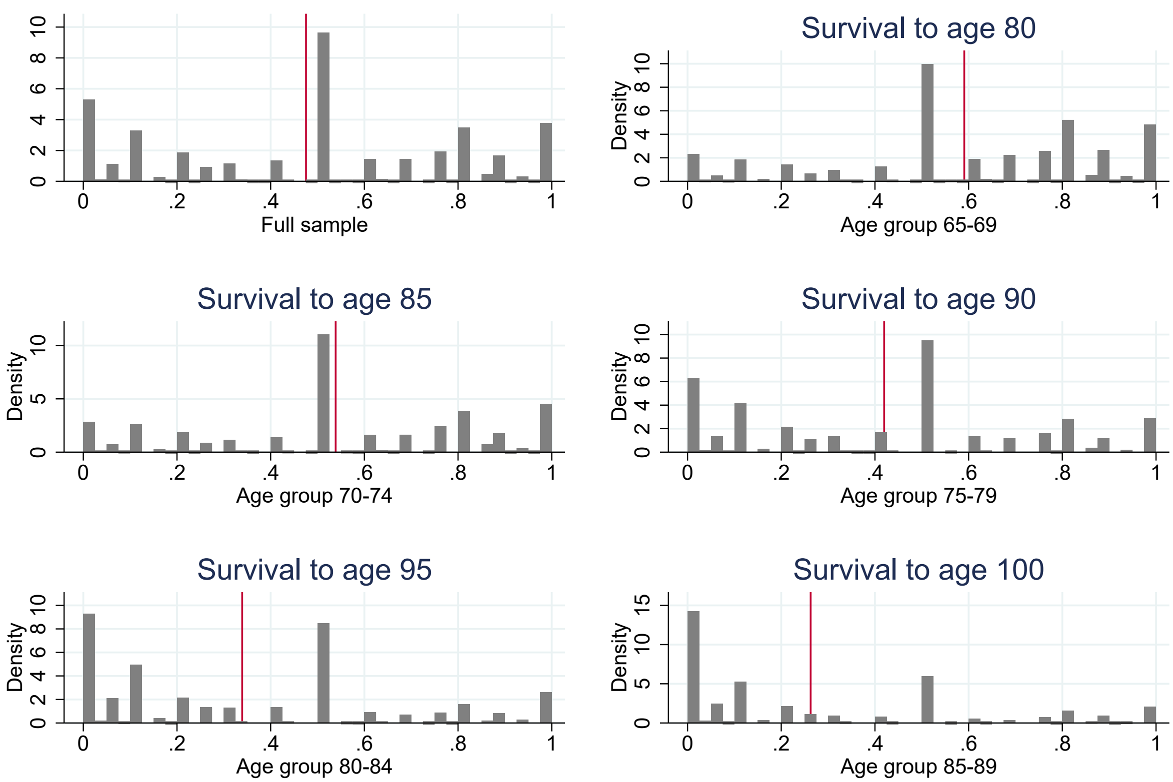
Notes: Plotting estimated average survival probabilities for different two-year agebins (blue dots) against the fraction of survivors from the data. Panels depict different time intervals ranging from 14 to 4 year survival probabilities, where the final year is always 2014, e.g., the 14 year survival probability corresponds to the fraction of people surviving between 1998 and 2014.

Figure 9: Histograms of OSPs



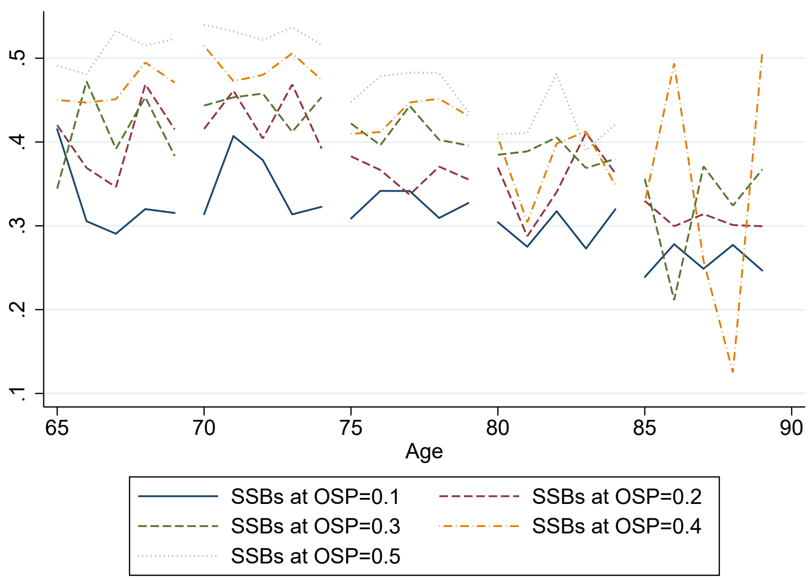
Notes: The red vertical line indicates the average objective survival probability. *Source*: Own calculations, Health and Retirement Study (HRS).

Figure 10: Histograms of SSBs



Notes: The red vertical line indicates the average subjective survival belief. *Source*: Own calculations, Health and Retirement Study (HRS).

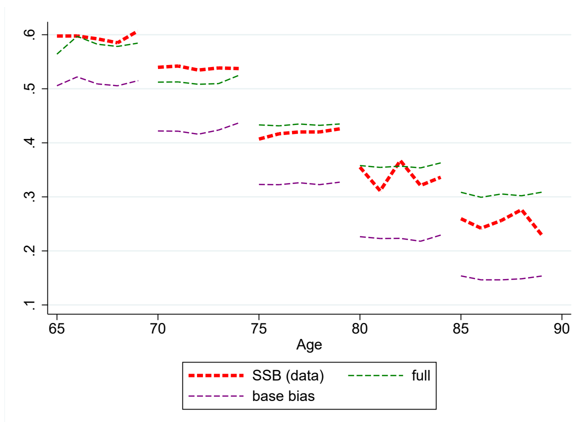
Figure 11: Subjective Survival Beliefs by Age Holding Constant Objective Survival Probabilities



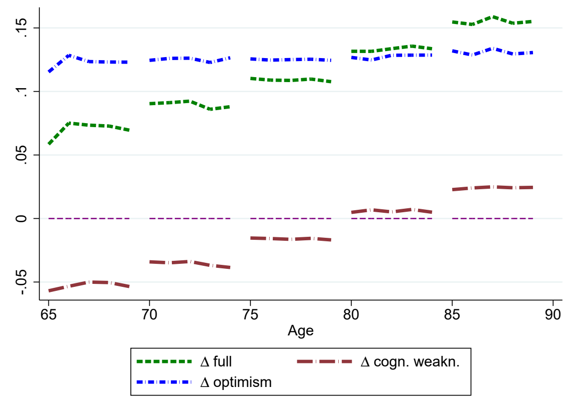
Notes: This figure shows average SSBs over age by OSP bins of $[0.05, 0.15)$, $[0.15 - 0.25)$, $[0.25 - 0.35)$, $[0.35 - 0.45)$, and $[0.45 - 0.55)$.

Figure 12: Neo-Additive (Linear) PWF: Decomposition over Age

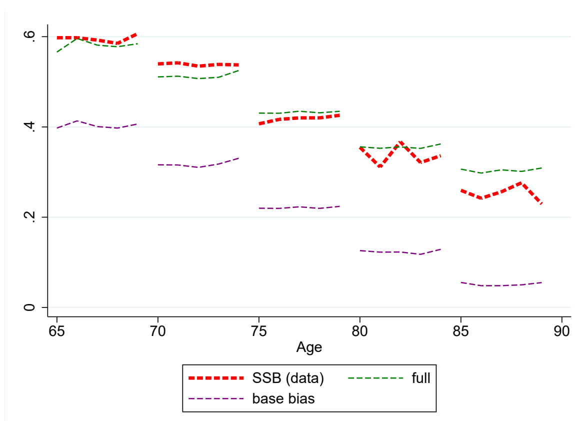
(a) Structural Model



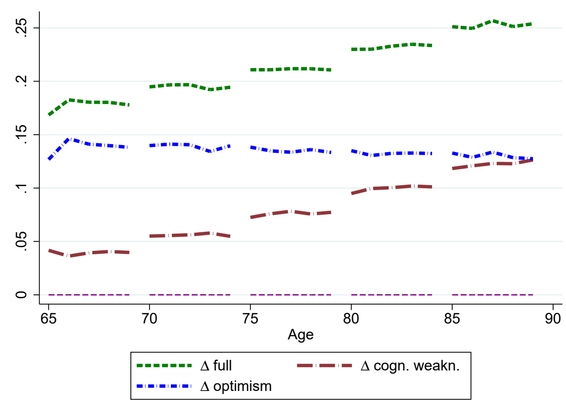
(b) Struct. Model: Additional Effects



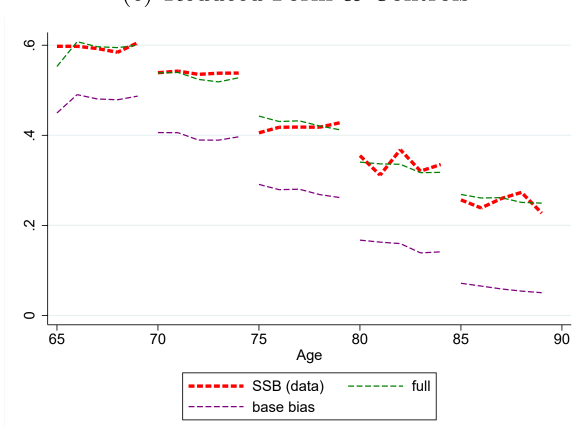
(c) Reduced Form



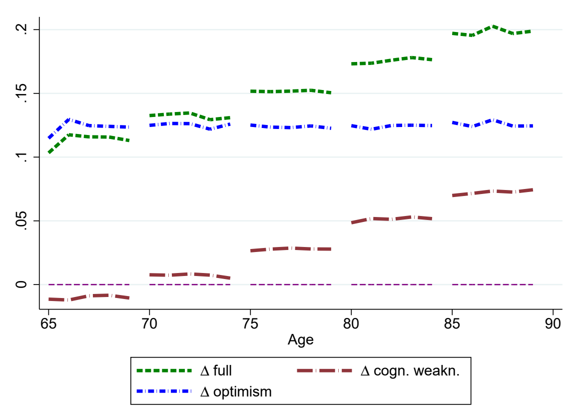
(d) Red. Form: Additional Effects



(e) Reduced Form & Controls



(f) Red. Form & Contr.: Add. Eff.



Notes: Sample averages of predicted subjective survival beliefs according to equations (12) and (11) by age; "full": $\widehat{SSB}$; "base bias": $\widehat{SSB}^b$; "Δ full": $\widehat{SSB} - \widehat{SSB}^b$; "Δ cogn. weakn.": $\widehat{SSB}^{bc} - \widehat{SSB}^b$; "Δ optimism": $\widehat{SSB} - \widehat{SSB}^{bc}$.

Online Appendix

A Reduced Form Regressions

We directly investigate the impact of psychological and cognitive measure on the biases of survival beliefs, which we define as the difference between subjective and objective probabilities, $SSB_{i,h,m(h)} - OSP_{i,h,m(h)}$. Without imposing any structural assumptions from theory, we estimate the following linear model

$$SSB_{i,h,m(h)} - OSP_{i,h,m(h)} = \beta_0 + \beta_1 c_{i,h-2} + \beta_2 o_{i,h-2} + \beta \mathbf{X_i} + \epsilon_{i,h,m(h)}.$$

As controls, we include objective survival probabilities, $OSP_{i,h,m(h)}$, interaction terms $c_{i,h-2} \cdot OSP_{i,h,m(h)}$, $o_{i,h-2} \cdot OSP_{i,h,m(h)}$, and $c_{i,h-2} \cdot o_{i,h-2}$, as well as the additional control variables used in our Model 3 of the main robustness checks in the main text. We expect $\beta_2 > 0$ reflecting overestimation by optimists. To investigate the effect of cognition, we use the *absolute* error $|SSB_{i,h,m(h)} - OSP_{i,h,m(h)}|$ as the dependent variable and thus run the regression

$$|SSB_{i,h,m(h)} - OSP_{i,h,m(h)}| = \beta_0 + \beta_1 c_{i,h-2} + \beta_2 o_{i,h-2} + \beta \mathbf{X_i} + \epsilon_{i,h,m(h)}.$$

Since according to our theory increasing lack of cognition leads to a clockwise tilting of the PWF, an increase in the lack of cognition increases the imprecision of the SSB compared to the OSP. Hence, in this setting we expect $\beta_1 > 0$. Our results on these additional robustness checks confirming our main findings are summarized in Table 10.

B Quantile Regressions

We now investigate the robustness of our main findings through quantile regressions. This allows us to detect relationships that are not captured by mean effects. In our quantile regressions, we take the difference between SSBs and OSPs as a dependent variable. Additionally, we include the level of the objective survival probability in our set of explanatory variables because the interval of our dependent variable is directly linked to the level of the OSP. We analyze every decile and estimate the results for all deciles jointly. As previously, standard errors are bootstrapped. Our regression specification including control variables is

$$SSB_{i,h,m(h)} - OSP_{i,h,m(h)} = \beta_0 + \beta_1 OSP_{i,h,m(h)} + \beta_2 c_{i,h} + \beta_3 o_{i,h-2} + \mathbf{x}_i' \beta + \epsilon_{i,h,m(h)}. \quad (15)$$

Table 10: OLS Estimates

	SSB-OSP (Relevant for Optimism)			|SSB-OSP| (Relevant for Cognition)		
Optimism_{t-2}	0.111^{***}	0.172^{***}	0.0987^{***}	-0.0186^{*}	-0.00761	-0.00731
	(7.07)	(11.75)	(3.60)	(-1.86)	(-0.74)	(-0.71)
$\text{Cognitive weakness}_{t-2}$	0.459^{***}	0.0822^{***}	0.0825^{***}	0.207^{***}	0.114^{***}	0.0821^{***}
	(19.34)	(2.91)	(2.92)	(13.59)	(5.73)	(2.61)
OSP_t		-0.577^{***}	-0.701^{***}		-0.101^{***}	-0.127^{***}
		(-15.06)	(-12.82)		(-3.75)	(-3.83)
Optimism_{t-2} x OSP_t			0.172^{***}			
			(3.19)			
$\text{Cognitive weak}_{t-2}$ x OSP_t						0.0778
						(1.33)
Constant	-0.210^{***}	-21.32^{**}	-21.67^{**}	0.186^{***}	13.10^{**}	13.29^{**}
	(-13.44)	(-2.48)	(-2.52)	(18.49)	(2.16)	(2.19)
Control Variables	No	Yes	Yes	No	Yes	Yes
Observations	11,950	11,950	11,950	11,952	11,950	11,950
Adjusted R^2	0.031	0.211	0.212	0.0172	0.0325	0.0326

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

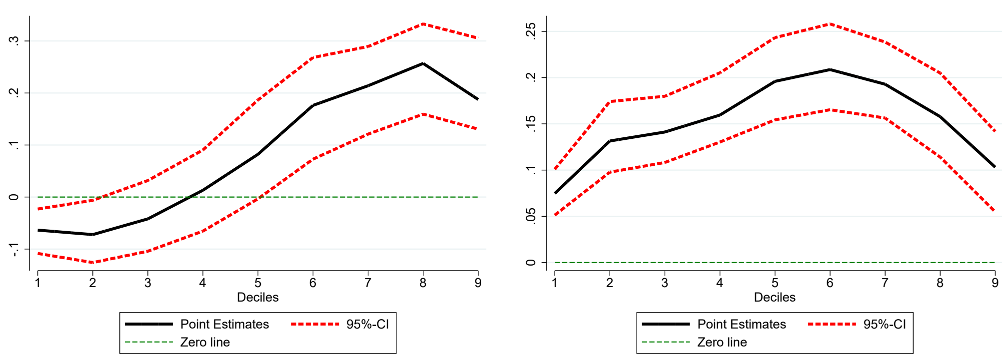
Notes: Columns 2-4 are relevant for the association between optimism and the difference $SSB - OSP$, adding control variables and an interaction term one at a time. Columns 5-7 is relevant for the association between cognitive weakness and the *absolute* difference $|SSB - OSP|$ between the subjective and objective survival probability.

By including the OSP on the right-hand-side of the regression, we control for biases induced by truncation and censoring, as underestimators cannot report SSBs less than zero and overestimators cannot report SSBs above one. The clockwise tilting of the PWF from increasing cognitive weakness we identified earlier is consistent with negative estimates of β_2 in lower percentiles and positive estimates in upper percentiles. This means that increasing cognitive weakness leads to a more pronounced underestimation for underestimators (who, on average, have high OSPs) and a more pronounced overestimation for overestimators (who, on average, have low OSPs). Irrespective of the percentiles, we also expect that $\beta_3 > 0$ because optimism leads to overestimation and $\beta_4 < 0$ because higher OSPs decrease the distance between SSBs and OSPs.

We report our results in Figure 13, thereby confirming our hypotheses. Interestingly, we also find that the effects of optimism are strongest for the intermediate percentiles. This is consistent with the non-linear probability weighting function: in the lowest percentiles, we have individuals with, on average, high OSPs, where the structure of the non-linear PWF forces subjective beliefs to converge to 1, cf. Figure 2. Likewise, in the highest percentile, individuals have, on average, low OSPs, which forces subjective beliefs to converge to 0. Thus, under a non-linear PWF, there is less room for motivational variables to impact the formation of SSBs at extreme OSPs of 0 and 1.

Figure 13: Quantile Regression: Coefficient Estimates

(a) Δ Cogn. Weakn. (b) Optimism

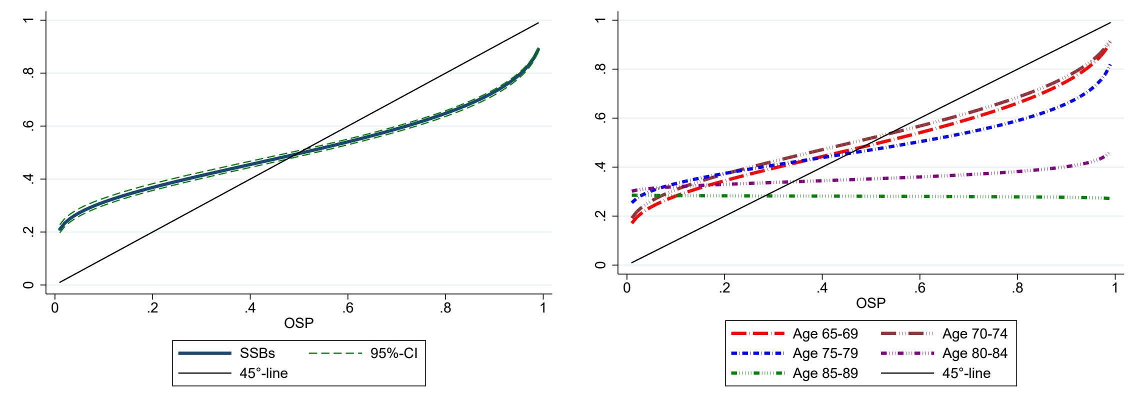


Notes: Coefficient estimates of equation (15) by deciles of underestimation and the respective bounds of the 95%-confidence intervals, which are calculated with the percentile method (1,000 replications). *Source*: Own calculations, Health and Retirement Study (HRS), Human Mortality Database (HMD).

C Focal Point Answers

To investigate the sensitivity of our results with respect to focal point answers, we repeat the estimation of non-linear PWFs by excluding observations with focal point answers at SSBs of 0%, 50% and 100%. Results are presented in Figure 14. In contrast to the corresponding Figure 4, probability weighting functions for the highest target age group are now downward sloping. Since we regard upward sloping PWFs as plausible, this finding is another indication (beyond the histograms shown in Appendix A) that focal point answers do have information content, which justifies including all these observations in our main analyses.

Figure 14: Non-Linear PWFs: Excl. All Focal Point Answers



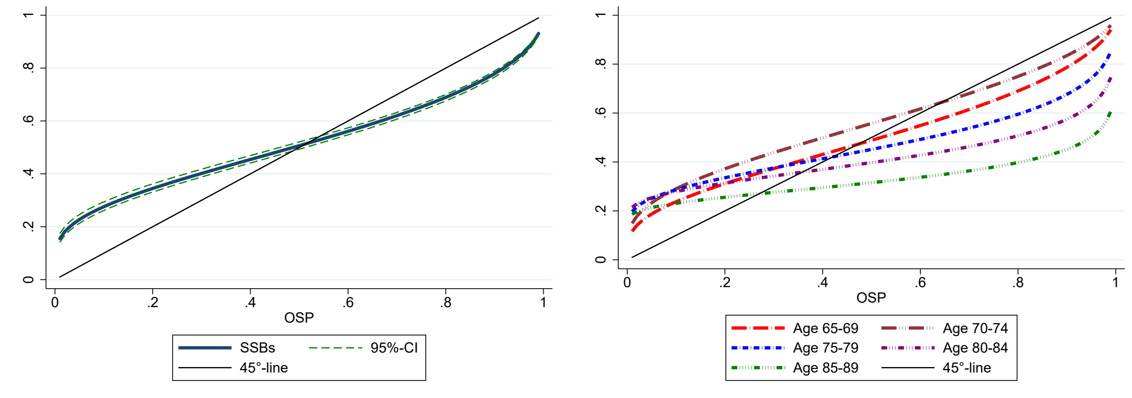
Notes: Estimated Prelec probability weighting functions when focal point answers at $0, 0.5, 1$ are excluded. Parameters estimated with non-linear least squares. *Source*: Own calculations, Health and Retirement Study (HRS), Human Mortality Database (HMD).

An alternative perspective to take is to only exclude focal point answers at 0.5. Through this we directly address the concern that our results are driven by a 50-50 answering heuristic that does not contain any information. Results shown in Figure 15 reveal that this is not a concern. Now, the PWFs look almost identical to those shown in the main text in Figure 4.

Based on this sample, we reestimate our baseline specification and conduct the decomposition analysis as in Figure 7. Results shown in Figure 16 are very similar to our main results. The main change concerns the effect of optimism, which now leads to an upward bias of about 13%p compared to about 10%p in our baseline results.

Finally, to underscore that focal point answers do contain information for our question at hand, we run logistic regressions of the probability of providing a focal point answer on our measures of cognitive weakness, optimism, the objective survival probability, with and without control variables. Results shown in Table 11 show that with increasing cognitive

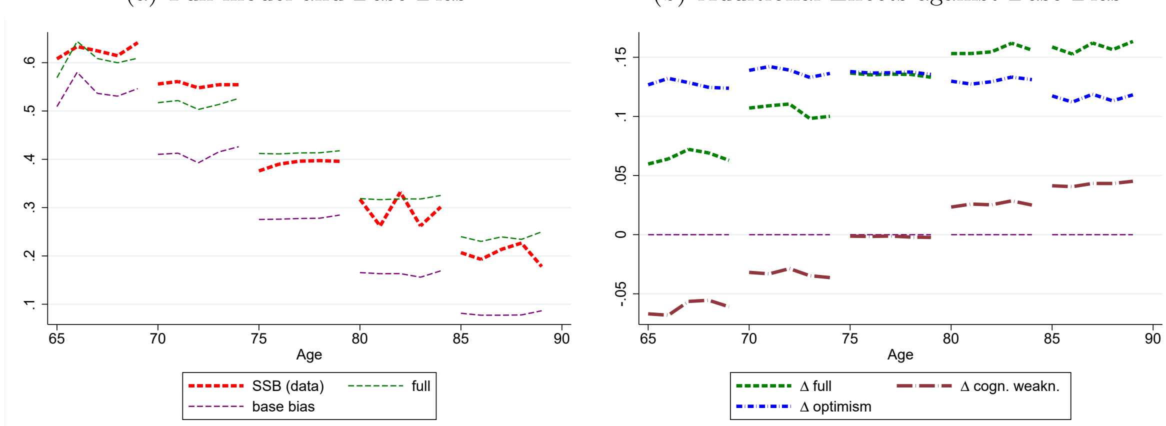
Figure 15: Non-Linear PWFs: Excl. Focal Point Answers at 0.5



Notes: Estimated Prelec probability weighting functions when focal point answers at 0.5 are excluded. Parameters estimated with non-linear least squares. *Source*: Own calculations, Health and Retirement Study (HRS), Human Mortality Database (HMD).

Figure 16: Non-Linear PWF: Decomposition over Age, Excluding Focal Point Answers at 0.5

(a) Full model and Base Bias (b) Additional Effects against Base Bias



Notes: Sample averages of predicted subjective survival beliefs according to equations (6) and (7) by age, excluding focal point answers at 0.5; Panel (a): "full": $\widehat{SSB}$; "base bias": $\widehat{SSB}^b$; Panel (b): "Δ full": $\widehat{SSB} - \widehat{SSB}^b$; "Δ cogn. weakn.": $\widehat{SSB}^{bc} - \widehat{SSB}^b$; "Δ optimism": $\widehat{SSB} - \widehat{SSB}^{bc}$.

weakness respondents are more likely to provide focal point answers at 0 and 1, respectively. This is consistent with Hill et al. (2004) who show that uncertainty with respect to survival beliefs increases in cognitive weakness. With increasing optimism, the probability to provide a focal point answer of 0 decreases.

Table 11: Focal Point Answers, Marginal Effects of Logit Regression

	$SSB = 0$		$SSB = 0.5$		$SSB = 1$	
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive weakness$_{t-2}$	0.131***	0.0926**	-0.0933**	-0.0306	0.270***	0.175***
	(5.83)	(3.21)	(-2.65)	(-0.70)	(13.18)	(6.97)
Optimism$_{t-2}$	-0.101***	-0.0831***	-0.0186	-0.00505	0.0460***	0.0426**
	(-6.75)	(-5.54)	(-0.85)	(-0.22)	(3.47)	(3.17)
OSP	-0.330***	-0.277***	0.0913***	0.0799	0.117***	0.141***
	(-25.33)	(-7.69)	(5.53)	(1.32)	(11.07)	(3.91)
Control variables	No	Yes	No	Yes	No	Yes
Observations	11,950	11,950	11,950	11,950	11950	11950
Adjusted R^2	0.0911	0.125	0.00419	0.0124	0.0206	0.0351

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Extending the Non-Linear PWF

We now relax our structural interpretation of parameters ξ_h and δ_h in terms of cognition and optimism by rewriting (5) as

$$\xi_{i,h} = \xi_0 + \xi_1 c_{i,h-2} + \xi_2 o_{i,h-2} \tag{16a}$$

$$\theta_{i,h} = \theta_0 + \theta_1 o_{i,h-2} + \theta_2 c_{i,h-2} \tag{16b}$$

and thus the nonlinear PWF becomes

$$SSB_{i,h,m(h)} = \left(\exp\left(-\left(-\ln\left(OSP_{i,h,m(h)}\right)\right)^{\xi_0+\xi_1 c_{i,h-2}+\xi_2 o_{i,h-2}}\right)\right)^{\theta_0+\theta_1 o_{i,h-2}+\theta_2 c_{i,h-2}} \tag{17}$$

Table 12 compares our baseline results to those of estimating the non-structural non-linear model (17). We find that the estimates of the new coefficients ξ_2, θ_2 enter significantly, and that inclusion of these additional coefficients mainly affects the intercept term ξ_0.

We interpret these results by help of the decomposition of the PWF in Figure 17. As for the baseline specification increasing cognitive weakness leads to a clockwise tilting of the PWF. The new additional effect of $\theta_2 < 0$ is that with increasing cognitive weakness the PWF is shifted up, similar to the effect of optimism. As a consequence the intersection point (OSP_0, SSB_0) moves up. Switching on optimism leads to an upward shift, as in our baseline results, and, since the new slope coefficient $\xi_2 > 0$ (and thus of opposite sign to ξ_1) it additionally leads to a counter-clockwise tilting.

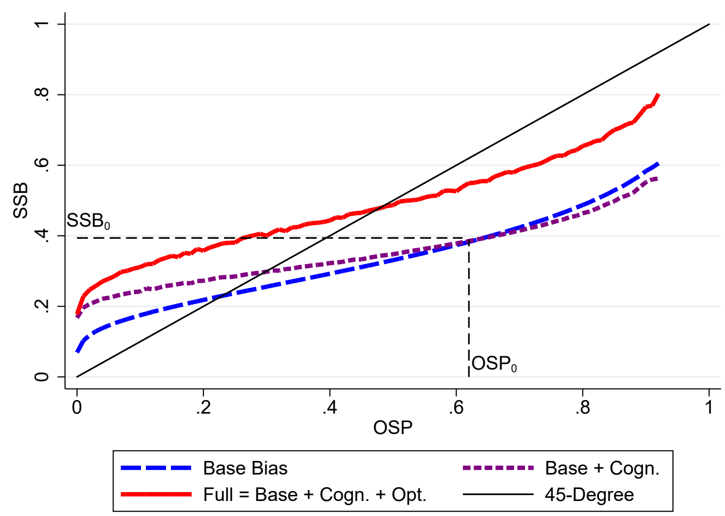
Table 12: OLS Regressions

	Baseline	Non-structural
ξ_0 Intercept Cognition	0.540***	0.380***
	(19.33)	(7.77)
ξ_1 Slope Cognition	-0.399***	-0.323***
	(-5.60)	(-4.45)
θ_0 Intercept Optimism	1.140***	1.270***
	(42.31)	(34.59)
θ_1 Slope Optimism	-0.433***	-0.454***
	(-12.14)	(-12.53)
ξ_2 New Slope Optimism		0.213***
		(4.26)
θ_2 New Slope Cognition		-0.310***
		(-5.59)
Observations	11,954	11,954

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 17: Decomposition of Non-linear PWFs with Equation (17)



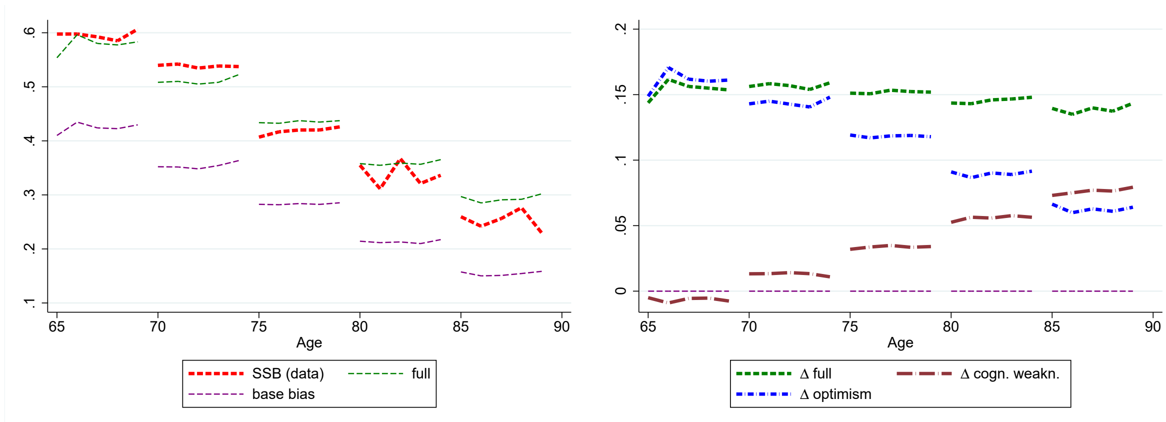
Notes: Sample averages of predicted non-linear probability weighting functions according to equations (6) and (7); "base bias": $\widehat{SSB}^b$; "base + cogn. weakn.": $\widehat{SSB}^{bc}$; "full": $\widehat{SSB}$.

The decomposition over age shown in Figure 17 shows that the differential effect of cognitive weakness is more or less as before in our baseline results, i.e., with increasing cognitive weakness individuals over the life-cycle overestimate their survival probabilities more. We now find that the overall effect of optimism is downward sloping because of the additional counter-clockwise tilting of the PWF. Thus, if anything, then the effect of optimism is decreasing with age. This reinforces our interpretation of our main results that increasing optimism is not the reason for the overestimation of old-age survival probabilities.

Figure 18: Non-Linear PWF with Equation (17)

(a) Full model and Base Bias

(b) Additional Effects against Base Bias



Notes: Sample averages of predicted subjective survival beliefs according to equations (6) and (7) by age; Panel (a): "full": $\widehat{SSB}$; "base bias": $\widehat{SSB}^{b}$; Panel (b): "Δ full": $\widehat{SSB} - \widehat{SSB}^{b}$; "Δ cogn. weakn.": $\widehat{SSB}^{bc} - \widehat{SSB}^{b}$; "Δ optimism": $\widehat{SSB} - \widehat{SSB}^{bc}$.

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