Biased survival expectations and behaviours: Does domain specific information matter?

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Abstract

We study the formation of biased *expectations across domains and* examine whether they have a unique influence on health and financial behaviors. Combining individual-level longitudinal, retrospective, and end of life data from several European countries for more than a decade, we estimate the time-varying individual level bias in 'survival expectations' (BSE) and compare it to a similar type of bias in the formation of 'meteorological expectations' (BME). We exploit the variation across individual's family history (parental age at death) to evaluate the causal effect of BSE on health and financial behaviors, and we compare it to the effect of BME. This allows to investigate whether the BSE effect is due to *private information, or another mechanism.* We find that BSE increases the likelihood of engaging in less risky health and financial behaviors. We estimate that a one standard deviation increase in BSE reduces the average individual probability of smoking by 48% (and increase the probability of holding retirement accounts by 69%). In contrast, BME has little effect on healthy behaviors, and is only associated with a change in some financial behaviors.

Keywords Biased expectations · Survival expectations · Meteorological expectations · Longevity optimism · Private information · Health behaviours · Financial behaviours

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1 Introduction

Rational expectations models (e.g., rational addiction models) are grounded on the assumption that individuals accurately form their survival expectations (Yaari, 1965). Consistently, some research has documented that subjective survival expectations are *on average* consistent with life table probabilities (Hurd & McGarry, 1995; Hurd & McGarry, 2002; Palloni & Novak, 2016). However, more recent studies show that aggregate life table realizations do not account for individual-specific heterogeneity (Gan et al., 2004).[1] The availability of end-of-life data makes it possible to precisely compare individual level objective and subjective survival expectation evidence.[2] After examining subjective longevity expectations over an individual's life cycle, some studies find evidence of an underestimation (overestimation) of subjective survival at younger (older) age (Elder, 2007; Hurd et al., 2009), suggesting a life course explanation for a bias in survival expectations formation. However, do such biases in expectation formation have an effect on behaviour? Does the specific information domain matter in the formation of biased expectations? Does the domain specific bias reveal a consistent effect across different behaviours?

This paper examines the formation of individual-level biased expectations across two specific domains, namely one's own longevity and the (predicted) weather. More specifically, we measure biased survival expectations (BSE) by studying individual self-reports in both main and in end-of-life exit interviews in Europe, and we then compare their *actual survival realizations* (and predicted survival for those alive) with their *expectations*. Similarly, we estimate individual-level 'biased meteorological expectations' (BME), that is, how individuals' weather predictions compare to weather realisations.

Next, upon documenting evidence of biased expectations, we then examine the impact of such biased expectations on health and financial behaviours. More specifically, we test whether private information drives such effects by exploiting the individual level variation in an individual's family longevity history (parental age at death) to identify the causal effect of biased expectations on several health (e.g., preventive actions) and financial behaviours (e.g., saving for retirement). The underlying intuition is that, the overestimation of one's subjective survival can be explained by an individual's private information about their objective survival probability. This information can arise either from knowledge of either technological or medical reasons influencing a persons survival, including individual-specific genetic information (Martin et al, 2007).[3] We study different mechanisms including whether the effect of individual biased expectations varies depending on the extent of individual control over different life domains (e.g., higher control over ones health than over the weather).

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[1] De Bresser (2017) draws on two Dutch surveys, administered to the same respondents during the same month, documenting similar relationships between socio-demographic covariates and the objective and subjective survival expectations.

[2] Some datasets, such as the Health and Retirement Survey (HRS) in the United States and the Survey of Health Ageing and Retirement in Europe (SHARE) contain a specific module with an end-of-life panel component which exhibits to date a reasonable sample and response rate. Some studies have already documented evidence of an age specific distribution of subjective and objective survival in the United States (Bissonnette et al., 2017; Palloni & Novak, 2016).

[3] Alternatively, behavioural biases such as longevity *optimism,* or the individual specific tendency to view the future more in one's favour, *can underpin* individuals' differences in survival expectations.

We add to the literature in several ways. First, we take advantage of unique data from the end-of-life questionnaire of the Survey of Health Ageing and Retirement in Europe (SHARE) and its retrospective wave (SHARELIFE), which allows us to precisely estimate individual level survival expectations and compare them to the respondent's actual observed survival.[4] Second, we study BSE using longitudinal data from several European countries, which exhibit a large cross-cultural variation in behavioural reference points. These heterogeneity can influence the formation of expectations compared to similar studies using United States data. Third, unlike previous studies, we are able to identify the bias is expectation formation in two domains, including one's own survival (or health), and the expected weather (or methodological expectations). Finally, we extend the previous literature[5] by providing causal estimates of the effect of biased expectations on specific financial and health behaviours.[6] Hence, we contribute to the still growing literature on the formation of biased expectations and specifically, on the role of private information (Kim et al., 2017), as a driver of biased expectations.

The next section describes in more detail how this paper relates to the existing literature. Section three describes the data, and the empirical strategy is reported in section four. We report the main results in section five. Section six reports a battery of robustness check, and section seven documents evidence of other potential pathways. A final section concludes.

2 Related literature

Biased Survival Expectations (BSE). Subjective survival expectations are central to long-term decision-making regarding saving and consumption (Levhari & Mirman, 1977; Hamermesh, 1985; Hurd, 1989), retirement and employment (Hurd et al., 2004; Cocco & Gomes, 2011), as well as risky health behaviours (Khwaja et al., 2007). However, to date, most of the evidence of bias in expectation formation mainly comes from comparing cross-sectional expectation data and survival life tables. According to Post and Hanewald (2013), the dispersion of subjective survival expectations is more similar to the dispersion of survival life tables. However, life table models are affected by selection, individual heterogeneity, potential cohort effects and individual non-response of those with a higher mortality risk (Bissonnette et al., 2017). In contrast, evidence like the one presented in this study

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[4] We use the stock sampling approach reported in Jenkins (1995), which allows us to change the unit of analysis from the individual to the time at risk of death, and in turn simplifies the complex sequence of likelihoods to the standard estimation of a binary outcome.

[5] So far, most of the literature examines how survival expectations are modified by changes in health behaviours (Smith et al., 2001), genetic information (Hurd and McGarry, 1995; Perozek, 2008), better knowledge of parents' health (van Doorn & Kasl, 1998) and health-related experiences in life (Benítez-Silva, 2008; Costa-Font & Costa-Font, 2011). Previous evidence supports the idea that subjective survival expectations are accurate predictors of longevity (Hurd & McGarry, 1995, 2002).

[6] For instance, Salm (2010) found that a 1% higher subjective mortality rate was associated with an annual decrease in consumption of non-durable goods of 1.8%. Groneck et al. (2017) claim that under-estimation of young age and overestimation of old age survival probabilities might give rise to the occurrence of over and under saving, respectively. Similarly, Puri and Robinson (2007) found that over-estimated survival (from life tables) gives rise to more conservative saving behaviours (more savings). However, they identify a non-linearity at the top share of the survival distribution.

is retrived from exit interviews and is less prone to selection biases. That is, it can precisely identify survival at the individual level.

Cognitive Biases and Optimism. According to the literature, it is unclear whether BSE are the result of individual specific cognitive biases (e.g., optimism bias), or other alternative explanations such as individual differences in access to private information regarding their survival. All of the latter explain why people differ in their ability to judge their own mortality risk (Lichtenstein et al., 1978). Younger respondents tend, on average, to underestimate their objective survival chances, and the opposite is true for older people (Groneck et al., 2017). Similarity, gender plays a role, though according to Steffen (2009) both men and women underestimate their survival, and Teppa and Lafourcade (2013) estimate that women exhibit a systematic lower subjective survival probability relative to actuarial survival probabilities. Viscusi and Hakes (2003) elicit individual subjective survival probabilities and document that they capture a generalised assessment of an individual's health status. Other research has found that age, gender and socio-economic status all have a systematic influence on individual subjective survival expectations (Hamermesh, 1985; Hurd & McGarry, 1995; Khwaja et al., 2007). Consistently with the influence of cognitive biases, Mirowsky (1999) argues that surviving at older ages may give rise to to a feeling of optimism. We will return to this point later in Sect. 6.

Finally, in estimating survival probabilities, there are other important reporting biases to account for such as the rounding of the data and, the presence of focal points (e.g., 0.5) as discussed in Bruine de Bruin et al. (2002). A nontrivial issue is how to estimate survival expectations by age from expectation questions eliciting the probability of survival of an additional target age, which is dealt with in the literature by examining a subjective hazard function under some distributional assumptions (see Bissonnette et al., 2017).

Behaviour and BSE. Although some studies document the presence of discrepancies between perceived and realized survival, there is limited, or no consensus on the effect of BSE on actual behaviour. Groneck et al., (2017) find no evidence that biased survival expectations affect financial behaviours. In contrast, other studies identify an effect of survival expectations on retirement (O'Donnell et al., 2008; van der Klaauw & Wolpin, 2008), demand for annuities (Schulze & Post, 2010; Teppa & Lafourcade, 2013), portfolio allocation (Kézdi & Willis, 2011), education (Arcidiacono et al., 2012), migration (McKenzie et al., 2013), savings (Bloom et al., 2006) and smoking behaviour (Balia, 2011). However, the majority of such studies do not take into account the endogeneity of survival expectation formation. This paper exploits accounts for such endogeneity by drawing on an instrumental variable strategy as described below.

3 The data

We use data from SHARE (the Survey of Health, Ageing and Retirement in Europe)[7], the European equivalent of the Health and Retirement Survey in the United States. Our variables of interest can be found in the "Main Questionnaire" of waves 1 (2004–05), 2 (2006–07), 3 (2009), 4 (2011), 5 (2011) and 6 (2015) and the "End of life" module for waves 2 (2006–07), 3 (2009), 4 (2011–13), 5 (2013) and 6 (2015). We also link the data with the retrospective SHARELIFE records, especially in our robustness checks. Our final samples are obtained by following several steps (see Table B1 from Appendix B). Using the initial samples for waves 1 to 6 (N=260,244), we have initially selected those countries which are available for all waves (i.e., Austria, Belgium Denmark, France, Germany, Italy, Spain, Sweden, and Switzerland; N=160,388). Second, we have then selected observations with non-missing values to calibrate the sampling weights[8] (N=156,320). Third, we have merged each consecutive waves of SHARE. Whilst for survivors two consecutive "Main Questionnaires" of SHARE are used, for the deceased we have merged the "Main Questionnaire" of one wave with the "End-of-life Questionnaire"[9] of the next wave (N=118,025). We identify 29,376 non-follow-up respondents, that is, respondents who have only participated in one wave. Next, we compare the characteristics of the non-follow-up respondents with those of the survivors and deceased subsamples. Finally, we distinguish those respondents who have answered the expectations module from those who have not.[10] Retention rates[11] increase remarkably over time in all countries resulting in very high overall panel stability after several waves (Table B2 from Appendix B).

Subjective survival. Subjective survival. The "Main Questionnaire" includes an "Expectations" module that begins with a warm-up question that asks, "*What do you think the chances are that it will be sunny tomorrow?*" This warm up question should help respondents feel at ease with the numerical scale used in the whole set of questions in this module. To ease the question understanding, these questions are accompanied by cards, with a numerical probability sequence ranging from 0, meaning absolutely no chance, to a value of 100, meaning absolute certainty. Furthermore, respondents are asked to state their subjective survival probability (SSP) on a scale from 0 to 100 using the following question: "*What are the chances that*

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[7] The SHARE target population consists of all persons aged 50 years and older at the time of sampling who have their regular domicile in the respective SHARE country, which contains micro level information on demographics, socio-economic status, health status, social and family networks. Persons are excluded if they are incarcerated, hospitalized, or out of the country during the entire survey period or unable to speak the country's languages (Bergman et al., 2019).

[8] Calibrated sampling weights are missing for respondents younger than 50 years (i.e., age-ineligible partners of an age eligible respondent) and those with missing information on the set of calibration variables (i.e., age, gender and NUTS1 code).

[9] The "End of life" module in the event of death is completed between two waves (questions are answered by a proxy respondent). Using the unique identifier assigned to each respondent, it is possible to link the "End of life" module with the "Main questionnaire" of the wave immediately preceding it.

[10] This last step configures our final samples: 2,040 for the deceased's subsample and 67,860 for the survivors' subsample, and we test if there is a sample selection problem due to the exclusion of those who have not reported their survival expectations.

[11] In order to correct for potential selection bias resulting from non-response and panel attrition, the SHARE study suggests using calibrated sampling weights using the methodology designed by Deville and Särndal (1992).

you will live to be age [T] or more?", being T a target age that takes the values {75, 80, 85, 90,…,120} depending on the age of the respondent. Respondents aged below 65 at the time of the interview are presented a target of 75, while those aged between 65 and 69 have a target of 80, and so on (T = 85 for 70–74 years, T = 90 for 75–79 years, T = 95 for 80–84 years, T = 100 for 85–89 years, T = 105 for 95–100, T = 110 for 100–104 years and T = 120 for 105 years and older).

Biased Survival Expectations (BSE). Figure B1 shows the evolution of SSP across the six waves. We find no significant differences and a modest reduction in survival probabilities as people age. Given the significant reduction in sample size, we compare the density function of the survival subjective probability of follow-up respondents and non-follow up respondents. Similarly, to test the validity of SHARE information, Schulz and Doblhammer (2011) compared age-specific death rates for all countries available in wave 1 with age-specific death rates from the Human Mortality Database. They found that empirical death rates mostly ranged within the confidence interval up to age 65, but among individuals older than 65, they were predominantly below the lower bound of the confidence interval.[12] Hence, older respondents institutionalized shortly before death are coded as attrition cases, rather than deceased.

Kernel density functions are displayed in Figure B2 (Appendix B) and results of the test of equality of distributions are reported in Table B3. When examining all waves pooled or paired, we identify comparable density functions, which leads us to reject the null hypothesis of equality of distributions.[13] Table B4 displays the mean survival subjective probabilities by country and target (T) using the final sample (N = 69,900). We identify large cross-country heterogeneity in survival expectations across European countries. We corroborate such evidence by performing F tests comparing the highest and lowest means across countries. More specifically, Danish respondents reveal the largest survival expectations for targets 75, 80 and 85 (when compared to other average country respondents), whereas Italians have the highest survival expectations for the oldest cohorts.[14] In contrast, while Belgians exhibit the lowest expectations for the youngest cohort, Germans reveal the lowest

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[12] Two reasons may explain this underestimation namely, that (i) the institutionalized population is missing in the first wave of SHARE, and although respondents are followed into institutions in the second wave, the institutionalization rate in SHARE is still very low, and that (ii) except for France, the mortality follow-up is not based on registers, but retrived from the "End-of-life interview".

[13] We only reject the null hypothesis when comparing follow-up and non-follow-up respondents between waves 2 and 4 (which could be justified given the greater time interval between both waves).

[14] This fact may be explained by the combination of a high life expectancy (80.2 years in 2015) and being one of the countries in the world with the highest number of centenarian population. Source: Health status—Life expectancy at birth—OECD Data.Countries With the Most Centenarians—WorldAtlas.

expectations for targets 80, 85, and 90, and Swedish seniors are the most pessimistic of all the countries studied.[15]

4 Empirical strategy

4.1 Main specification

Using the Weibull specification (commented in Sect. 4.1; see Appendix C for the explanation of the duration model), we first estimate the predicted survival probabilities for each individual, which we denote as "objective survival probabilities" (OSP_{ict}). Accordingly, we define our biased survival expectations indicator as the difference between subjective and objective survival expectations as follows:

$$BSE_{ict} = SSP_{ict} - OSP_{ict} \tag{1}$$

Next, we measure the effect of biased survival expectations (BSE_{ict}) for *an* individual i living in country c at time (wave) t; on several behaviours' (D_{ict}) in health and financial domains (including health behaviors, savings, financial investments, and risk taking; see Table A3), as follows:

$$D_{ict} = \alpha_0 + \alpha_1 BSE_{ict} + \alpha_2 X_{ict} + T_t + C_c + \epsilon_{ict} \tag{2}$$

where D_{itc} refers to the behaviour indicator under consideration for an individual i residing in country c at time (wave) t; X_{itc} refers to a vector of explanatory variables,[16] T_t and C_c denote wave and country fixed effect respectively, and ϵ_i refers to the error term. We include three groups of explanatory variables: (i) socio-demographic characteristics, (ii) economic controls and (iii) health-related controls. Additionally, we include a definition of each is control variable in Table A2.

4.2 Endogeneity of biased survival expectations on behaviour

Given the potential endogeneity of biased survivaled expectations in explaining health and financial behaviours, we follow an instrumental variable approach (to correct mainly for reverse causality and omitted variable bias). In the first stage, we estimate the following equation

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[15] Considering the classification of countries proposed by Lewis (1996), we noticed that: Group III (Austria and Denmark) exhibits the highest SSP for target ages 75, 80 and 85, whereas Group IV (Italy and Spain) shows the highest SSP for the oldest cohorts. In contrast, Group II (Belgium and France) is the group with the lowest SSP for all targets except T = 90 years (see classification of countries on Table A4). Table B5 reports survival expectations by gender across different target ages. Importantly, we find that among the survivor's women tend to exhibit higher subjective survival probabilities, but the effect seems to decline when target ages are expanded, and at age 90 men have higher survival probability among survivors.

[16] Gender, age, age squared, level of education, marital status, number of days stayed in hospital during the last year (surgery or medical tests), number of days stayed at hospital during the last year (mental health), number of days stayed at other institutions during the last year, number of visits to general practitioner during the last year, relation with economic activity, living in a rural area/village/small town, living alone, wealth and income (adjusted by household size and in 1,000 PPP).

$$BSE_{ict} = \beta_0 + \beta_1 MAD_{ict} + \beta_2 FAD_{ict} + \beta_3 ML_{ict} + \beta_4 FL_{ict} + \beta_5 X_{ict} + T_t + C_c + \varepsilon_{ict}$$

$$(3)$$

where MAD_{itc} and FAD_{itc} depict mother's and father's age at death, respectively, ML_{ict} and FL_{ict} are binary variables that take the value 1 if the mother (father) is alive at the time of the survey binary, and 0 otherwise. A valid instrument should be uncorrelated with the error term of (2) but should correlate with BSE_{ict}. Hurd and McGarry (2002) and Dormont et al. (2014) have shown that death of a parent is associated with a reduction in subjective survival expectations. Additionally, genetic factors or parental ill health, can be regarded as a form of private information that is available to individuals in the formation of expectations of their own and their descendants' future health status. Therefore, the validity of our instruments relies on the fact that parents' living status affects children's behaviours only through their effect on biased survival expectations. More specifically, we have selected four instruments: father's age at death, mother's age at death, whether the father and/or the mother are alive. Here, we exploit the link between parents and childrens' objective longevity.[17]

In measuring the effect of parent's age at death we have distinguished between individuals whose parents have already passed away at the time of the survey, from those who are still alive. In the former case, we have used the reported age of death. In the latter, we draw on the predicted age of parental death using multiple imputation (Rubin, 1987). A detailed explanation of the imputation process is reported on Appendix B. The density function and descriptive statistics of deceased parents (reported age of decease in SHARE) and living parents (imputed age of decease) are shown on Figure B3 and Table B7[18]. Sections 6.3 and 6.4 reports robustness checks testing for the validity of our instruments. Finally, the predicted values of BSE_{ict} ($\widehat{BSE}_{ict}$) are used instead of the original values of BSE_{ict} in Eq. (1).

$$IND_{ict} = \gamma_0 + \gamma_1 \widehat{BSE}_{ict} + \gamma_2 X_{ict} + T_t + C_c + \omega_{ict} \qquad (4)$$

For each indicator (IND_{ict}) we have estimated four different models, gradually adding new explanatory variables (X_{ict}). That is, different specifications vary depending on the inclusion of socio-demographic controls[19], country fixed effects and wave fixed effects. Next, we consider a series of health controls, including the number of days spent in hospital in the previous year (due to surgery or medical tests), the number of days

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[17] Ikeda et al. (2006) showed that the older the age of death of both mothers and fathers, the lower the probability of death for adult children aged between 40 and 79 years. It also seems that longevity is more strongly associated with maternal death age than parental death age and that mother's longevity reduces the incidence of some pathologies such as pulmonary disease or hypertension (Gjonca & Zaninotto, 2008; Goldberg et al., 1996).

[18] The predicted kernel density function (using the imputed values for the living parents' subsample) is skewed to the right in comparison to the density function for deceased parents. Imputed age of death is on average around two years higher that the average parents' reported age, regardless of the adult's child gender.

[19] Including gender, age, age squared, level of education (no education, primary education, lower secondary education, higher secondary education, post-secondary non-tertiary education, and tertiary education (omitted)), marital status (married/cohabiting, separated/divorced, single and widow (omitted)).

stayed at hospital during last year (mental health), the number of days at other institutions during last year and the number of visits to a general practitioner during the previous year[20]. For each indicator and each model specification we provide three test statistics for the IV estimation (see Tables B13 to B16)[21].

4.3 Biased meteorological expectations

To identify whether individual biased expectations vary by domain, we have constructed an indicator that compares the subjective probability (prediction) that the following day after the interview is going to be a sunny day with the actual ('objective') meteorological realisation. Meteorological data is retrieved from the Gaisma website[22] which provides sunrise and sunset information as well as dusk times for thousands of locations all over the world. For each month and region, we have computed average daylight minutes ($DMD_{m,r}$) as the difference between sunrise and sunset times (see Table B9). The World Meteorological Organization[23] provides the mean number of sunshine hours per month, year, and region. First, we have defined the number of sunshine minutes per month m of year y in region r ($SMM_{m,y,r}$), where region r is the equivalent of NUTS-2 of SHARE. Second, we have computed the average sunshine minutes per day in month m of year y in region r ($SMD_{m,y,r}$) as the ratio between sunshine minutes per month and days per month for each year (to consider leap years) (see Table B10).

$$SMD_{m,y,r} = \frac{SMM_{m,y,r}}{Days\ per\ month_y} \tag{5}$$

The meteorological probability of a sunny day in month m of year y in region r ($MetSD_{m,y,r}$) is defined as the ratio between sunlight minutes per day ($SMD_{m,y,r}$) and daylight minutes per day ($DMD_{m,r}$) (see Table B11):

$$MetSD_{m,y,r} = \frac{SMD_{m,y,r}}{DMD_{m,r}} * 100 \tag{6}$$

$MetSD_{m,y,r}$ is regressed over country and regional fixed effects from which we obtain the predicted probability of a sunny day ($\widehat{MetSD}_{m,y,r}$).

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[20] Finally, a third specification considers a series of controls for economic activity Such as employment retirement status, home working, living in a rural area/village/small town, living alone, wealth and income (adjusted by household size and in 1,000 PPP).

[21] The rejection of the null hypothesis in the Durbin-Wu Hausman test indicates that the OLS estimations are inconsistent and that the IV technique is required. The Stock and Yogo critical values at 5% are lower than the Cragg-Donald statistic, which tests for weak instruments. Finally, as we have one endogenous variable and two instruments, we perform an overidentification test. The p-value from the Sargan test shows that the instruments are uncorrelated with the error term of the outcome equation, and thus are valid instruments.

[22] https://www.gaisma.com/en

[23] http://data.un.org/Data.aspx?d=CLINO&f=ElementCode%3A15

The expectations' module of SHARE include the following question: "what do you think the chances are that it will be sunny tomorrow? For example, '90' would mean a 90 per cent chance of sunny weather. You can say any number from 0 to 100". We use the answer to this question to define reported probability of a sunny day by an individual i interviewed in month m of year y in region r ($Rep_{i,m,y,r}$)[24].

"Meteorological expectations" of individual i interviewed in month m of year y in region r, $BME_{i,m,y,r}$ is the difference between reported probability of a sunny day and meteorological predicted probability of a sunny day:

$$BME_{i,m,y,r} = RepSD_{i,m,y,r} - \widehat{MetSD}_{m,y,r} \qquad (7)$$

Table B12 compares both indicators of biased expectations. Our estimates suggest that about 56% of individuals exhibit both positively biased survival and meteorological expectations (e.g., BSE > 0 and BME > 0) and about 8% exhibit negatively biased expectations for both domains. The share of respondents exhibiting positively biased expectations on both domains is 9.2 pp is higher among men though biased expectations differ by age. Similarly, we estimate that biased expectations are 3.5 pp higher for survivors, compared to deceased individuals[25]. Finally, we estimate OLS regressions for the same set of indicators used in Eq. (4), but we now use the expectations based on the meteorological domain ($BME_{i,m,y,r}$):

$$IND_{ict} = \delta_0 + \delta_1 ME_{i,m,y,r} + \delta_2 X_{ict} + T_t + C_c + \varsigma_{ict} \qquad (8)$$

where X_{ict} is the same set of control variables used in (4) and we proceed in a similar fashion, adding them gradually; T_t and C_c are fixed and country fixed effects and ς_{ict} is an error term.

5 Results

5.1 Biased subjective survival

We begin by estimating BSE among survivors and the individual characteristics predicted to influence BSE. Table B8 reports estimates of a discrete-time hazard model, and identifies a long list of unhealthy lifestyles that correlate with objective survival across waves. Estimates indicate that the hazard rate (1.429) rises over time but such decline tails off. At each survival time point examined, men tend to exhibit a higher hazard ratio (+88.4%) than women. Compared to individuals who have never

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[24] The sample of respondents to this question is 69,315 as compared with the total sample which amounts to 69,900 observations.

[25] Finally, we find that Austria and Denmark exhibit the highest share of individuals with positively biased expectations, whereas Belgium, France and Germany exhibit the highest of negatively biased expectations (e.g., with the highest percentage for BSE < 0 and BME < 0).

smoked, we find that the hazard rate is 52.4% higher among current smokers[26] and 36.6% higher for past smokers. Consistently, we estimate a higher hazard rate among respondents that fail to perform any moderate or vigorous physical activity, and similar estimates are retrieved for those who drink every day or almost every day (23.4%). Being diagnosed with cancer[27] and Alzheimer's increases mortality risk by 156.6% and 58.5%, respectively, and we document that similarly, those who have suffered a stroke exhibit a 54.3% higher hazard ratio. Individuals feeling depressed exhibit an 18.1% higher hazard ratio which confirms previous evidence regarding the relationship between depression and mortality (Mykletun et al., 2009). Finally, we document a negative association between the survival hazard rate and educational attainment[28].

Figure 1 displays the average estimates of both subjective survival (SSP) and objective survival probabilities (OSP) across different individual age groups. Consistently with the hypothesis of biased survival expectations, we find evidence of biased expectations, both among survivors and the deceased. However, such bias widens over time among the deceased whilst it remains relatively stable among survivors.

Table 1 examines age differences in BSE between deceased and survivors. For each age cohort, the column SSP indicates the average subjective survival probability of reaching target T (between 0 and 100) and the column OSP displays the average objective survival probability (between 0 and 100) estimated from a duration model with the Weibull specification[29]. For instance, we find that BSE is not significantly different across the age cohorts 65–69 and 70–74. The last two columns in Table 1 display the percentage of individuals revealing both a positive and negative bias. More specifically, we define an individual as exhibiting positive BSE if SSP is higher than the predicted OSP, whereas we classify the reverse as negatively biased. The percentage of individuals with biased survival expectations among survivors is stable, and it only peaks at age 95. In contrast, among the deceased, biased survival expectations peak at age 80. One explanation for the overestimation of survival expectations among the older cohort of individuals is the detrimental effect of ageing on cognitive abilities[30] (Elder 2007). Other explanations include the effect of an age increasing optimism, alongside the presence of other cognitive biases (e,g., overconfidence bias).

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[26] Being a smoker was found to be equivalent to being at least four years older in terms of its negative effects on two-year survival (Wang, 2014).

[27] The high impact of cancer on mortality is consistent with evidence reported by Hurd and McGarry (2002) who found that cancer was the strongest predictor of mortality, increasing two-year mortality rate by 150%.

[28] The hazard ratio for no education and primary education are 53.1% and 57.5% higher than the omitted category (tertiary education). Furthermore, the hazard rate for those who have 1,000 PPP additional units of adjusted wealth is 66.3% of the hazard rate for those who do not have such wealth.

[29] For example, for the age cohort 50-64, we estimate the average SSP of reaching target age T = 75 years at 50.88 for the deceased subsample and 68.06 for the survivor's subsample. In contrast the objective survival probability of reaching target age T = 75 years is 34.64 for the deceased subsample and 56.57 for the survivor's subsample. This implies that the gap between SSP and OSP is higher for the deceased subsample (16.24 pp vs. 11.51 pp for the survivors).

[30] Similarly, Grevenbrock et al. (2016) finds that cognitive impairments cause upward biases in survival beliefs for the oldest age group (age group 85-89) which leads to an overestimation of survival chances by about 15 percentage points. An alternative explanation proposed by Kahneman and Tversky (1979) is that individuals tend to overweight small probabilities and underweight large probabilities.

Survivors

Deceased
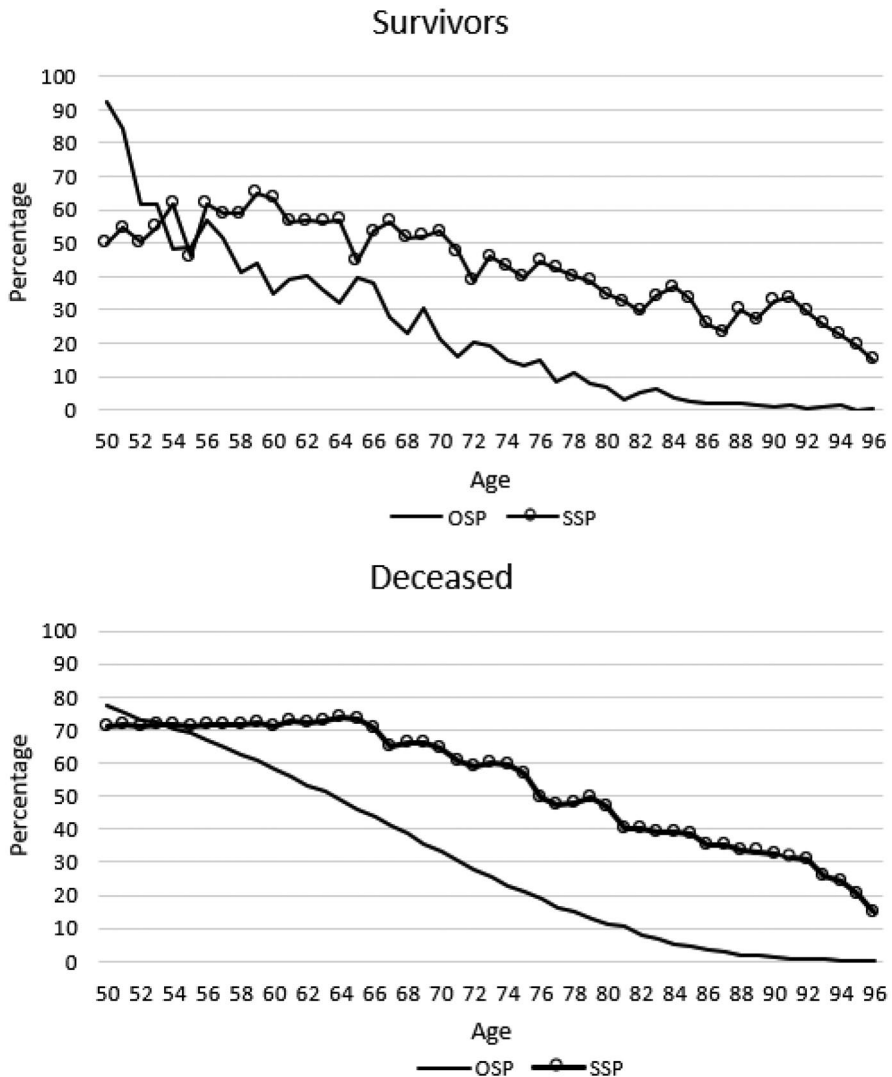
Fig. 1 Trends and gaps of subjective survival and objective survival probability by age of the respondent. Note: These figures display objective survival expectations (OSP) and subjective survival expectations (SSP) for the subsample of survivors and deceased. The distance between OSP and SSP is what we have defined as "biased survival expectations· in Eq. (1)Subjective survival probabilities (SSP) corresponds to the answers to the question of SHARE questionnaire "What are the chances that you will live to be age [T] or more?". The target T takes the values {75, 80, 85, 90,…,120} depending on the age of the respondent. Respondents aged under 65 at the time of the interview are presented a target of 75, while those aged between 65 and 69 have a target of 80, and so on (T=85 for 70-74 years, T=90 for 75-79 years, T=95 for 80-84 years, T=100 for 85-89 years, T=105 for 95-100, T=110 for 100-104 years and T=120 for 105 years and older)

Table 1 Comparison of subjective survival probability and objective survival probability by age at baseline

All subsample (by age at baseline)

Age at baseline	N	Survival expectations					Meteorological expectations	
		SSP (%)	OSP (%)	BSE Difference SSP-OSP	BSE>0 (%)	BSE<0 (%)	BME>0 (%)	BME>0 (%)
50–64	55,609	67.79 (26.94)	56.22 (25.39)	11.57 (33.89)	63.96	36.04	74.87	25.13
65–69	7,065	49.43 (31.21)	20.07 (20.14)	29.36 (36.78)	75.64	24.36	72.77	27.23
70–74	4,404	40.84 (31.30)	11.20 (15.61)	29.64 (34.79)	76.69	23.30	75.70	24.30
75–79	2,110	33.04 (31.97)	3.84 (8.00)	29.19 (32.99)	73.87	26.13	68.34	31.66
80–84	617	34.86 (30.90)	1.41 (4.28)	33.45 (31.39)	78.28	21.72	74.35	25.65
85–94	83	31.88 (31.09)	0.76 (2.94)	31.13 (30.79)	75.70	24.30	71.16	28.84
95–100	12	41.58 (29.51)	0.00004 (0.00012)	41.58 (29.51)	75.83	24.17	64.84	35.16
All	69,900	62.48 (29.87)	47.00 (29.72)	15.48 (34.99)	66.53	33.47	74.49	25.51

Deceased subsample (by age at baseline)

Age at baseline	N	Survival expectations					Meteorological expectations	
		SSP (%)	OSP (%)	BSE Difference SSP-OSP	BSE>0 (%)	BSE<0 (%)	BME>0 (%)	BME>0 (%)
50–64	823	50.88	34.64	16.24	67.01	32.99	71.73	28.27

Table 1 (continued)

All subsample (by age at baseline)

Age at baseline	N	Survival expectations					Meteorological expectations	
		SSP (%)	OSP (%)	BSE Difference SSP-OSP	BSE>0 (%)	BSE<0 (%)	BME>0 (%)	BME>0 (%)
65–69	346	42.45 (32.26)	13.28 (18.89)	29.17 (34.73)	74.35	25.65	66.33	33.67
70–74	358	36.68 (32.00)	6.57 (12.18)	30.11 (35.35)	73.21	26.79	78.59	21.41
75–79	312	25.68 (30.29)	2.05 (5.46)	23.64 (30.13)	62.54	37.46	57.99	42.01
80–84	164	28.96 (27.94)	1.57 (3.75)	27.39 (27.97)	80.01	19.99	67.33	32.67
85–94	31	22.82 (27.32)	0.62 (3.00)	22.20 (26.84)	70.79	29.21	70.30	29.70
95–100	6	38.41 (32.36)	0.00 (0.00)	38.41 (32.36)	65.92	34.08	76.30	23.70
All	2,040	40.63 (32.87)	17.18 (24.54)	23.44 (34.82)	70.04	29.96	70.02	29.98

Survivors subsample (by age at baseline)

Age at baseline	N	Survival expectations					Meteorological expectations	
		SSP (%)	OSP (%)	BSE Difference SSP-OSP	BSE>0 (%)	BSE<0 (%)	BME>0 (%)	BME>0 (%)
50–64	54,786	68.06	56.57	11.49	63.91	36.09	74.92	25.08

Table 1 (continued)

All subsample (by age at baseline)

Age at baseline	N	Survival expectations					Meteorological expectations	
		SSP (%)	OSP (%)	BSE Difference SSP-OSP	BSE>0 (%)	BSE<0 (%)	BME>0 (%)	BME>0 (%)
		(26.76)	(25.19)	(33.84)				
65–69	6,719	49.81 (31.12)	20.44 (20.14)	29.37 (36.89)	75.71	24.29	73.11	26.89
70–74	4,046	41.28 (31.20)	11.69 (15.85)	29.59 (34.73)	77.06	22.94	75.39	24.61
75–79	1,798	34.21 (32.08)	4.13 (8.30)	30.08 (33.35)	75.68	24.32	69.99	30.01
80–84	453	37.24 (31.74)	1.34 (4.48)	35.90 (32.38)	77.58	22.42	77.18	22.82
85–94	52	35.90 (32.03)	0.82 (2.94)	35.08 (31.80)	77.88	22.12	71.54	28.46
95–100	6	47.08 (27.31)	0.00006 (0.00015)	47.08 (27.31)	92.98	7.02	45.01	54.99
All	67,860	63.21 (29.48)	47.99 (29.35)	15.21 (34.96)	63.41	36.59	74.65	25.35

Note: SSP stands for subjective survival probability. Indicates the average subjective survival probability of reaching target age T (T=75 years if Age<65; T=80 years if $65 \leq Age < 70$; T=85 years if $70 \leq Age < 75$; T=90 years if $75 \leq Age < 80$; T=95 years if $80 \leq Age < 85$; T=100 years if $85 \leq Age < 94$; T=105 years if $95 \leq Age$. OSP: objective survival probability. Indicates the average objective survival probability predicted from duration model for the same target age T. Standard errors in brackets. Using calibrated sampling weights

Next, when we estimate BSE by gender (in Table C2 in the appendix). Estimates suggest that consistently with prior research, men are more likely to exhibit biased survival expectations than women for both deceased and survivors[31], though the bias is higher in the deceased subsample. That is, although women tend to reveal more negatively biased expectations, deceased women exhibit more positively biased expectations than surviving women[32]. Similarly, when we examine differences across populations and countries (Table C3)[33], we find that two thirds of the population exhibit positively biased expectations and one third negatively biased expectations[34].

5.2 Explaining biased survival expectations

Following the proposed instrumental variable approach, Table D1 displays the covariates predicting BSE which make up the first stage instrumental variable regression[35]. Consistently, the four instruments considered are statistically significant and exhibit the expected signs. The effect sizes suggest that the effect of age at death and living status is higher for fathers than for mothers. On average, each year of maternal (paternal) age at death raises BSE by 0.0012 points (0.0017 points). Individuals with a living mother (or father) exhibit higher BSE and more specifically 0.0114 points (0.0248 points) higher BSE. Men are more likely to exhibit biased expectations than women (12.42 points), and each year of life increases BSE by 7.62 points[36]. Consistently, those who are coded as having stayed in hospital are more likely to show negatively biased expectations. In contrast, stays at other institutions due to convalescence or rehabilitation are associated with only a slight increase in negatively biased expectations.

Time invariant fixed effects reduce BSE by 30.2 points between waves 2 and 4, which corresponds to the period 2007–2011. Furthermore, estimates suggest that the influence of education is U-shaped, revealing that individuals with no completed education, those with primary education and those with post-secondary and tertiary education exhibit more positively biased expectations than those with lower secondary education. Consistently with previous research (Hurd & McGarry,

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[31] See as Kutlu-Koc and Kalwij (2017) and Teppa and Lafourcade (2013) found this for the Netherlands; O'Donnell et al. (2008) for the UK; and Perozek (2008) and Bissonnette et al. (2017) for the US.

[32] The first result is in line with previous evidence: (i) Wenglert and Rosén (2000) and Wu et al. (2013) found that women are more pessimistic than males in projecting survival probabilities, (ii) Hurd and McGarry (2002) and Gan et al. (2005) observed that men tended to overestimate their lifetimes.

[33] Group I: Italy and Spain. Group II: Belgium and France. Group III: Austria and Denmark. Group IV: Germany, Sweden and Switzerland.

[34] Among the sample of diseased, Italians are on average those that reveal the highest share of positively bias, whilst the Swedish reveal highest share of negatively biased. In contrast, among survivors, Belgians, Germans and French respondents exhibit the highest share of negative bias, and Danish and Spanish the highest share of positive bias.

[35] Table D3 reports the results of the regressions introducing the four instruments, wave and country fixed effects. In most regressions, the four instruments are not significant, confirming that parents' living status only affects offspring's behaviors through the channel of LO.

[36] Living in Denmark and Spain increases the probability of positive biased survival by 16.5 and 15.1 pp respectively, as opposed to living in Germany, where expectations only increase by 2.2 pp.

Table 2 Effect of one standard deviation increase (or decrease) of biased survival expectations (BSE) and biased meteorological expectations (BME) over health related behaviors

	One standard deviation increase of BSE > 0	One standard deviation increase of BSE < 0	One standard deviation increase of BME > 0	One standard deviation increase of BME < 0
Smokes now				
Effect in percentual points	-13.07 pp	14.64 pp	-0.193 pp	0.198 pp
With respect to the mean probability	-48.41%	54.21%	-0.71%	0.73%
Has never smoked				
Effect in percentual points	24.94 pp	-26.57 pp	0.117 pp	-0.326 pp
With respect to the mean probability	51.1%	-54.4333%	0.2399%	-0.6680%
Drinks every day or 5/6 times per week				
Effect in percentual points	-19.90 pp	16.18 pp	-0.648 pp	0.392 pp
With respect to the mean probability	-71.192%	57.887%	-2.317%	1.403%
Has not drunk during last 3 months or less than once per month				
Effect in percentual points	28.847 pp	-8.522 pp	1.024 pp	-0.245 pp
With respect to the mean probability	94.83%	-28.01%	3.37%	-0.81%
Sedentary lifestyle				
Effect in percentual points	-24.498 pp	15.074 pp	-0.720 pp	1.09 pp
With respect to the mean probability	-211.558%	130.17%	-6.21%	9.44%

Note: The effects for BSE are obtained after estimating Eq. (4) with the explanatory variables included in specification M3. Estimated coefficients are reported on Table B13 (and on Table D1 for first-stage regression). The effects for BME are obtained after estimating Eq. (8) with the explanatory variables included in specification M3. Estimated coefficients are reported on Table B6. Mean values for the dependent variables are reported on Table B13.

2002), we find that income plays a larger influence than wealth, and that high-income people exhibit higher BSE. Each 1,000 PPP units of adjusted income (wealth) increase BSE by 66.4 pp (1.2 pp).

Figure B4 displays the predicted estimates of biased subjective longevity by respondent's age, gender and parents' living status. When both parents are alive, BSE increases with respondent's age (e.g., BSE for men (women) aged 70–74 years old is eight (seven) times higher than BSE for men (women) aged 50–54 years old). In contrast, when both parents are deceased, we find a considerably smaller effect among individuals over 75. Comparing BSE by respondent's gender, we find that biased survival is higher for men regardless of parents' living status except for the first age cohort (50–54 years). When both parents are deceased, BSE for men gives rise to an inverted U-shape peaking at 75–79 years, whereas BSE for women remains relatively stable for the three last age cohorts.

5.3 Effects of biased survival expectations on health behaviours

Next, we turn to examine the effect of BSE on health behaviours. Table 2 reports the estimated effect of BSE on a number of health behaviours using instrumental variables. Table B13 in the appendix reports the effect of a one standard deviation increase in BSE and BME. IV estimates suggest that positively *biased survival expectations reduce the probability of unhealthy lifestyles such as smoking, alcohol intake and sedentary lifestyles*. This evidence is consistent with the hypothesis that individuals who expect to live longer adjust their behaviours accordingly. Estimates in Table 2 suggest that one standard deviation increase in BSE reduces (increases) the likelihood of smoking (never having smoked) by 13 pp (24.9 pp), which is an average decrease (increase) of 48% (51%)[37]. Similarly, a one standard deviation increase in BSE reduces (increases) the probability of daily alcohol consumption (not having drunk alcohol during the last 3 months or less than once per month) in 19.9 pp (28.8 pp)[38]. These results are consistent with previous evidence that finds that binge and heavy binge drinkers overestimate both their driving ability and their tolerance to alcohol (Sloan et al., 2013). We estimate that a one standard deviation increase in BSE, reduces sedentary lifestyles, raising the probability of moderate or vigorous physical activity in 24.5 pp.

We find that both positive and negative biased subjective expectations (BSE) exert comparable (and opposite) effects on smoking behaviour. However, we identify heterogeneous effects on other behaviours. In contrast, when we examine the effects of meteorological expectations (ME), we observe a similar sign and consistent effect, but its magnitude, except for "sedentary lifestyles", is almost negligible.

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[37] This result may result from the fact that smokers perceive that they are more likely to experience certain diseases (Sloan et al., 2001) and it is consistent with rational addiction theory according to which smokers are forward looking individuals who internalize the detrimental effects of smoking (Becker & Murphy, 1988).

[38] These effects entail a 71.1% (94.83%) increase (decrease) with respect to the mean probabilities.

Table 3 Effect of one standard deviation increase (or decrease) of biased survival expectations (BSE) and biased meteorological expectations (BME) over health and anthropometric outcomes

	One standard deviation increase of BSE> 0	One standard deviation increase of BSE <0	One standard deviation increase of BME> 0	One standard deviation increase of BME <0
Normal weight				
Effect in percentual points	17.89 pp	-11.7843 pp	0.04 pp	-0.048 pp
With respect to the mean probability	47.50%	-31.291%	0.105%	-0.129%
Obese or overweight				
Effect in percentual points	-27.76 pp	21.90 pp	-1.118 pp	0.855 pp
With respect to the mean probability	-46.767%	36.90%	-1.88%	1.44%
Ten word listing (first recall)				
Effect in words	0.523 words	-0.118 words	0.084 words	-0.002 words
With respect to the mean probability	10.47%	-2.37%	1.69%	-0.04%
Ten word listing (second recall)				
Effect in words	0.548 words	-0.336 words	0.001 words	-0.0003 words
With respect to the mean probability	15.344%	-9.41%	0.018%	-0.009%
Maximum grip strength measure				
Effect in percentual points	1.469 kilos	-1.097 kilos	0.015 kilos	-0.006 kilos
With respect to the mean probability	4.32%	-3.22%	0.043%	-0.018%

Note: SE estimates are obtained from Eq. (4) with the explanatory variables included in specification M3. Estimated coefficients are reported on Table B14 (and on Table D1 for first-stage regression). BME are obtained after estimating Eq. (8) with the explanatory variables included in specification M3. Estimated coefficients are reported on Table B14. Mean values for the dependent variables are reported on Table B6

5.4 Effects on anthropometric health outcomes

Next, we turn to examining anthropometric and health outcomes (Table 3)[39]. Table 3 suggest that an increase in BSE increases the likelihood of a normal weight and decreases the likelihood of obesity. A one standard deviation increases in BSE increases (decreases) the probability of being normal weight (obese) by 17.9 pp (27.8 pp), which implies an increase (decrease) by 47.5% (46.7%) with respect to the average probability of being normal weight (obese). These results confirm previous hypothesis that individuals with BSE generally exhibit better physical health.

5.5 Effects on cognitive abilities

Next, we turn to cognitive abilities. Individuals with positively biased survival expectations can recall more words. One standard deviation increase in an individual's BSE increases the number of words recalled. Furthermore, we find that BSE increases an individual's maximum grip strength test scores. A one standard deviation increase in an individual's BSE leads to an increase in the maximum grip strength test by 1.47 kg, or an average increase in 4.3% with respect to the average score. Consistently, negatively BSE deliver a consistent effect with an opposite sign. However, when we look at effect sizes, we find that positively biased expectations (BSE > 0) produce a larger effect than negatively biased expectations (BSE < 0). In contrast, the effect of BME, albeit consistent, is more modest.

5.6 Effects on financial behaviours[40]

We then estimate the effect of biased survival expectations (BSE) on a number of financial behaviours, and more specifically on the probability of owning financial assets, including cash and increased household wealth. We estimate that one standard deviation change in BSE increases the probability of ownership of bonds by 2 pp, mutual funds by 3.8 pp and individual retirement accounts by 5 pp[41]. Consistently, it decreases the probability of having a bank account by 17.4 pp, investing in stocks by 2.3 pp, having a mortgage by 5.4 pp and having other debts by 5.3 pp[42]. Negatively biased survival

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[39] Table B3 reports the estimated coefficients and Table B14 reports the effect of a one standard increase of LO and ME.

[40] Table B4 reports the estimated coefficients and Table B15 reports the effect of a one standard increase of LO and ME.

[41] These effects entail an average change in 45% for bonds, 76% for shares, 50% for mutual funds (specifically, -16.2% for funds invested mostly in stocks; -19.80% for funds equally divided in stocks and bonds; 52.3% for funds mostly invested in bonds) and 69.2% for retirement accounts.

[42] These effects entail and average decrease by 18.66% (bank accounts), 37.17% (stocks), 50.05% (mortgage) and 46.93% (other debts) with respect to mean probabilities.

Table 4 Effect of one standard deviation increase (or decrease) of biased survival expectations (BSE) and biased meteorological expectations (BME) over some financial behaviours

	One standard deviation increase of BSE > 0	One standard deviation increase of BSE < 0	One standard deviation increase of BME > 0	One standard deviation increase of BME < 0
Bank account				
Effect in percentual points	-17.44 pp	16.42 pp	-0.151 pp	0.087 pp
With respect to the mean probability	-18.66%	17.571%	-0.162%	0.093%
Government or corporate bonds				
Effect in percentual points	2.05 pp	-2.70 pp	0.61 pp	-0.47 pp
With respect to the mean probability	45.45%	-59.77%	13.49%	-10.49%
Stocks or shares (listed or unlisted in stock market)				
Effect in percentual points	-2.26 pp	2.77 pp	0.032 pp	0.17 pp
With respect to the mean probability	-37.17%	45.708%	0.529%	2.81%
Mutual funds				
Effect in percentual points	3.79pp	-4.69 pp	0.127 pp	-0.032 pp
With respect to the mean probability	50.12%	-62.03%	1.67%	-0.43%
Mutual funds: mostly in stocks				
Effect in percentual points	-5.53 pp	2.18 pp	0.10 pp	0.13 pp
With respect to the mean probability	-16.22%	6.41%	0.31%	0.37%
Mutual funds: half in stocks, half in bonds				
Effect in percentual points	-8.89 pp	21.30 pp	-0.33 pp	0.216 pp
With respect to the mean probability	-19.80%	47.42%	-0.74%	0.48%
Mutual funds: mostly in bonds				
Effect in percentual points	10.97 pp	-9.22 pp	1.68 pp	-0.07 pp
With respect to the mean probability	52.31%	-43.97%	8.01%	-0.32%
Individual retirement accounts				
Effect in percentual points	5.04 pp	-5.82 pp	0.19 pp	-0.042 pp

Table 4 (continued)

	One standard deviation increase of BSE>0	One standard deviation increase of BSE<0	One standard deviation increase of BME>0	One standard deviation increase of BME<0
With respect to the mean probability	69.21%	-79.88%	2.69%	-0.58%
Life insurance				
Effect in percentual points	-5.26pp	6.12 pp	-2.72 pp	1.74 pp
With respect to the mean probability	-43.61%	50.72%	-22.54%	14.48%
Mortgage				
Effect in percentual points	3.81 pp	-2.33 pp	3.99 pp	-0.290 pp
With respect to the mean probability	35.27%	-21.61%	36.92%	-2.691%
Other debts (excluding mortgage)				
Effect in percentual points	3.48 pp	-2.851 pp	0.53 pp	-0.316 pp
With respect to the mean probability	30.55%	-25.01%	4.64%	-2.77%
Total wealth amount (1,000PPP)				
Effect in 1,000 PPP	5.20 pp	-11.55 pp	0.24 pp	-0.02 pp
With respect to the mean probability	3.11%	-6.90%	0.144%	-0.013%

Note: SE are obtained after estimating Eq. (4) with the explanatory variables included in specification M3. Estimated coefficients are reported on Table B15 (and on Table D1 for first-stage regression). The effects for BME are obtained after estimating Eq. (8) with the explanatory variables included in specification M3. Estimated coefficients are reported on Table B15. Mean values for the dependent variables are reported on Table B6

expectations (BSE<0) explain some financial investments in an inverse manner[43]. These results point to an intense deaccumulation of assets, and paradoxically, a simultaneous higher concern for the well-being of the family (purchase of life insurance).

Compared to health behaviours, biased meteorological expectations exert a more modest and divergent effect on a few financial behaviours. If heterogeneity in BME is mostly due to private information, one might expect the absolute difference to correlate with behaviors or lifestyle. For instance, people who work outside the household, or follow the news may get more accurate weather estimates than the authors' benchmark. As expected, we find that negative and positive ME seem to exhibit opposite effects in a number of behaviours. Indeed, we find that a one standard deviation change in positively (negatively) meteorological biased expectations (BME) increases (decrease) investments in bonds (life insurance) by 13.5% (22.5%) with respect to its average probabilities. It also increases the probability of having a mortgage by 36.92%. In comparison, the effect of one standard deviation increases in negatively biased meteorological expectations (BME<0) is more modest (10.5% and 14.5%, respectively) (see Table 4).

5.7 Effects on financial risk-taking attitudes[44]

Finally, Table 5 reports the effect of BSE on above average financial risk taking attitudes. We document that a standard deviation increase in negatively biased survival (BSE<0) increases the likelihood of prudent financial behaviours. Finally, on average we find that the effect of positively biased survival expectations (BSE>0) is twice that of negatively biased expectations (BSE<0). Furthemore, we document that the effects for BME are in line with those of BSE but again, they appear to be significantly smaller.

6 Robustness checks

6.1 Focal responses

One potential explanation of our results is the presence of focal responses. Focal responses refer to expectations clustered around certain 'focal points' of the distribution (Hurd & McGarry, 2002). From the histograms depictions (Figure D1), it becomes clear that this is indeed the case in our study. For example, 17.2% of the deceased reported a null probability, 20.8% of the survivors and 18.9% of the deceased sample reported a survival probability of 50%, and 17% of the survivors reported a probability of 100%. Some authors suggest that these responses may are suggestive of the individual struggle with answering probabilistic questions (Bruine de Bruine et al., 2002), while others emphasize their valuable information (Manski

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[43] A one standard deviation change in BSE<0 reduces investment in bonds by 2.70 pp (0.65 pp as compared to BSE>0), mutual funds by 4.69 pp (0.9 pp as compared to BSE>0), total wealth by 11.55 (1,000 PPP), and increases life insurance uptake by 6.12 pp (0.86 pp as compared to BSE>0).

[44] Table B5 reports the estimated coefficients and Table B16 reports the effect of a one standard increase of BSE and BME.

Table 5 Effect of one standard deviation increase (or decrease) of biased survival expectations (BSE) and biased meteorological expectations (BME) over the extent of financial risk that the respondent is willing to take when making investments

	One standard deviation increase of BSE > 0	One standard deviation increase of BSE < 0	One standard deviation increase of BME > 0	One standard deviation increase of BME < 0
Take substantial risk expecting to earn substantial returns				
Effect in percentual points	0.60 pp	-0.50 pp	0.11 pp	-0.22 pp
With t to the mean probability	6.978%	-5.85%	1.29%	-2.60%
Take above average financial risks expecting to earn above average returns				
Effect in percentual points	25.86 pp	-17.17 pp	0.52 pp	-0.78 pp
With t to the mean probability	83.11%	-55.19%	1.68%	-2.50%
Take average financial risks expecting to earn average returns				
Effect in percentual points	-1.63 pp	1.817 pp	-0.07 pp	0.17 pp
With t to the mean probability	-6.54%	7.28%	-0.30%	0.71%
Not willing to take any financial risks				
Effect in percentual points	-13.58 pp	6.27 pp	-0.20 pp	0.24 pp
With t to the mean probability	-38.23%	17.67%	-0.57%	0.68%

Note: The effects for BSE are computed after estimating Eq. (4) with the explanatory variables included in specification M3. Estimated coefficients are reported on Table B16 (and on Table D1 for first-stage regression). The effects for BME are obtained after estimating Eq. (8) with the explanatory variables included in specification M3. Estimated coefficients are reported on Table B16. Mean values for the dependent variables are reported on Table B6

& Molinari, 2010). Bruine de Bruin et al. (2002) coined the term "epistemic uncertainty" to describe the behaviour of respondents who reported a 50 per cent probability, and argue that in this case, the response would be treated as a "*don't know*".

Other research claims that the likelihood of providing focal points is positively associated with lower cognitive performance. Perry (2005) found that individuals reporting focal responses of zero and one were on average less educated, held fewer assets and had lower income than the rest of the sample[45]. Such evidence is validated in the estimates in Table D3 reporting cognitive and economic related correlates of focal and non-focal respondents[46].

As a robustness check, we have re-estimated the model excluding focal responses. Table B1 displays the characteristics of the sample for survivors and deceased after excluding focal responses (0, 50 and 100)[47]. The estimated coefficients and hazard ratios for the preferred Weibull specification are reported in Table B8 (3rd column). Our estimates suggest that the magnitude and significance is very similar to the original sample. Figure D2 compares the density function for the "biased survival" indicator including and excluding focal points. Again, differences between both density functions are almost negligible, which suggests that the inclusion of focal responses are consistent with our previous estimates (as has been also observed by Kleinjans & van Soest, 2014).

6.2 Respondents' understanding of probabilities

A prerequisite for the consistent interpretation of subjective survival expectations is that respondents can answer probabilistic questions (Manski, 2004). Hence, as an additional robustness check, we have excluded those individuals who provided an erroneous response to the following probabilistic question: "*If the chance of getting a disease is 10 per cent, how many people out of 1000 (one thousand) would be expected to get the disease?*"[48]. Again, compared to the baseline coefficients and hazard ratios, estimates resulting from the re-estimated model are of similar magnitude. Figure D3 shows the kernel density function of the "biased survival" indicator for both the total sample and the reduced sample after applying the exclusion criteria. Importantly, the shape of both density functions does not suggest evidence of bias.

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[45] Likewise, Hurd et al. (1998) and Kleinjans and van Soest (2014) observed that more educated individuals were less prone to reveal focal points.

[46] In order to correct for focal responses several alternatives have been proposed: (i) bayesian updating mechanism to smooth focal points (Gan et al, 2005), (ii) replacement of focal point answers at zero with 0.01 and focal point answers at 100 with 99.9 (Picone et al., 2004), (iii) instrumental variables for subjective mortality expectations in order to adjust for focal answers (Delavande et al., 2006). However, other authors have decided against correcting probabilities. Khwaja et al. (2007), Salm (2010) and Post and Hanewald (2013) consider that focal responses are still what agents base their decisions on. Hill et al. (2005) consider that an answer of 50 per cent may be the true probability, if the respondent believes that the event of dying is equally likely to occur or not to occur.

[47] In this re-estimation process, we test which hazard function fits better to the data. Cox-Snell residuals and information criteria point to the Weibull function as before (graphs are available upon request; AIC and BIC shown in Table C1).

[48] With the reduced sample (N = 22,198) we have re-estimated the discrete-time hazard model (see Table B1 for a description of the sample). The information criteria (reported in Table C1) and the Cox-Snell residuals (available upon request) show that the Weibull specification provides the best fit. The estimated coefficients and hazard ratios for the preferred specification are reported in Table B8 (4th column).

6.3 Use of (private) medical information from SHARELIFE

Another concern refers to the imputed parental age at death when parents are alive at the time of the survey, given that parental age at death is not time varying. Hence, we use retrospective data from parental vital status available in SHARE Wave 3, known as SHARELIFE[49]. We can test for the effects of private information with regards to one's own health consistently with previous studies (Viscusi & Hakes, 2003). Accordingly, we have re-estimated our models using two additional instruments: blood pressure being checked during the previous year, and having his/her blood tested[50], as both questions proxy some form of private health information. Consistently, we find that the magnitude and significance of the estimated coefficients compares to that of the entire sample[51].

Table D1 (4th column) reports the results of the IV estimates for BSE, and we find that the values of the corresponding instruments compare to those using the entire sample. Having blood pressure checked in the last year reduces BSE in 11.6 and having blood tested in the last year reduces BSE by 8.1 pp. However, Table D4 reveals that even after such adjustment, the effect of the BSE confirms our previous conclusions.

Figure D4 compares the observed BSE for the total sample, with the predicted BSE for the subsample of respondents who also completed SHARELIFE using all instruments (parents' age of decease, blood pressure and blood check) and the predicted BSE using only two instruments (blood pressure and blood check; 5th column of Table D1). Although the differences are not large, we find that when all the instruments are used, the predicted BSE is closer to the observed BSE.

6.4 Instrument validity

In interpreting the effect of BSE as the difference between objective and subjective survival expectations, one potential explanation is that private information (unknown to the econometrician) influences expectations above and beyond other more general biases such as optimism. To examine these concerns more closely, Figure D5 compares the observed BSE, the predicted BSE (according to estimations of Table D1) and the predicted BSE taking the average for each survey respondent. Consistently with

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[49] SHARELIFE collects respondent's life histories, including medical tests, and the disadvantage is that merging SHARELIFE with our sample implies an important reduction in the number of observations (from 69,900 to 33,269).

[50] The rationale lies in the known link between parent's history of health conditions, such as blood pressure and diabetes, and the probability that children suffer the same pathology (Hakonarson et al., 2007; Newton-Cheh et al., 2009). Therefore, offspring who have a higher risk of suffering a heart attack or developing diabetes may be more concerned about their survival probabilities.

[51] Consistently, Table B8 (5th column) reports the results for the discrete-time hazard model using the new sample (N = 33,269).

the hypothesis that BSE reflect partially an effect of unknown private information, we observe that, for both survivors and deceased samples, the predicted BSE is smaller but still significant and exhibit a large effects size, in line with previous estimates.

To check the reliability of our instruments, we re-estimate the first-stage regression using lagged instruments. Although the sample size is considerably reduced, Table D5 shows that the instrumental variable estimates[52] are relevant, significant, and robust. Similarly, to enhance the causal claims of our estimates, we have then examined the two bound weak instrument method proposed by Conley et al. (2012)[53]. Figure E1 displays the estimates using "father's age of death" as the instrument (similar results have been obtained for the other instruments, available upon request). On the left side we show the graphs for the Local-to-Zero approach. The solid line depicts the 2SLS father's age of death effect estimate for the respective indicator (for simplicity, we only show the results for one indicator of each group). The two dashed lines depict upper and lower limits of the respective test scores. Overall, the results confirm that even with substantial deviation from the exclusion restriction, the instrument still has a considerable effect over the outcome variable[54].

Finally, Figure E1 also displays the 95% confidence bounds of the instrumental variable's coefficient using father's age of death. Taking as reference the zero-line (red-line), once the confidence bounds include the zero-value, the 2SLS are no longer significant at the 95% level of significance. In contrast, if the upper limit crosses the zero-line at a high value of δ, then the 2SLS estimates are robust to possible violations of the exclusion restriction assumption. Similar figures have been obtained for the instrument "mother's age of death" (figures available upon *request).*

6.5 Inclusion of parental characteristics in the discrete hazard model

As a final check, we have re-estimated the discrete hazard model including as explanatory variables the age at death of the parents and the fact of having a living parent. Table C1 shows that, once again, the Weibull model is the preferred model. Using this specification, Table E2 displays the estimated coefficients and hazard ratios for the initial sample, excluding focal responses, those who answered probabilistic questions erroneously and the subsample that answered SHARELIFE. Although the variable measuring the presence of a living mother and father shows now non-significant effects, age at death reveals the expected negative effect on the probability of death.

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[52] The first column corresponds to the estimates using the entire sample and current instruments. The second and third columns correspond to estimations of those individuals for whom lagged observations are available: using current instruments in the second column and delayed instruments in the third column.

[53] This allows us to retrieve inferences even when the instrumental variables do not satisfy the exogeneity restriction (see Appendix E for explanation of both approaches).

[54] In the right column figures we report the confidence intervals. The x axis measures how strong the violation of the exclusion restriction needs to be for the instrument to turn insignificant. In all figures, the confidence intervals do not include the value 0 (red line), so we can infer that the IV estimations are robust to possible violations of the exclusion restriction.

7 Mechanisms

The Nature of Private information. To examine whether BSE convey the effect of respondent's private information, or measurement error, we estimate the effect of lagged BSE alongside the death of a brother, sister, or child as other form of private information in addition to one's parents. The results (Table E1 in the appendix) show that the effect of lagged BSE is significant at 1% and such significance is preserved when the explanatory variables are progressively included, and when the death of the brother, sister or child is added. However, the death of a sibling is not significant at 5% level, nor is the death of a child. Hence, we conclude that the nature of private information matters. More specifically, only parental longevity plays a significant role in expectation formation.

Finally, we examine the effect of two additional pathways, one is the effect of BSE on social contacts, as well as the individual sense of control of one's life, so called locus of control.

Social contacts. Individuals with BSE who as a result engage in more social contacts are less likely to exhibit sedentary lifestyles. We estimate Eqs. (4) and (8) using as the dependent variable a binary indicator that takes the value 1 if the respondent has participated in the last month in voluntary or charity work, attended a sports or social club, taken part in political community activities, as well as event organised by religious organization, attended educational or training courses, and 0 otherwise (see Table A3 for definitions). Table B17 reports the estimated coefficients and Table B18 reports the effect of a one standard increase of BSE and ME. We find that one standard deviation change in BSE increases the probability of social contacts by 6.08 pp (or 38.7% with respect to the mean probability). Similarly, we find that one standard deviation change in BME increase social contacts by 5.8 pp (37% with respect to the mean probability).

Locus of control. Another potential driver of our results can be explained from changes in an individual's sense of control of their life as they age, which we refer to as locus of control (see Rotter 1954). We estimate Eqs. (4) and (8) using as dependent variables four binary indicators that take the value 1 if respondent answers that they feel that things are out of control: often, sometimes, rarely, and never. Table B17 reports the estimated coefficients and Table B18 reports the effect of a one standard increase of BSE and BME.

Consistently, we find that BSE is associated with a reduction in the probability of losing control. A Positive BSE increases the probability of people feeling "things are out of control: often" and increases the probability of feeling "things are out of control. In contrast, negative BSE gives rise to a large increase in the probability of often feeling overwhelmed, whilst the effects of BME is not as robust as those of BSE. These results confirm that BSE may give rise to active coping strategies and the feeling of control of their life (Lopes & Cunha, 2008).

8 Conclusion

We study the formation of biased expectations of both one's own survival and the weather, and we examine the extent to which they affect health and financial behaviours. That is, drawing from individuals level data we have estimated the (positively and negatively) bias in survival expectations (BSE), computed as the difference between actual and subjective survival using individual level longitudinal evidence of individuals in a list of European countries. Similarly, we estimate a measure of biased meteorological expectations (BME) comparing the difference between individual level weather predictions and the actual weather realisations. Next, we draw on an instrumental variable analysis that takes advantage of rich data on parental survival to estimate the effect of BSE on health and financial behaviour, which we compare to the effect of BME.

We document evidence of a bias between subjective and objective survival expectations across domains (survival and the weather), and we estimate that such domain specific bias heterogeneously influences health and financial behaviours. We further find a symmetric effect of positively and negatively biased survival expectations on behaviours[55]. BSE predicts some health and financial behaviours such as smoking, sedentary lifestyles, purchasing life insurance and saving for old age. However, BME *does not influence health behaviours in the same magnitude*. One standard deviation change in BSE is associated with an increase in the probability of healthier behaviors (such as never having smoked by 51%, not having used alchol in the last 3 months by 94.8%). Similarly, one standard deviation change in BSE increases the probability of taking above average financial risks, or the probability of expecting to earn above average returns (83%), investing to a larger extent in fixed income securities, such as corporate bonds, mutual funds (mostly in bonds), and individual retirement accounts.

In contrast, BME increases the probability of owning bonds (13.49%), holding mortgage (36.9%), but decreases the probability of purchasing life insurance (-22.5%). These results are consistent with evidence that biased expectations are domain specific. A clear policy implication emerges if more positive biased expectations can be learned. The latter might result from access to private information, as well as the influence of some cognitive biases such as optimism though our estimates cannot fully distinguish between the two[56].

Our estimates are consistent with Wang and Sloan (2018) who draw attention to the negative effects arising from the underestimation of the risks associated with non-adherence to a prescribed treatment. In their analysis of patients diagnosed with diabetes, they note that many patients were not conscientious in their adherence to medical recommendations. Similarly, Picone et al. (2004) document that women with biased survival expectations are more likely to perform breast self-exams and

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[55] In some cases, the effect of a one standard deviation increase of negative BSE is higher as compared to that of positive BSE. For example, an increase of negative BSE generates a strong disinvestment in bonds, mutual funds (mostly in bonds) and a significant decrease in total wealth.

[56] If we interpret our results as reflecting optimism (positive expectations about the future) then our estimates are consistent with twin studies showing that optimism during individuals' impressionable years can influence health behaviours (Plomin et al., 1992).

to request Pap smears and mammograms consistently with our estimates suggesting positive effects of BSE in increasing the probability of a "healthy" lifestyle, (i.e., smoking, drinking, physical exercise). Hence, we conclude that BSE vary across domains and exert economically relevant effects on health and financial behaviours.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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