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Determinants and Life-Cycle Effects of Survival Ambiguity

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Abstract

Sound retirement planning requires individuals to have precise beliefs about their survival chances. Based on an online survey experiment administered to a representative sample of the US population, we provide first evidence of the patterns of individuals' uncertainty about their survival probabilities, i.e., survival ambiguity, over the life-cycle. To this end, we devise a novel direct measure of survival ambiguity at the individual level, using the variance of the distribution of subjective survival probabilities. Leveraging experimental variation, we find that providing information about objective survival chances decreases individuals' degree of survival ambiguity. Further, we show that individuals' survival ambiguity is strongly negatively associated with individuals' savings rates. Finally, we provide a realistic life-cycle model of savings and portfolio choice that rationalizes the empirical evidence. Our findings provide an explanation for the observation that many individuals "save too little" for their retirement and support information campaigns about individuals' objective survival chances in addition to financial education programs to improve retirement security, as survival ambiguity presents a previously unexplored determinant of financial well-being.

JEL classification: D15, D91, G51

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1 Introduction

Why do some households save too little while others save too much? A central challenge in understanding household financial behavior lies in explaining why savings choices frequently deviate from the predictions of standard models. An emerging strand of research suggests that beyond financial literacy, income, and preferences, beliefs about survival prospects are central in shaping savings outcomes and determining retirement preparedness (Heimer et al., 2019; Yakoboski et al., 2023a,b; Foltyn and Olsson, 2024). In this context, sound retirement planning and, more generally, management of household finances, requires individuals to have precise beliefs about their survival chances. Although it has been noted that individuals may be unable to place precise probabilities about future events, no empirical evidence has been provided on the role of survival ambiguity, i.e., the dispersion of subjective survival probabilities, on individuals' savings decisions.

In this paper we provide first evidence on the patterns of survival ambiguity over the life-cycle and across sub-groups of the population, its determinants as well as its role on savings choices over the life-cycle. We do so by using novel data on subjective survival ambiguity at the individual level that we have collected for a representative sample of the US population. First, we document substantial heterogeneity in survival ambiguity among the population, with younger, less wealthy and less educated individuals having more imprecise beliefs about their survival chances. We then exploit an online experiment to show that providing information about objective life prospects significantly decreases the degree of individuals' survival ambiguity. Second, we document a strong and robust negative association between individual's survival ambiguity and savings rates that exceeds in magnitude the relationship between subjective survival probability and savings behavior. Finally, we extend an otherwise standard life-cycle model of savings and portfolio choice to allow for the presence of individuals' survival ambiguity. We show that the calibrated model provides a rationalization for the empirical evidence. Our findings suggest that including survival ambiguity in a calibrated life-cycle model of savings and portfolio choice can contribute further to understanding the well-documented puzzle in household finance that the young save too little (Skinner, 2007; Poterba et al., 2011).

Previous research has considered the role of objective life expectancy on saving behavior (De Nardi et al., 2009; Cocco and Gomes, 2012) and, more recently, the role of subjective survival probabilities on savings (Heimer et al., 2019) and demand for annuities (O'Dea and Sturrock, 2021). While information on individuals' subjective probabilities have previously been collected, e.g., by the *Health and Retirement Study* (HRS) and Heimer et al. (2019), no previous survey has collected a direct measure of the degree of respondents' survival ambiguity.[1] Armed with panel data on survival probabilities from the HRS, one could assume that an individual forms expectations about future ambiguity by taking into account the evolution of her past subjective survival probabilities over time. However, interpreting the volatility in individual survival probabilities over time as survival ambiguity is problematic since this is likely to also reflect measurement error as well as unobservable innovations in survival prospects. Further, the cross-individual heterogeneity in mean survival beliefs is likely to reflect differences in superior information, past experiences, or potentially unobserved characteristics among individuals and is not a satisfactory measure of *individual* survival ambiguity. Izhakian (2020) provides a general framework for measuring the degree of ambiguity as the variance of probabilities. Analogously, we devise a first direct measure of survival ambiguity by the variance of the distribution of individual's subjective survival probabilities.

The first goal of this paper is to document the extent of survival ambiguity in the population and its determinants. In particular, we hypothesize that individuals' superior information (i.e., informed beliefs about their own mortality) and individuals' sophistication (i.e., probability numeracy or understanding of objective mortality prospect in the general population) are important determinants of the degree of individuals' subjective survival ambiguity.

To elicit novel data on subjective survival ambiguity at the individual level, we conduct an online survey on a representative sample (N=12,833) of the US population. To create controlled variation in the hypothesized determinants of survival ambiguity, we conduct a randomized experiment within the survey. We randomly assign respondents to 1 out of 5 educational interventions or to a control group. Each intervention either provides information about the concept of probabilities or one version of information about average mortality probabilities in the US and/or the most common causes of death. The experiment within the survey allows us to disentangle the role of potential determinants within those two areas since the survey records respondents' individual information, such as their health status, and the experiment creates controlled heterogeneity in respondents' understanding of probabilities and knowledge about mortality prospects that respondents' can relate to their personal information. Specifically, we exploit the random variation from the experiment to investigate the role of limited probability numeracy and that of limited knowledge about longevity prospects.

We find evidence of substantial subjective survival ambiguity in the population. Further, using multivariate regressions, we show that subjective survival ambiguity is heterogeneous

[1] The HRS collects information on individuals' subjective probability to live at least until a certain age, which can be used to back-out subjective survival functions as in O'Dea and Sturrock (2021).

across sub-groups of the population. Specifically, we find that the degree of survival ambiguity decreases with individuals' age until retirement and is lower among women, higher income earners, people who attained some college education, individuals with higher cognitive skills and probability numeracy, individuals with a relatively high degree of optimism, and people in relatively good health. Our main experimental result is that, while our intervention aimed at teaching the concept of probability had no effect on respondents' survival ambiguity, providing information about objective life prospects significantly decreases the degree of individuals' survival ambiguity, whereas our probability education intervention has no effect on individuals' beliefs.

The second goal of this paper is to explore the role of survival ambiguity in the context of financial well-being. To that end, we investigate the effects of subjective survival ambiguity on participants' saving behavior. First, we explore the association of our measure of survival ambiguity with measures of savings behavior using multivariate regression models. We find a strong negative association between individuals' survival ambiguity and savings, using alternative measures of savings and uncertainty about survival probabilities. Remarkably, the strong negative association remains after controlling for a long list of individual and household characteristics that include demographics, preferences, detailed health conditions, individuals' financial sophistication and cognition, exposure to (causes) of death and the weight assigned to different life risks when assessing their own survival chances. Interestingly, while survival ambiguity remains a robust predictor of the savings rate even after controlling for a long list of individual characteristics, the association between subjective survival probabilities and savings is no longer significant after controlling for a broader set of covariates beyond standard demographic characteristics. The results on the association between savings and survival ambiguity are consistent across subgroups of the population characterized by different levels of cognitive ability, financial literacy and probability numeracy. Further, we show that survival ambiguity only affects the saving behavior of ambiguity-averse individuals. Finally, we find that the association between survival ambiguity and savings rates is primarily driven by younger (< 60) individuals. Implementing the coefficient stability test proposed by Oster (2019), we show that omitted variable bias is unlikely to confound the empirical relationship we find between measures of savings and survival ambiguity.

Next, we explore the implications of survival ambiguity in a life-cycle setting with the aim of rationalizing the empirical evidence and quantifying the importance of the observed degree of survival ambiguity on savings behavior. First, we show that survival ambiguity systematically induces a pessimistic distortion of continuation values in a life-cycle setting across alternative representations of the ambiguity structure—max–min expected utility (Gilboa and Schmeidler, 1989), smooth ambiguity (Klibanoff et al., 2005) and a variance-based representation in the spirit of Izhakian (2020)—thereby decreasing the incentive to save. Second, we incorporate subjective survival ambiguity in an otherwise standard, realistically calibrated, life-cycle model of savings and portfolio choice. The model is specified such that the role of ambiguity in beliefs is considered separately from risk and from ambiguity aversion in the vein of Bommier (2017) and Izhakian (2017), allowing us to closely link theory and evidence.[2] We show that the estimated life-cycle model—disciplined by the degree of survival ambiguity observed in the data and with plausible preference parameter values—successfully matches the magnitude of the negative effect of survival ambiguity on saving behavior documented in the data. We then use the estimated model to show that survival ambiguity is quantitatively important for understanding consumption-savings choices over the households' life cycle. The model predicts that the observed degree of survival ambiguity decreases accumulated wealth before retirement by around 18%, and consumption by around 5.6% during the retirement years, on average. Consistent with our empirical findings, the model predicts that survival ambiguity reduces savings only during the accumulation phase of the life cycle. We finally use the estimated model to quantify the effects of informational campaigns aimed at reducing the individuals' degree of survival ambiguity.

We provide evidence that survival ambiguity represents a distinct and previously unexplored channel through which mortality considerations affect financial decision-making and retirement security. Survival ambiguity complements established determinants of saving, helping reconcile life-cycle model predictions with observed consumption and saving behavior. Much of the recent literature on determinants of savings decisions and retirement preparedness has focused on the role of financial literacy (Lusardi and Mitchell, 2007, 2008; Anderson et al., 2017; Lusardi et al., 2017), subjected (distorted) survival beliefs (Hamermesh, 1985; Hurd et al., 1998, 2004; Salm, 2010; Spaenjers and Spira, 2015; Chen et al., 2020; Heimer et al., 2019), and longevity literacy (Hurwitz et al., 2022; Yakoboski et al., 2023a,b). More generally, the recent literature in household finance acknowledges the importance of accounting for households' subjective expectations to understand savings and investment decisions (e.g., D'Acunto and Weber 2024).

Many studies have analyzed the relationship between individuals' life expectancy and their consumption-savings behavior. E.g., De Nardi et al. (2009) investigate how much of the asset accumulation of older and richer households can be attributed to a longer life expectancy. The authors use a structural model to disentangle effects of variations in life expectancy by health, gender, and permanent income from other influences on retirement savings, such as medical expenditures. Their findings suggest that the risk of outliving

[2] Analogously to the definition of risk aversion as an aversion against mean-preserving spreads in outcomes, this framework defines ambiguity aversion as an aversion against mean-preserving spreads in probabilities.

one's net-worth has a sizeable effect on old-age savings decisions. Cocco and Gomes (2012) calibrate a life-cycle model with stochastic future survival probabilities considering shocks to aggregate survival probabilities based on the Renshaw and Haberman (2006) model. The authors assume that individuals form expectations about these probabilities when making their decisions about savings and retirement age. They find a positive reaction of optimal savings to an increase in survival probabilities and that individuals can greatly benefit from financial instruments designed to hedge such shocks.

The articles most closely related to our contribution are those analyzing life cycle consumption savings models taking into account individuals' self-reported subjective survival probabilities. Heimer et al. (2019) analyze the effect of subjective mortality on individual savings over the life-cycle. In a survey, the authors find evidence that, after controlling for financial literacy, younger individuals underestimate their own survival probability and older individuals overestimate it. This result is consistent with findings from previous studies (Hurd and McGarry, 1995; Elder, 2013; Post and Hanewald, 2013) and helps reconciling a puzzle in the literature by providing an explanation why the young "save too little". The authors further provide some survey-based evidence on the mechanism for changes in subjective mortality over the life-cycle: They suggest that mortality beliefs change over the life cycle together with the salience of age-cohort-specific causes of death. When younger individuals consider their mortality, they think of salient rare events such as plane crashes, for which they overweigh the probability of occurrence. Older individuals place more weight on natural aging, leading to higher subjective survival estimates.[3] Foltyn and Olsson (2024) explore how subjective heterogeneity in life expectancy interact with health status to affect savings behavior. They find that survival belief biases are even more important among the unhealthy. O'Dea and Sturrock (2021) look at the role of longevity risk misperception on the demand for annuity. Using data from the Health and Retirement Study (HRS), they find a similar pattern in the estimation errors of individuals' survival probabilities over the life-cycle as Heimer et al. (2019). Using a calibrated life cycle model, the authors show that accounting for subjective survival probabilities reduces the optimal demand for annuities, thereby providing a potential explanation for the famous annuity puzzle.

In this paper, we show that household savings decisions are not just affected by their subjective expected values of survival prospects but that individuals' uncertainty about survival rates plays an (even more) important role in household consumption-savings choices.

Our research is motivated by the observation that households base their choices on their given information set when making real-life savings decisions. That is, savings decisions

[3] We base many of our survey questions on the survey conducted by Heimer et al. (2019) in order to test whether their findings also apply in our context.

are likely driven by individuals' knowledge and beliefs about their life expectancy rather than by their objective life expectancy calculated based on nation-wide mortality tables. Bommier and Schernberg (2020) assume that individuals update the projections of their life expectancy based on incoming information over time. The authors show that, given these survival projections, temporally risk-averse agents prefer flexible levels of retirement income that depend on individuals' future mortality prospects over ex-ante fixed pensions. The evidence on the predictive validity of subjective survival probabilities is mixed (Hurd and McGarry, 1995, 2002; Perozek, 2008; d'Uva et al., 2017; Bissonnette et al., 2017; Bell et al., 2020). For respondents in the health and retirement survey (HRS), McGarry (2020) examines the correlates of individuals' subjective probabilities to live at least to age 75 or 85. She focuses in particular on how these subjective survival probabilities evolve over time and in response to major life events, such as health shocks, or the death of a family member.

A few studies have explored the concept of survival ambiguity across individuals, i.e., a measure based on the dispersion of mortality beliefs in a sample population, and its link to household financial decision making (Post and Hanewald, 2013; Groneck et al., 2016; Caliendo et al., 2020). The intuition of this approach is that individuals may find it more difficult to form an accurate prediction of their own survival probabilities, when they observe a higher variation in the survival outcomes of their peers. However, the dispersion of mortality beliefs in the sample population is not a satisfactory measure for **individual** survival ambiguity. Indeed, measures of cross-individual heterogeneity in subjective survival probabilities are likely to reflect disagreement across people due to systematic differences in superior information or potentially unobserved characteristics, rather than capture imprecision in beliefs (i.e., second-order subjective uncertainty). In order to link individuals' characteristics and behavior to survival ambiguity, a direct measure of survival ambiguity at the individual level is needed. We create such a first direct measure of survival ambiguity using the variance of the distribution of subjective survival probabilities - deriving it from Izhakian (2020), who defines the degree of ambiguity as the variance of probabilities. To our knowledge, this paper is the first to examine the determinants of individual subjective survival ambiguity as well as its role in a life cycle framework. Identifying the determinants and implications of subjective survival ambiguity on consumption and savings choices throughout the life cycle is an important step in guiding consumers towards retirement security.

In what follows, Section 2 outlines the survey and the experiment, as well as the detailed description of our measure of survival ambiguity. Section 3 analyzes the determinants of survival ambiguity. Section 4 investigates the effect that survival ambiguity has on savings behavior. In Section 5, we present a life cycle model with survival ambiguity. Finally, Section 6 concludes.

2 Survey and experiment design

We administered our survey of 12,833 respondents between the ages of 20 and 80, selected to be representative of the US population with respect to age, gender, income and race. The survey has been fielded in collaboration with Qualtrics Panels between August and October 2022.[4] The survey instrument consists of two modules. The first collects extensive information about respondents' characteristics, such as demographic background, subjective expectations, experiences, and preferences. It is split into one part at the beginning of the survey and one part at the end of the survey. The second module focuses on the experimental elicitation of determinants of survival ambiguity. Figure A1 in the Appendix illustrates the detailed timeline of the survey instrument. In this section, we first describe the set of information we collect using the survey questions. Next, we describe the experimental design and the treatment interventions.

2.1 Survey

Baseline socio-demographics and subjective survival probabilities First, we start by collecting demographic information of respondents that is necessary to customize the subsequent questions and treatment interventions shown to them. We collect information on age, gender, marital status, employment status, race, state of residence and education. Respondents in our sample are on average 46 years old, more than half (52.1%) are female, and 55.1% are married. About one fifth (20.6%) of the respondents is unemployed and one fifth (20.4%) retired. With 77.9%, the majority of the respondents is White. The second biggest racial group is Black or African-American (12.9%). Almost half of the sample (42.4%) has a Bachelor degree or a higher level of education. Descriptive statistics of demographic characteristics are reported in Appendix Table A1. In a second step, we elicit point-estimates of respondents' subjective one-year, two-year, and ten-year survival probabilities[5]. On average, respondents place a probability of 87.23%, 86.24%, and 78.26% on surviving at least one year, at least two years, and at least ten years, respectively.

Measuring survival ambiguity To distinguish between survival risk and survival ambiguity and to separate beliefs about survival prospects from risk preferences and ambiguity

[4] Appendix B provides a more detailed description of the survey organization.

[5] As in Heimer et al. 2019, we record the subjective survival probabilities for several periods to investigate consistency over planning horizons. The exact question reads the following. *How likely is it that you will still be alive one year from today? Please provide us with your best personal judgment. Using any number from zero to 100 where 0% equals absolutely no chance and 100% equals absolutely certain.* Table A2 in the Appendix reports descriptive statistics of subjective survival probabilities for all three periods.

preferences, we apply the approach proposed by Izhakian (2020). He shows that - similar to measuring the degree of risk as the volatility of outcomes - the degree of ambiguity can be measured by the expected volatility of the uncertain probability density across events. To explore the implications of survival ambiguity on retirement preparedness, we need a measure of survival ambiguity at the individual level. In light of this, we define the individual degree of survival ambiguity as:

$$\mho^2[p] = \int E[\phi(p)]Var[\phi(p)]dp \tag{1}$$

where $\phi(p)$ is the density function of one individual's subjective survival probabilities. In the (survival/death) two-outcome world, the ambiguity index collapses to the variance of the distribution of the individual's subjective survival probabilities.

We measure individuals' survival ambiguity applying the intuitive *bins-and-balls* procedure proposed by Delavande and Rohwedder (2008). We proceed in two steps: (i) we ask respondents to report an interval (i.e., the minimum and maximum values) for the survival measure (as in Dominitz and Manski 1997); (ii) we use the elicited minimum and maximum values of the interval as bounds to elicit our measure of survival ambiguity.

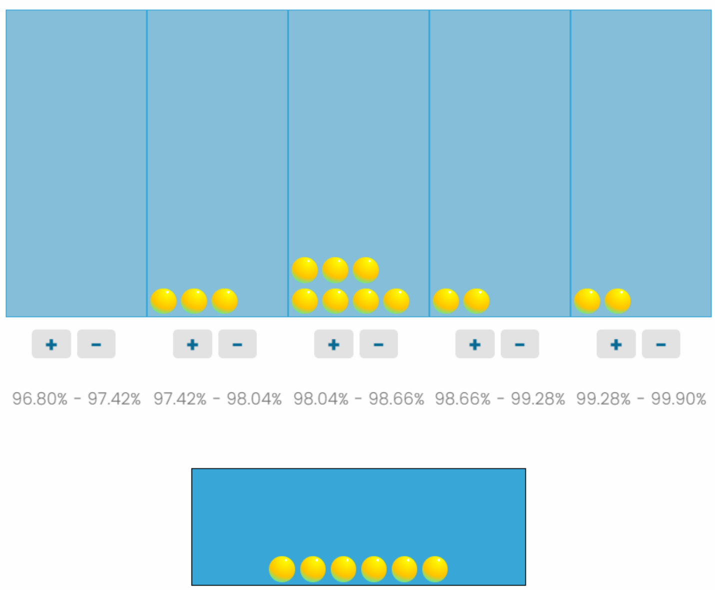
Using this two-step approach, we start by eliciting respondents' uncertainty about their age of death. Eliciting respondents' uncertainty about their remaining lifetime mainly serves as a practice run for the elicitation process with the *bins-and-balls* method before we use it to elicit our measure for survival ambiguity, i.e. ambiguity about survival probabilities. Therefore, we start by recording an interval for respondents' subjective remaining lifetime by asking them to provide us with the minimum and maximum age they believe they will live to.[6] In the second step, we elicit individuals' subjective distribution of their believed age at death (and therefore, using their current age, the distribution of respondents' subjective remaining lifetime) with the *bins-and-balls* procedure. Specifically, we provide participants with 20 virtual balls and line up 5 bins, each representing an interval of potential ages at death, where the overall interval borders are determined by subjects' previous responses. Participants are then asked to allocate the balls between the bins proportional to the chances of each possible outcome.[7]

[6] The exact questions read: *"What do you think is the minimum age that you will live to? Please provide us with your best personal judgement."* and *"What do you think is the maximum age that you will live to (the oldest you can get)? Please provide us with your best personal judgement."*. This approach is similar to that used in Guiso et al. (2013) to measure individuals' beliefs about the values of their replacement rates at retirement.

[7] The exact question reads: *"In the following figure, please tell us about the likelihood that you will die at a certain age. Please place the balls in each bin, proportional to the chances of each possible outcome. You have to allocate all balls using the "+" and "-" buttons before you can move on to the next question."*

After a practice run using the *bins-and-balls* procedure, we apply the two-step procedure to elicit the individual degree of survival ambiguity. Similarly to the elicitation method used for subjective uncertainty in remaining lifetime, we first ask respondents to provide us with the minimum and maximum values they would assign to their one-year, two-year, and ten-year survival probabilities.[8] Then, we elicit the individuals' subjective distribution of survival probabilities with the *bins-and-balls* procedure. We provide participants with 20 virtual balls and line up 5 bins each representing an interval of expected survival probabilities. Participants are then asked to allocate the balls between the bins proportional to the chances of each possible probability.[9] We use the individual extrema reported in the first step to define the overall interval over which the respondent is asked to allocate the probabilities. This second step is illustrated in Figure 1.

Figure 1: Visual elicitation of subjective distribution of survival probabilities.



Finally, coherently with the formal definition in Equation (1), we empirically measure an individual's ambiguity about her survival probability as the dispersion of this elicited subjective distribution of survival probabilities. While we use the method described above

[8]The exact questions read: *"You told us that you think there is a XX% chance you will survive at least one year from now on. You may have a range of possible probabilities in mind. What do you think is the minimum probability that you will survive at least one year from now on?"*, where the value of the subjective survival probability is imputed from the respondent's previous answer, and *"What do you think is the maximum probability that you will survive at least one year from now on?"*

[9]The exact question reads: *"In the following figure, please tell us how you perceive your probability to survive until at least one year from now on. Please, place the balls in each bin, proportional to the chances of each possible probability. You have to allocate all balls using the "+" and "-" buttons before you can move on to the next question."*

to elicit survival ambiguity over a 1-year horizon, a 2-year horizon, and a 10-year horizon, we only use the measure of 1-year survival ambiguity for our main analyses and when appropriate report the results to a long time horizon, i.e., 10-year survival ambiguity. Appendix Table A2 reports descriptive statistics for all three measures, and Table A3 in the Appendix shows that survival ambiguity over a horizon of 1 year is positively correlated with survival ambiguity over the 2-year and 10-year horizons.

Other post-intervention survey questions The remainder of the survey follows three main goals. The first goal is to record exogenous factors potentially determining individuals' survival ambiguity, such as individual skills, attitudes and superior information. Specifically, the survey collects information about respondents' financial literacy, cognitive ability, probability numeracy, health status, previous experience with mortality, e.g., parental mortality, and optimism. We measure financial literacy as the total number of correct answers to the Big Three financial literacy questions Lusardi and Mitchell (2007, 2023). The Cognitive Ability Score is the sum of correct answers to the cognitive reflection questions by Frederick (2005). Probability numeracy is measured using the 4-item probability numeracy battery presented by Hudomiet et al. (2018). Further, we ask a question on probability numeracy that is specifically tailored to survival probabilities (Boyer et al., 2020). Eliciting probability numeracy also allows us to test whether our intervention teaching about the concept of probability was effective in increasing probability numeracy among respondents in this treatment group. With a respective average score of 1.72 out of 3 and 1.91 out of 4, the respondents score relatively well on financial literacy and probability numeracy. Around 70% of the sample respond correctly to the probability numeracy question tailored to survival probabilities. The average number of correct responses to the questions testing cognitive ability is relatively low (0.37 out of 3). Perceived health status, health-related behavior, as well as superior information on one's health status and mortality related information about (grand)parents could be important determinants of survival ambiguity. Although a third (30.1%) of all participants currently smokes cigarettes and 45.2% are obese, almost half (46.3%) of the respondents perceive their own health state as very good or excellent, while only 22.5% report that they are in fair or poor health. With 28.6%, high blood pressure is the condition with which the most respondents were diagnosed. 37.2% of the sample has not received a diagnosis for any of the listed conditions.[10] We categorize these respondents

[10]Listed conditions include high blood pressure; hypertension; diabetes; high blood sugar; cancer or a malignant tumor (excluding minor skin cancer); chronic lung disease such as chronic bronchitis or emphysema; heart attack/ coronary heart disease; angina, myocardial infarction, congestive heart failure, abnormal heart rhythm, or other heart problems; stroke; emotional, nervous, or psychiatric problems; problems with depression; Alzheimer's Disease; dementia; senility or any other serious memory impairment; arthritis or rheumatism; a weakened immune system; a high blood cholesterol level; osteoporosis; any other condition.

as being in good health objectively. Generally, participants are not very optimistic, with a mean optimism score of 2.20 out of 6. In terms of parental mortality, half of the sample reports that their father is still alive, while 60.2% state that their mother is still alive. 22.4% and 20.6% of respondents still have a living Grandmother or Grandfather, respectively. Descriptive statistics for the respondents' health related characteristics are presented in Appendix Table A4. As a second goal, we aim to collect measures of savings behavior, such as households' saving rates and net worth, using battery questions similar to those on the Survey of Consumer Finances (SCF) and the HRS.

Finally, we measure ambiguity aversion as in Dimmock et al. (2016), defined as the difference between the matching probability reported by the respondent and 0.5, expressed in percent.[11] More than half of the sample is ambiguity averse (59.2%). This fraction is slightly larger than the share that Dimmock et al. (2016) have documented in their sample of the U.S. population (52%). Appendix Table A1 reports descriptive statistics for the measures of financials, sophistication, optimism, and preferences.

2.2 Validation of the measure of survival ambiguity

To validate the method used to create our measure of survival ambiguity, we explore different patterns of the distribution of subjective survival probabilities that could potentially be interpreted as inconsistent behavior or inattention of the participants. We identify individuals who choose to place all balls in the first interval ("AllMin"), individuals who choose to place all balls in the last interval ("AllMax"), and individuals whose allocation of balls results in some type of bimodal distribution, e.g., who allocate all balls between the first and the last interval ("Bimodal 1").[12] Table C1 in Appendix C summarizes the analyzed patterns and Table C6 presents the determinants of creating such patterns in the distribution of subjective survival probabilities. It shows, for instance, that cognitive skills are negatively related to creating the "Allmin" and "Allmax" pattern, and probability numeracy is negatively associated with the likelihood of creating an "Allmin" pattern or some kind of Bimodal distribution. More formally educated respondents and respondents who personally

[11] Ideally, we would measure ambiguity preferences in a mortality-related loss domain. To the best of our knowledge, no such measure is established in the literature. Therefore, we use the established measure for ambiguity aversion in a non-mortality-related gain domain as a proxy for ambiguity aversion in our context.

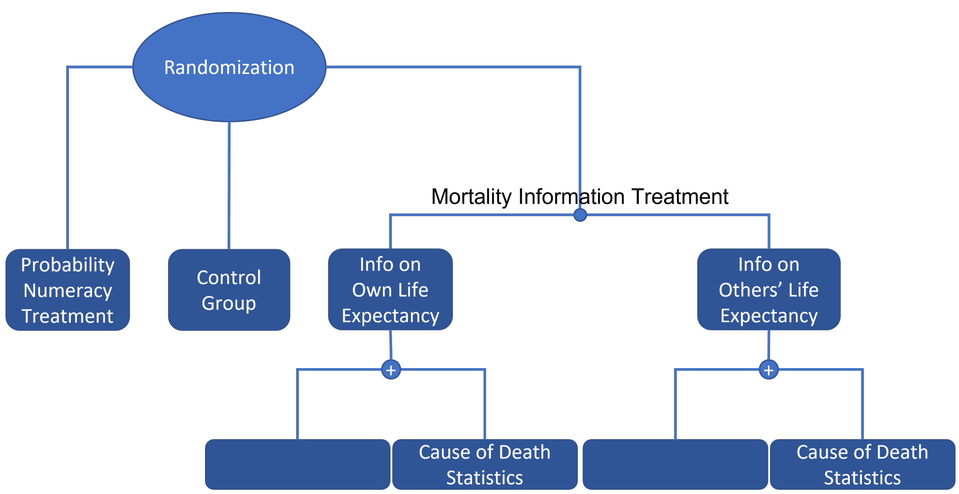
[12] While placing all balls in one of the first (last) is inconsistent with having stated an maximum (minimum) value outside of this interval (as it is the case for the patterns "AllMax" and "AllMin"), there is a possible interpretation of allocating the balls in a bimodal distribution. Similarly to the thought experiment of Schroedinger's cat, where a hypothetical cat in a closed box may be considered to be simultaneously both alive and dead, seemingly healthy participants may consider the possibility of unknowingly having a severe disease and allocate a certain mass to the lowest interval of survival probabilities in case they do have such a disease, and they allocate a certain mass to the highest interval of survival probabilities in case they do not have such a disease.

knew someone who died due to a risky lifestyle (e.g., base jumping, scuba diving, skiing) are less likely to build an "Allmax" pattern, while optimistic respondents are more likely to do so. In Appendix C, we show that all our empirical results are robust to excluding the identified patterns of the distributions of survival probabilities.[13]

2.3 Experimental design

In order to explore potential determinants of survival ambiguity, we conduct a randomized experiment within the survey. Specifically, we explore the role of probability literacy, knowledge of survival probabilities for different groups in the population, as well as knowledge about the percent of deaths by causes of death as potential determinants of survival ambiguity. We randomly assign 5,903 respondents to 6 groups.[14] As shown in Figure 2, the first level of randomization splits the sample of respondents in 4 groups of almost equal size: a control group receiving no information and three treatment groups. The second and third treatment groups are further randomly split into a subgroup receiving no additional information and a group receiving additional information. After the treatment intervention aimed at creating controlled variation in probability literacy and in the knowledge on survival probabilities and causes of mortality, we elicit individuals' survival ambiguity as described in the previous section. In the rest of this section, we describe the interventions in more detail.

Figure 2: Random Allocation of the Treatments



[13]In addition to these patterns, we have identified participants who state the same minimum probability of survival as their maximum probability of survival. Only 19 of our participants report the same number for their minimum survival probability and their maximum survival probability. Since no interval for the bins-and-balls procedure could be formed in this case, the value for survival ambiguity for these participants is missing, and these observations are excluded from our analyses. In Appendix C, we also show that all our empirical results are robust to including these 19 participants with an assigned survival ambiguity of 0.

[14]We only use a part of the sample for the experimental analyses as we further describe in Appendix B.

2.4 The treatments

Teaching about the concept of probability Having precise beliefs about own survival probabilities critically relies on the understanding of the basic concept of probabilities. However, previous studies have documented limited probability numeracy among the population. To quantify the importance of limited probability numeracy in explaining our measurement of survival ambiguity, we teach a randomly selected group of respondents the concept of probabilities. This educational treatment was designed based on the questions that Hudomiet et al. (2018) introduce to measure probability numeracy and based on one question that Boyer et al. (2020) have adapted to the mortality context. We later use the exact questions from this literature to explore the variation in probability numeracy that this treatment has generated in our sample.[15]

"Own" objective life expectancy and survival probabilities We formulate the hypothesis that survival ambiguity may be explained by limited knowledge about the objective survival probability of different "type" of individuals in the population. We first explore the role of the objective survival prospects of one's "own" group. We do this considering the individual characteristics considered by the National Center for Health Statistics in the US to construct life tables. The second intervention consists then in providing information about the survival chances of the respondent's demographic group based on age, gender and race. We provide personalized information to the respondent regarding objective life expectancy, one-year survival probabilities and probability to be alive at the age of 80. We do this by linking information that respondents provide in the first part of the survey regarding their age, gender and ethic group to life expectancy, one-year survival probabilities and the probability to be alive at the age of 80, as computed by the National Center for Health Statistics.

"Others"' objective life expectancy and survival probabilities To further explore whether survival ambiguity depends on the individual's limited knowledge about objective life prospects, we consider the role of the objective dispersion in survival prospects across different groups in the population. To this end, we again rely on the heterogeneity in life prospects across groups in the population defined by the individual characteristics considered to construct life tables by the National Center for Health Statistics.

Therefore, the third intervention adds to the information about "own" survival prospects

[15] In unreported results, we find that the effect of the probability numeracy treatment on the probability numeracy score is positive and statistically significant. The treatment has, however, no significant effect on the likelihood of responding correctly to the probability numeracy question in the mortality context.

provided in the second treatment, information on the survival chances of other groups of individuals in the US population. Specifically, we also provide information about life expectancy, one-year survival probabilities and probability to be alive at the age of 80 of different, but "similar" groups of individuals. We first provide survival statistics for an individual of the same age and racial group, but opposite sex. Further, survival statistics are also shown for an individual of the same age and gender, but different race.[16]

Importance of different causes of death The second and third treatment groups are randomly split into a subgroup receiving no additional information and a subgroup receiving additional information on the percent of deaths by cause of death. This intervention aims to disentangle the role of limited knowledge about the probability of dying for a specific reason, from that of individual superior information regarding the probability to contract a certain disease, or be exposed to injuries because of risky behavior. Specifically, we report the percent of total deaths in 2019 due to likely causes of death in the US, as reported by the National Center for Health Statistics.[17] Further, we inform respondents that, according to calculations of the Centers of Disease Control and Prevention, in 2021 in the U.S., the percent excess mortality due to COVID-19 infections was 17.27 percent.

3 Determinants of survival ambiguity

This part of the empirical analysis has two goals. First, we wish to provide novel evidence on patterns of survival ambiguity over the life-cycle and across different groups of the population. This also serves as a validation of our measure of survival ambiguity. Second, leveraging the experimental variation, we explore the importance of probability literacy and knowledge about objective survival chances as determinants of individual survival ambiguity.

3.1 Key facts about survival ambiguity

We start our empirical analysis by documenting patterns of individuals' survival ambiguity over the life-cycle, and across sub-groups of the population.

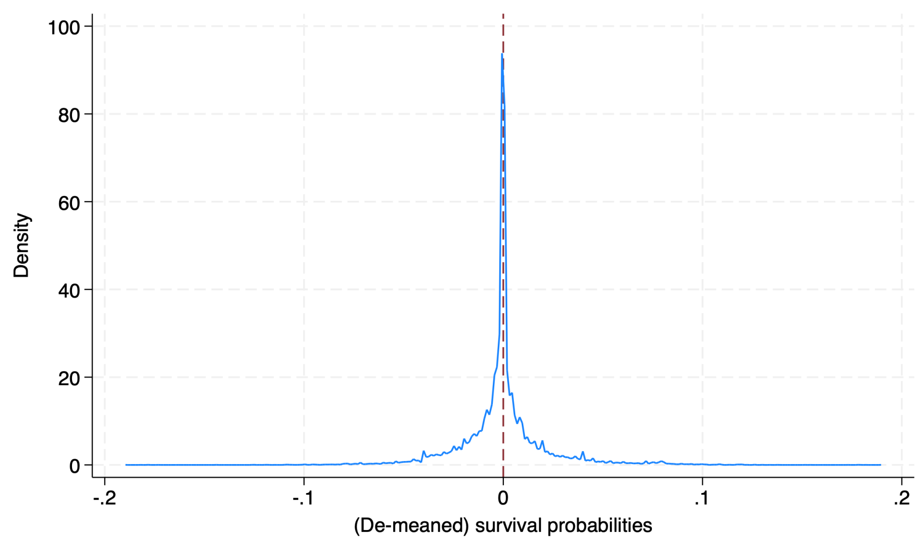
As a first step, we document the extent of subjective survival ambiguity in the data. To this end, we consider the cross-sectional distribution of (de-meaned) subjective survival

[16]We randomly allocate individuals to receive information about any alternative racial group with equal probability.

[17]The causes of death include diseases of heart, malignant neoplasm (cancer), accidents (unintentional injuries), chronic lower respiratory diseases, cerebrovascular diseases (that include e.g., stroke, thrombosis, cloth formation, embolism, cerebral aneurysm), alzheimer disease, diabetes mellitus, influenza and pneumonia.

probabilities. These are constructed based on the distributions of individual subjective survival probabilities elicited with the *bin-and-balls* procedure described above. In order to construct the cross-sectional distribution of (de-meaned) subjective survival probabilities, we pool the individual distributions of subjective survival probabilities for all respondents. The resulting cross-sectional pooled distribution, shown in Figure 3, reflects the overall variability in subjective survival probabilities in the population. Note that, were there no ambiguity in survival beliefs, the entire distribution in Figure 3 would be concentrated around zero. In contrast, we find that individuals' subjective survival probabilities are rather imprecise, deviating by $\simeq$ 6pp from their own mean probability on average.

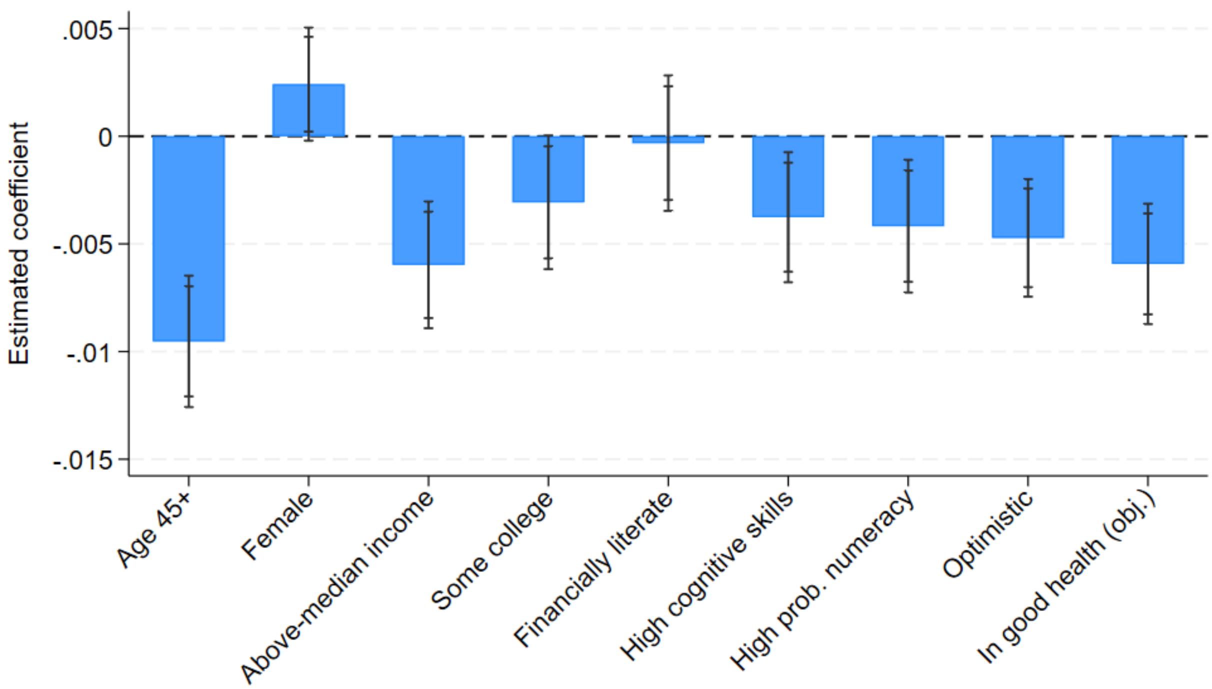
Figure 3: Cross-sectional distribution of subjective survival probabilities



The wide heterogeneity in survival ambiguity in the population is confirmed when we consider the distribution of our measure of survival ambiguity, i.e., the cross-sectional distribution in the individuals' volatility of survival probabilities (see Figure A2).

What are the determinants of such heterogeneity? Is the variation in our measure of survival ambiguity capturing an economically meaningful source of individual subjective uncertainty or is merely reflecting measurement error or respondents' confusion? We analyze which factors explain the degree of individuals' survival ambiguity in the cross-section using multivariate regression models. We focus on the role of individual's age, gender, education, labor income, financial sophistication, probability numeracy, cognitive skills, optimism, and health status. Figure 4 illustrates the estimated coefficients. The regressions also control for the one-year subjective survival probability, marital status, household composition, labor market status, race and state of residence.[18] Interestingly, we find that our individual-level measure of subjective survival ambiguity is strongly correlated with several socio-economic respondent's characteristics.

Figure 4: Determinants of Survival Ambiguity



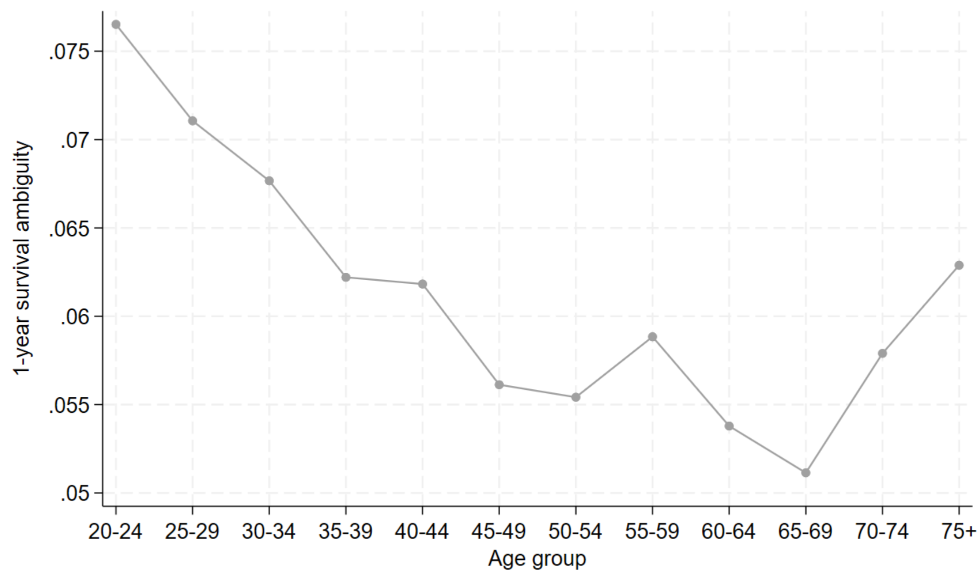
We find that, ceteris paribus, survival ambiguity is lower among men, higher income earners, people who attained some college education, more sophisticated individuals (though, we find no significant relation between survival ambiguity and financial literacy), individuals with a relatively high degree of optimism, and people who are in good health to the extent that they have not been diagnosed with any of the listed conditions.[19] While high probability numeracy and cognitive skills are significant positive determinants of survival ambiguity, sophistication (or lack thereof) is by far not the only source of variation in survival ambiguity. The correlation between our measure of survival ambiguity and different measures of *mistakes* with respect to objective life prospects is low. For

[18] Figures A3, A4, A5, A6, and A7 present the coefficients for a range of variables categorized by demographics, health status, experience with mortality, and sophistication stemming from one regression of survival ambiguity that includes all those characteristics as independent variables.

[19] The majority of these results is robust to using the long-term (10-year) measure of survival ambiguity. The significant effects of high cognitive skills and high probability numeracy become insignificant for survival ambiguity over the period of 10 years. Appendix Figure **??** illustrates the coefficients determining 10-year survival ambiguity. Appendix Table A5 presents the corresponding regression results for the two different time horizons.

example, we define as a measure of general mistakes, the difference between objective 1-year survival probability and subjective 1-year survival probability in absolute terms, i.e., |obj. survival probability - subj. survival probability|. The correlation between this measure of general mistakes and survival ambiguity is 0.0956. Consistently, we show below that our results are largely unaffected when we focus on sophisticated subgroups of the population.

Figure 5: Survival Ambiguity by Age



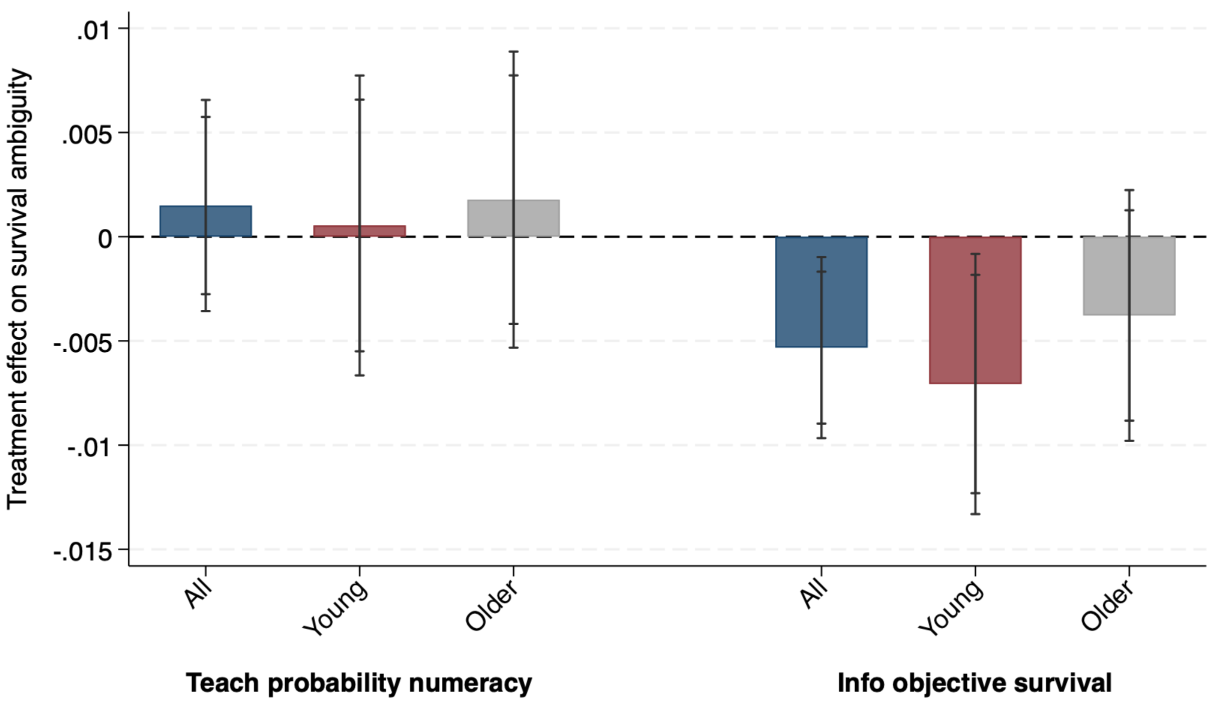
One striking fact revealed by the data is a strong negative association between survival ambiguity and individual's age up to retirement age, as shown in Figure 5. The decrease in survival ambiguity with age remains after controlling for several individual characteristics, as reported in Figure 4. This evidence is consistent with individuals learning about their *type* during their life-cycle as they perhaps receive news regarding their health. The life-cycle pattern in subjective survival ambiguity that we find resembles that documented in Guiso et al. (2013) regarding subjective uncertainty about future pension benefits reflecting, in that case, individuals learning about the realization of labor income shocks.

Tables C2 and C3 contrast the results of our analyses of the determinants of survival ambiguity based on the full sample with the results of the same regressions based on reduced samples that exclude the identified patterns of the distributions of survival ambiguity. We find very similar coefficients across subgroups, suggesting that our measure of survival ambiguity is not distorted by individuals with specific patterns of the bins-and-balls distribution.

3.2 Experimental results

Next, we leverage the random variation from the experiment to study the role of limited probability numeracy and that of limited knowledge about own and others' longevity prospects. We find that the treatment assignment was unconfounded[20]. Therefore, exploiting the random variation in intervention exposure, we can then obtain the intent-to-treat effects of our interventions by simply regressing our measure of survival ambiguity on treatment dichotomous indicators.

Figure 6: Treatment Effects on Survival Ambiguity



Note: Younger individuals are aged 45 (median-age of the sample) or younger.

Specifically, we regress survival ambiguity on a dummy variable that takes value one if the individual was randomly assigned to the short introduction on the concept of probability, and a dummy variable that takes value one if the individual was randomly allocated to any of the objective mortality information treatments. The experimental results are reported in Figure 6. We find no effect of our intervention that aimed at teaching the concept of

[20]Tables A6 and A7 confirm the random allocation into control group and treatment groups. The t-tests presented in Table A6 compare the composition of each individual group with the baseline ("Treatment 1") as an ex-post evaluation of the randomization procedure. The logit regressions in Table A7 explore whether individuals with certain demographic characteristics were more likely to be allocated into a particular treatment group than into the others.

probability on survival ambiguity, whereas we find that providing information about objective (own or others') life prospects decreases the degree of individuals' survival ambiguity. As shown in Figure 6, we further find the treatment effects of the objective mortality information intervention are concentrated among younger individuals (aged 45 or less) that is the subgroup of the population we found to be associated with a higher degree of survival ambiguity (see Figure 4).[21]

4 Survival ambiguity and savings behavior

The ideal setting to study the effect of survival ambiguity on individual financial decision making over the life-cycle would be one in which we can exogenously vary individuals' subjective survival ambiguity and then observe their retirement saving decisions over time. However, the implementation of such an experimental design in this context is difficult because any changes in beliefs may reflect into future behavior but hardly on outcomes that are measurable today.

To investigate the effect of survival ambiguity on retirement planning-related decision making, we adopt two complementary strategies. We start by analyzing whether our measure of survival ambiguity is associated with indicators of individual saving choices. Using the survey data[22] we collect as described above, we estimate the following simple regression:

$$y_i = \gamma \mho_i^2 + \beta X_i + \epsilon_i \tag{2}$$

where y will be either the past (in 2021) or planned (in the 12 months after the interview) savings rate, or the net worth-to-income ratio, $\mho^2$ is our measure of survival ambiguity as defined in Equation (1) and X includes a set of controls. The baseline regressions control for a large number of individual characteristics potentially correlated with both survival ambiguity and individual choices.

Interestingly, we find that our measure of survival ambiguity is strongly negatively correlated with past savings rates, even after controlling for a large number of individual and

[21] Instead of pooling all information treatments, Appendix Figures A8 and A9 present the treatment effects for each treatment group individually. The figures show that the treatment effect is only statistically significant for the group that receives information about others' mortality prospects. Further, Appendix Figure A10 illustrates that the treatment effect 10-year survival ambiguity is statistically insignificant - both for the probability numeracy treatment as well as the treatment with objective mortality information.

[22] Since the time of accumulating the base of human capital as well as the first years in the job market often constitute a unique situation in terms of savings decisions, the literature on consumption and savings choices over the life cycle often imposes a lower bound to individuals' ages. Correspondingly, we limit the sample for the analyses on savings decisions and for the life cycle analyses to individuals above the age of 25.

household characteristics (see Column 1 of Table 1). The interpretation of the magnitude of this coefficient is not straightforward. However, to compare the relative importance of survival ambiguity and survival probability for savings behavior, Table A9 in the Appendix reports that changing survival ambiguity by 1 standard deviation is associated with a decrease of the savings rate by 0.7 percentage points, while changing survival probability by 1 standard deviation does not have a statistically significant association to a change in savings.[23] Figure A11 further illustrates the additional explanatory power that individuals' survival ambiguity has over subjective survival probabilities when it comes to savings decision during the accumulation phase of the life cycle.

We find consistent results when we use planned savings rate and wealth-to-income ratio as dependent variables, or the coefficient of variation as alternative measure of the degree of individual uncertainty about subjective survival probabilities (see Table A8). This robustness to using different measures of savings and uncertainty about survival probabilities reduces concerns about measurement error issues. Importantly, as shown in Columns (2)-(7) of Table 1, we find that the results are largely unaffected when we control for: (i) demographics, i.e., individual's subjective one-year survival probability, a third-order polynomial in individual's age, gender, education dummies (for bachelor and graduate degrees), log household income, a dummy for whether the respondent had some education in economics, dummies for whether the respondent is unemployed or retired, marital status, household composition (dummies for number of total household members and kids), dummies for race, and dummies for the state of residence (ii) detailed health indicators (subjective health condition, individual's BMI, smoking behavior, and information on several health conditions); (iii) individual's financial literacy, probability numeracy, cognitive skills and degree of optimism; (iv) individual's experiences with (specific causes of) death; (v) the weights assigned by the respondent to different life risks when evaluating the subjective survival chances; (vi) individual's time, risk and ambiguity preferences. In contrast, we find that the association between subjective survival probabilities and savings is only positive when we control for respondents' standard demographic characteristics (Column 2). After controlling for the broader set of covariates (Columns 3-7), the association between subjective survival probabilities and savings is no longer significant (and economically close to zero).

Although we wish to be cautious in interpreting these associations as causal, the robustness of the negative association between savings and survival ambiguity to controlling for a long list of individual and household characteristics alleviates concerns about omitted vari-

[23] Table A9 in the Appendix reports the same regression results as Table 1 in column (7) with the difference that the measures of survival ambiguity and survival probability are standardized in terms of the respective standard deviation.

Table 1: Effect of Survival Ambiguity on Savings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Savings rate						
Survival ambiguity	-0.0952***	-0.0713**	-0.0709**	-0.0911***	-0.0775**	-0.0765**	-0.103***
	(0.0366)	(0.0333)	(0.0315)	(0.0312)	(0.0323)	(0.0321)	(0.0336)
Survival probability		0.000241*	-0.000150	0.0000512	0.0000362	0.00000999	-0.0000529
		(0.000134)	(0.000132)	(0.000131)	(0.000133)	(0.000132)	(0.000142)
Demographics	No	Yes	Yes	Yes	Yes	Yes	Yes
Health indicators	No	No	Yes	Yes	Yes	Yes	Yes
Sophistication scores	No	No	No	Yes	Yes	Yes	Yes
Life/death experiences	No	No	No	No	Yes	Yes	Yes
Risk factors	No	No	No	No	No	Yes	Yes
Preferences	No	No	No	No	No	No	Yes
Observations	8,505	7,979	7,940	7.940	7,512	7,512	6,890

Note: This table presents results from OLS regressions of individuals' past savings rate on survival ambiguity. Column (1) presents unconditional results. The specification in column (2) controls for individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence. The specification in column (3) also controls for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other. Specification (4) controls also for sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. In addition, specification (5) controls for dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle. To the list of controls, specification (6) adds *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, specification (7) controls additionally for preferences, such as risk preferences, ambiguity preferences, and patience. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

able bias. In particular, we address concerns about cognitive skills affecting our estimate for the effect of survival ambiguity by showing that our results are robust to controlling for various measures of sophistication and cognition. Moreover in Appendix Table A10, we present our baseline results separately for more sophisticated and less sophisticated subgroups. We show that the negative relationship between survival ambiguity and savings is statistically and economically equivalent across subgroups characterized by different levels of probability numeracy. If anything, the association is even stronger for individuals with high cognitive ability or high financial literacy than for individuals with lower cognitive ability or financial literacy scores. Table A11 also shows that the negative relationship between survival ambiguity and savings is driven by participants who are negatively affected by perceived ambiguity in beliefs, i.e., ambiguity-averse individuals. These results further contribute to limiting concerns about omitted variable bias, as any omitted variable would have to drive the negative association between survival ambiguity and saving behavior only for ambiguity averse people in order to bias our estimates. In the Online Appendix, we also formally assess how large the selection on unobservables would have to be to explain our results by applying the procedure proposed by Oster (2019). As shown in Table A12, all estimates comfortably pass this coefficient stability test, indicating that omitted variable bias is unlikely to confound the estimated relationship between savings and survival ambiguity.

One could hypothesize that, with high levels of survival ambiguity, household savings could be crowded out by contributions to annuities, long-term care insurance, or universal life insurance. In this case, survival ambiguity would be positively related to investments in annuities, long-term care insurance, or universal life insurance. In contrast, as reported in Tables A13, A14, and A15 respectively, we find survival ambiguity to be negatively related to the market value / account balance of annuities as well as to the market value / account balance of universal life insurance. The relationship between survival ambiguity and the market value of a participant's long-term care insurance is insignificant.

When differentiating by age groups, we find that survival ambiguity only has a statistically significant effect on younger individuals' (< 60) past and planned savings rates as well as wealth-to-income ratios (Table 2). These results highlight that life-cycle dynamics are central to understanding how survival ambiguity affects household decision-making.

We conduct several robustness exercises. Specifically, to further limit concerns about cognitive skills affecting our estimate of survival ambiguity, the results in Tables C4 and C5 illustrate that the negative relationship between survival ambiguity and savings rates persists (albeit quantitatively stronger) when we exclude individuals who create distributions of subjective survival probabilities according to specific patterns that could be interpreted as inconsistent behavior, e.g., individuals who place all balls in one extreme interval as well as those who assign the balls to a bimodal distribution. Appendix Table A16 shows that the unconditional relationship is also robust with respect to the time period used to measure survival ambiguity: the measure for 10-year survival ambiguity is similarly negatively correlated with past savings rates, although the relationship becomes insignificant when including the entire range of control variables.

Table 2: Effect of Survival Ambiguity on Savings by Age Groups

	Past savings rate		Planned savings rate		Wealth-to-income ratio	
	Younger	Older	Younger	Older	Younger	Older
	(1)	(2)	(3)	(4)	(5)	(6)
Survival ambiguity	-0.147***	-0.0463	-0.0865*	-0.0436	-7.017*	-4.948
	(0.0446)	(0.0460)	(0.0478)	(0.0485)	(3.818)	(6.429)
Survival probability	-0.0000402	0.0000564	0.0000829	0.000241	-0.0134	0.00248
	(0.000170)	(0.000244)	(0.000174)	(0.000244)	(0.0196)	(0.0326)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Health indicators	Yes	Yes	Yes	Yes	Yes	Yes
Sophistication scores	Yes	Yes	Yes	Yes	Yes	Yes
Life/death experiences	Yes	Yes	Yes	Yes	Yes	Yes
Risk factors	Yes	Yes	Yes	Yes	Yes	Yes
Preferences	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,757	2,133	4,755	1,987	5,173	2,369

Note: This table presents results from OLS regressions of individuals' past savings rate (columns 1 and 2), planned savings rate (columns 3 and 4) and wealth-to-income ratio (columns 5 and 6) on survival ambiguity by age group. Individuals under the age of 60 are classified as "Younger", wheres the "Older" group comprises individuals aged 60 and older. In all models, we control for an extensive list of characteristics, including individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence; health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other; sophistication scores, such as probability numeracy, financial literacy, and cognitive ability; dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle; *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood as well as preferences, such as risk preferences, ambiguity preferences, and patience. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

5 Survival ambiguity in a life-cycle setting

Can we rationalize the empirical evidence presented above about the effects of survival ambiguity on savings behavior? At first, the negative relation between survival ambiguity and households' savings decisions might seem counter-intuitive, as one may expect survival ambiguity to increase savings for precautionary reasons: if households are uncertain about how long they will live, they may wish to self-insure by accumulating more wealth. We first show that this intuition is misleading. In fact, in the most widely-used recursive ambiguity models—max–min expected utility (Gilboa and Schmeidler, 1989) and smooth ambiguity (Klibanoff et al., 2005)—, ambiguity about survival decreases the effective future continuation value, thereby reducing the incentive to save. This is a direct implication of how ambiguity aversion interacts with recursive preferences in the presence of ambiguity in survival beliefs. Second, to quantify the importance of survival ambiguity on savings behavior over the households' life cycle, we develop (and estimate) a life-cycle model that closely links theory and evidence, drawing on the theoretical framework proposed by Bommier (2017) and Izhakian (2017, 2020).

5.1 Survival ambiguity and the value of saving

Consider a standard life-cycle setting in which a household chooses consumption c_t in each period they are alive. Allow for the household to face ambiguous survival beliefs: let s_t denote the uncertain survival probability to period $t+1$, and $\bar{s}_t$ the expected survival probability. Denote by $S_t = \mathbb{E}[V_{t+1}(a_{t+1})]$ the expected continuation value conditional on survival. The household's recursive optimization problem can be written as:

$$V_t \;\; = \;\; \max_{c_t} \left\{ u(c_t) + \beta \Psi_t \left(S_t \right) \right\}$$

where $\Psi_t(\cdot)$ is the continuation aggregator implied by the specific ambiguity representation, and β is the standard discount rate. Let R denote the gross wealth return between t

and $t+1$. The Euler equation is then:[24]

$$u'(c_t) = \beta R \frac{\partial \Psi_t}{\partial S_t}\, \mathbb{E}[u'(c_{t+1})].$$

Thus ambiguity in survival beliefs affects savings behavior through the aggregator's marginal sensitivity $\partial\Psi_t/\partial S_t$, which plays the role of *effective* survival probability in the presence of survival ambiguity.[25] We next characterize Ψ_t under alternative ambiguity structures—max–min, smooth ambiguity (KMM), and a variance-based representation in the spirit of Izhakian (2020)—and discuss their implications for saving.

Max–min ambiguity Under max–min (Gilboa and Schmeidler, 1989) ambiguity, the household has beliefs over survival probabilities $s \in [p_L, p_H]$ and the continuation aggregator takes the simple form:

$$\Psi_t^{MM}(S_t) = \min_{s\in[p_L,p_H]} \{sS_t\}$$

Because $S_t > 0$, the minimum is associated with the lowest survival probability p_L, which plays the role of *effective* survival probability ($\frac{\partial \Psi_t^{MM}}{\partial S_t} = p_L$). Therefore, ambiguity replaces $\bar{s}_t$ in the standard Euler equation with the worst-case value $p_L < \bar{s}_t$: the household's marginal return to saving falls, current consumption rises, and saving declines.

Smooth ambiguity (KMM) The household is facing multiple "models" about survival probabilities, each with some belief weight. Let $\{s_j\}_{j=1}^J$ denote possible survival probabilities to period $t+1$, with associated belief weights $\{\mu_j\}$, $\sum_{j=1}^J \mu_j = 1$. Conditional on model j,

[24] If bequests are incidental, as in the most traditional life–cycle model with mortality risk (e.g. Yaari, 1965), next–period assets affect utility only through survival, so the implications discussed in the text are unchanged. If instead bequests are intentional and depend on next–period assets, as in De Nardi's (2004) luxury bequest specification, saving raises utility both in the survival and death states. In this case the Euler equation becomes:

$$u'(c_t) = \beta R \left[\frac{\partial \Psi_t}{\partial S_t}\, \mathbb{E}[u'(c_{t+1})] + \frac{\partial \Psi_t}{\partial D_t}\, B'(a_{t+1})\right]$$

where $D_t = B(a_{t+1})$ denotes the continuation value in the death state. The qualitative implication of ambiguity on saving behavior discussed in this Section continues to hold provided the survival–consumption channel dominates the bequest channel, i.e. $\frac{\partial \Psi_t}{\partial S_t}\, \mathbb{E}[u'(c_{t+1})] > \frac{\partial \Psi_t}{\partial D_t}\, B'(a_{t+1})$. This condition is mild and standard in the life–cycle literature: it is equivalent to requiring that higher survival probabilities increase saving. Our objective is not to claim that survival ambiguity necessarily reduces saving under all preference specifications and parameterizations, but rather to show that introducing ambiguity about survival beliefs can reduce saving in otherwise standard life–cycle environments. In the next section, we show that the qualitative implications of survival ambiguity persist when we introduce intentional bequests in a a realistically calibrated life-cycle model.

[25] That is, compared to the standard Euler equation with (subjective) mortality risk but unambiguous beliefs ($u'(c_t) = \beta R\, \bar{s}_t\, \mathbb{E}[u'(c_{t+1})]$), ambiguity replaces $\bar{s}_t$ with the aggregator's marginal $\frac{\partial \Psi_t}{\partial S_t}$.

continuation utility is $CE_j = s_j S_t$.[26]

Under smooth ambiguity preferences Klibanoff et al. (2005), the continuation aggregator is:

$$\Psi_t^{KMM}(S_t) = \phi^{-1}\left(\sum_{j=1}^{J} \mu_j \phi(CE_j)\right),$$

where ϕ is strictly increasing, strictly concave, and continuously differentiable.

The marginal continuation value can be written as:

$$\frac{\partial \Psi_t^{KMM}}{\partial S_t} = \underbrace{\frac{\sum_{k=1}^{J} \mu_k \phi'(CE_k)}{\phi'(\Psi_t^{KMM}(S_t))}}_{\equiv \tilde{\kappa}_t} \sum_{j=1}^{J} \underbrace{\frac{\mu_j \phi'(CE_j)}{\sum_{k=1}^{J} \mu_k \phi'(CE_k)}}_{\equiv w_j} s_j$$

where $\tilde{\kappa}_t$ reflects the curvature of the ambiguity aggregator and w_j is the effective weight to survival probabilities. Since ϕ is strictly concave, ϕ' is strictly decreasing, implying that models with lower survival probabilities receive greater weight in the aggregation (as continuation utilities $CE_j = s_j S_t$ are increasing in s_j). Therefore, whenever survival beliefs are ambiguous (i.e., non-degenerate):

$$\sum_{j=1}^{J} w_j s_j < \sum_{j=1}^{J} \mu_j s_j \equiv \bar{s}_t,$$

In the presence of ambiguous survival beliefs, smooth ambiguity lowers the marginal return to saving through a pessimistic distortion of survival beliefs, generating a robust force toward lower saving in otherwise standard life-cycle environments.[27]

[26] In Klibanoff et al. (2005), continuation utility within each model is evaluated using standard expected utility. A natural extension, often used in quantitative macro, incorporates *risk-sensitive* (entropic) evaluation *within* each model:

$$CE_j = \frac{1}{\theta} \log\left[(1 - s_j) + s_j e^{\theta S_t}\right]$$

Whether continuation values within a model are evaluated using standard expected utility or using a risk-sensitive operator, the implications of survival ambiguity on savings behavior apply unchanged.

[27] The overall effect of ambiguity on saving depends on the product $\tilde{\kappa}_t \sum_{j=1}^{J} w_j s_j$. While $\tilde{\kappa}_t$ rescales all continuation values uniformly, the pessimistic reweighting $\sum_{j=1}^{J} w_j s_j$ operates directly on survival probabilities. Compared to the benchmark with unambiguous beliefs, introducing a mean-preserving spread in survival beliefs decreases $\sum_{j=1}^{J} w_j s_j$ while leaving $\tilde{\kappa}_t$ unchanged, implying a decline in the marginal return to saving.

Variance-based representation In the spirit of Bommier (2017) and Izhakian (2017), a variance-based representation of the continuation aggregator can be written as follows:

$$\Psi_t^V(S_t) = \bar{s}_t \left(1 + \frac{\Upsilon''(\bar{s}_t)}{\Upsilon'(\bar{s}_t)} Var[s_t]\right) S_t$$

where Υ is a strictly increasing, concave and differentiable function characterizing individuals' ambiguity aversion, and $Var[s_t]$ is the variance of survival probabilities (i.e., measure of the degree of survival ambiguity). Therefore, the marginal continuation value (i.e., the effective survival probability) is simply given by $\left(\bar{s}_t \left(1 + \frac{\Upsilon''(\bar{s}_t)}{\Upsilon'(\bar{s}_t)} Var[s_t]\right)\right)$. Also this variance-based representation of the ambiguity structure has straightforward implications for savings behavior: because $\left(-\frac{\Upsilon''(.)}{\Upsilon'(.)} > 0\right)$, survival ambiguity (i.e., $Var[s_t] > 0$) decreases the effective survival probability, thus lowering the marginal return to saving, compared to a benchmark model with unambiguous beliefs (i.e., $Var[s_t] = 0$).

5.2 A quantitative life-cycle model with survival ambiguity

Having established the robustness of the qualitative implications of survival ambiguity on savings behavior under alternative canonical ambiguity representations (Gilboa and Schmeidler, 1989; Klibanoff et al., 2005), we now turn to quantifying the importance of the elicited degree of survival ambiguity. To this end, we introduce survival ambiguity in an otherwise standard life-cycle model that builds on the seminal contributions of Carroll (1997) and Attanasio et al. (1999). In particular, our benchmark model—without survival ambiguity—is close to the life-cycle model with subjective survival beliefs in Heimer et al. (2019). We extend this standard life-cycle setting using a variance-based representation of ambiguity, in the vein of Bommier (2017) and Izhakian (2017, 2020).[28] In the Expected Utility with Uncertain Probabilities (EUUP) theory, individuals' ambiguity attitudes are defined by preferences over mean-preserving spreads in probabilities, analogously to the definition of risk aversion as an aversion against mean-preserving spreads in outcomes. The motivation for adopting this framework is not to privilege it as a structural specification of ambiguity, but rather to exploit its applicability. Unlike max–min and smooth ambiguity preferences, the variance-based representation permits a clean separation between risk and ambiguity, as well as between ambiguity beliefs and ambiguity attitudes. This feature delivers a direct mapping between observable dispersion in survival beliefs and savings behavior, enabling us to discipline the model using the elicited degree of survival ambiguity and to compare model-predicted effects with the corresponding empirical relations documented in Section

[28]This framework has been applied to explore the implications of ambiguity in beliefs in the asset pricing literature (Izhakian and Yermack, 2017; Augustin and Izhakian, 2020).

4. As discussed in the previous section, this representation of ambiguity captures the same underlying economic mechanism as that delivered by max-min expected utility and smooth ambiguity representations—namely, that survival ambiguity induces a pessimistic distortion of continuation values and lowers the marginal return to saving—while allowing us to quantify the magnitude of this channel in a life-cycle setting.

In the model, risk averse and ambiguity averse individuals choose consumption and the allocation of their wealth between riskless and risky assets in the face of labor income risk, risky returns to financial wealth and subjective mortality ambiguity.

Ambiguity in survival beliefs We denote as s_t the subjective probability that individuals attach to surviving to period $t+1$, conditional on being alive in period t, in the absence of survival ambiguity. Households live at most until age T. Therefore, we assume individuals attach a zero subjective survival probability to transitioning to period $T+1$.

We further allow individuals to face uncertainty about their survival probabilities. That is, in each period individuals have subjective expectations over the distribution of the probability to survive until the next period. More formally, individuals in each period t possess a set S of subjective cumulative probabilities P of surviving to period $t+1$. Each cumulative probability P is in turn provided with a subjective marginal probability ξ. In the absence of ambiguity, there is only one subjective probability distribution (i.e., the set of probabilities S is singleton). To capture the evidence on the life-cycle patterns in survival ambiguity that we documented, we allow the degree of survival ambiguity to be a function of individuals' age. We parameterise this function using a second-order polynomial in age and estimate it directly from the data.[29]

Preferences Individuals have distinct preferences over risk and ambiguity. Preferences over risk are characterized by an intertemporally separable utility function. Individuals derive utility from consumption C_t according to the period utility function:

$$u(C_t; z_t) = q(z_t)\frac{\widetilde{C}_t^{1-\gamma}}{1-\gamma}$$

[29]This is effectively a reduced-form approach to capture the process of learning and updating beliefs about survival - reducing survival ambiguity - that individuals exhibit following, for example, Bayes' rule (see, e.g., Peijnenburg 2018 for an application to learning about the equity risk premium). While such models could easily explain the decrease in survival ambiguity observed during individuals' working life, they would have hard time rationalizing the increase in survival ambiguity that we observe after retirement age. In this paper, we focus on the model-predicted effects of survival ambiguity and leave the characterization of the endogenous survival ambiguity dynamics to future research.

where $q(z_t)$ is a function of household demographics z_t (number of adults and number of children in the household) and $\widetilde{C}_t = \frac{C_t}{q(z_t)}$.

Preferences regarding ambiguity are defined by preferences over mean-preserving spreads in probabilities and characterized by a strictly increasing and twice-differentiable function $\Upsilon : [0,1] \to \mathbf{R}$, called the outlook function (as in the EUUP introduced by Izhakian 2020). In the model, we allow for individuals to be ambiguity averse.[30] Individuals' ambiguity aversion is characterized by an outlook function featuring constant relative ambiguity aversion (CRAA):

$$\Upsilon(P_t) = \frac{P_t^{1-\rho}}{1-\rho}$$

where P_t is the cumulative distribution function of survival probabilities.

To credibly assess the relevance of survival ambiguity, it is important to capture the heterogeneity in savings incentives over the households' life cycle induce by bequest savings motives. Households value bequests according to the bequest function $b(A_t) = \theta \frac{(A_t+\zeta)^{1-\gamma}}{1-\gamma}$, where ζ is the parameter controlling the curvature of the bequest function and θ captures the strength of the bequest motive (as in De Nardi 2004).

Asset returns In each period, households choose the allocation of their wealth, $A_{i,t}$, between a riskless asset $B_{i,t}$ and a risky asset $S_{i,t}$. The share of risky assets, $\alpha^s_{i,t} = S_{i,t}/A_{i,t}$, lies between zero and one.[31] The return from a household's portfolio can then be written as:

$$r^p_{i,t} = r^b + \alpha^s_{i,t-1}(r^s_t - r^b) \tag{3}$$

where r^f is a constant return on riskless assets (e.g., cash and bonds), and r^s_t the stochastic return on risky assets (e.g., stocks, private equity). The excess return on risky assets $(r^s_t - r^f)$ is given by:

$$r^s_{i,t} - r^b = \mu_S + \xi^s_{i,t} \tag{4}$$

where $\mu_S > 0$ is the average risk premium and $\xi^s_{i,t}$ are independently and identically distributed according to $\mathcal{N}(0, \sigma^2_S)$. We allow for tail risk in the risky assets return distribution (with return in the tail event r_{tail} occurring with probability p_{tail}). Finally, we assume households need to pay a per-period fixed cost κ to access the return from the risky asset (this captures costly collection and processing of financial information).

[30] Similarly to the characterization of risk aversion, ambiguity aversion takes the form of a concave $\Upsilon(.)$. Ambiguity averse individuals in this framework therefore prefer the expected value of an uncertain probability of each payoff over the uncertain probability itself.

[31] We take standard assumptions regarding borrowing constraints ($B_{i,t} \geq 0$) and short-sale constraints ($S_{i,t} \geq 0$).

Earnings During their working life, households receive labor income $Y_{i,t}$ which follows a standard permanent-transitory type process: We write log earnings of household i at time t as:

$$Y_{i,t} = X_{i,t} G_t u_{i,t}$$

where G_t is the age-varying growth rate of earnings, $u_{i,t}$ is an idiosyncratic transitory shock and $X_{i,t}$ is the permanent income component, with innovation $v_{i,t}$:

$$X_{i,t} = X_{i,t-1} v_{i,t}$$

In the model, households retire exogenously at age N and start drawing Social Security benefits Y_i^p. These are computed as a fraction c of permanent income before retirement $Y_i^p = cX_{i,N-1}$.

5.3 The optimization problem with survival ambiguity

The recursive formulation of the household problem can be written as follows:[32]

$$\begin{aligned} V_t(A_t, X_t) \quad = \quad & \max_{c,\alpha_t} \Bigg\{ u(C_t) + \beta \Bigg[E[p_t] \left(1 + \frac{\Upsilon''(E[P_t])}{\Upsilon'(E[P_t])} Var[p_t] \right) \mathbb{E}[V_{t+1}(A_{t+1}, X_{t+1})] \\ & + E[1-p_t] \left(1 - \frac{\Upsilon''(E[P_t])}{\Upsilon'(E[P_t])} Var[1-p_t] \right) b(A_{t+1}) \Bigg] \Bigg\} \end{aligned} \quad (5)$$

where β is the standard discount rate or time preference, and expected marginal and cumulative probabilities are computed, using the probability density function $\phi(p_t)$ associated with P_t, as:

$$E[p_t] = \int \phi(p_t) d\xi \qquad \text{and} \qquad E[P_t] = \int P_t d\xi$$

and the variance of probabilities is given by:

$$Var[p_t] = \int \left(\phi(p_t) - E[p_t]^2 \right) d\xi$$

That is, in this framework, ambiguity affects the expected continuation value through individuals' *perceived* (or effective) survival chances $\left(E[p_t] \left(1 + \frac{\Upsilon''(E[P_t])}{\Upsilon'(E[P_t])} Var[p_t] \right) \right)$. These might be interpreted as the survival probabilities weighting the next-period value in the standard life-cycle setting, adjusted for ambiguity.[33] Perceived survival chances are a func-

[32] This extends the static representation of Izhakian (2020) to a dynamic setting.

[33] Conversely, the perceived probability of death is given by $E[1-p_t] \left(1 - \frac{\Upsilon''(E[P_t])}{\Upsilon'(E[P_t])} Var[1-p_t] \right)$.

tion of the extent of ambiguity in individual's survival beliefs, measured by $Var[p_t]$, and the individual's degree of ambiguity aversion, captured by the concavity of the outlook function $\left(-\frac{\Upsilon''(.)}{\Upsilon'(.)} > 0\right)$. Therefore, greater ambiguity in survival beliefs or greater ambiguity aversion decrease (increase) the perceived survival probability (probability of death).

Note that in case the individual is ambiguity neutral, i.e, Υ is linear, or the individual does not have ambiguous survival beliefs, i.e. $Var[p_t] = 0$, the perceived probability of surviving is simply given by $s_t = E[P_t]$, and the value function collapses to the standard form:

$$V_t(A_t, X_t) = \max_{c,\alpha_t} \{u(C_t) + \beta [s_t \mathbb{E}[V_{t+1}(A_{t+1}, X_{t+1})] + (1 - s_t) b(A_{t+1}]\} \tag{6}$$

The recursive representation of the model provides a simple intuition about the role of survival ambiguity: compared to the life-cycle model in which individuals are ambiguity neutral or have unambiguous survival beliefs, an ambiguity-averse individual with ambiguous survival beliefs perceives lower survival chances. As a result, the model predicts that survival ambiguity induces ambiguity-averse individuals to place less value on future utility relative to current utility, shifting consumption toward the present. In what follows we assess the quantitative importance of survival ambiguity on life-cycle outcomes in a credibly calibrated life-cycle setting.

5.4 Model estimation

To rationalize the empirical evidence on the effects of survival ambiguity on savings decisions, and to investigate how survival ambiguity affects households' decisions over their life-cycle, we conduct two estimation exercises. We start by estimating the baseline life-cycle model with subjective survival beliefs (but without survival ambiguity) and compare its predictions with those of the model in which we incorporate survival ambiguity.[34] We then estimate the model incorporating survival ambiguity to formally assess its importance in explaining wealth accumulation decisions. The estimation of the model follows a standard two-step procedure. We first set parameters outside of the model using auxiliary estimation, details of the institutional setting, and prior literature. These include the parameters governing the earnings process, the risky asset returns distribution and the demographic shifters. Using data from the Panel Study of Income Dynamics (PSID) for the period 1999-2019, we estimate the parameters characterizing the earnings process (the age-specific labor income growth and the variance of the permanent earnings shocks) and the demographic shifters.

[34]For a discussion of the effects of subjective survival beliefs on households' decisions over the life cycle, see Heimer et al. (2019).

5.4.1 Survival beliefs and survival ambiguity

Solving the baseline model requires estimating the conditional survival probabilities s_t for each age t, which give the subjective likelihood of surviving an additional year, conditional on having survived until age t. As in Heimer et al. (2019), we obtain the age profile of subjective survival probabilities by running OLS regressions of survival beliefs on a second-order polynomial in individual's age, and then take the predicted survival probability by age. To capture the age-profile of survival probabilities, we use the 1-, 2-, and 10-year survival probabilities elicited with our survey.[35]

The solution of the model with survival ambiguity also requires estimating the expected cumulative (one-year) survival probabilities $E[P_t]$ and the variance of (one-year) survival probabilities $Var[p_t]$ for each age t. To do this, we exploit information on survival beliefs in our data. To construct the age profile of $E[P_t]$, we replicate the same exercise described above for the estimation of the age-profile of point subjective survival probabilities (while using the 1-, 2- and 10-year expected cumulative survival probabilities). To construct the age profile of $Var[p_t]$, we estimate OLS regressions of the variance of (one-year) survival probabilities on a second-order polynomial in individual's age, and then take the predicted values by age.

5.4.2 Preference and fixed cost parameters

We set the curvature of the bequest motive k to $\$1,000,000$, which corresponds (in 2014 dollars) approximately to the value of $\$500,000$ set by French (2005). The strength of the bequest motive is set to match the marginal propensity to bequeath (0.88) estimated by De Nardi et al. (2010). The value of the stock market participation cost (\$1000) is chosen to fall within the range of estimates reported in the literature (Vissing-Jorgensen, 2004). In the model without survival ambiguity, the coefficient of risk aversion, together with the value of the discount factor, determines the age profile of wealth accumulation. As is well known in the literature, separately identifying discount factor and degree of risk aversion requires (at least) exploiting variation on both asset accumulation age profiles as well as data on households' asset allocation decisions. Since the focus of this paper is on studying the implications of survival ambiguity on households' savings choices, we estimate the value of the discount factor while fixing the value of the coefficient of relative risk aversion at $\gamma = 6$, a value commonly used in the household finance literature (e.g., Heimer et al. 2019).

We estimate the remaining structural parameters $\Lambda = (\beta, \rho)$ using a Simulated Method

[35] Following Heimer et al. (2019), we winsorize the bottom 1% of survey responses to limit the effect of outliers and transform the 2- and 10-year survival beliefs into conditional transition probabilities assuming constant hazard within the horizon.

of Moments (SMM) approach. We minimize the weighted distance between target moments estimated in the data and the corresponding moments simulated by the model. To avoid the small-sample bias issues of the optimal weighting matrix discussed by Altonji and Segal (1996), we use the inverse of the diagonal elements of the bootstrapped variance-covariance matrix of the target moments as weighting matrix.

Moments We target two sets of moments. The first set of moments describes the accumulation of assets over the households' life cycle (average wealth-to-income ratio in the age groups 25-34, 35-44, 45-54 and 55-64). Using data from the 1998-2018 waves of the PSID, we run OLS regressions for the wealth-to-income ratio against a third-order polynomial in the household head's age, dummies for the number of adults and kids, unemployment and retirement dummies, cohort and year fixed effects. We separate age effects from cohort and year effects by assuming that year dummies sum to zero and are orthogonal to a time trend (Deaton and Paxson, 1994). We then take the predicted values of wealth-to-income ratio for each age group. When we estimate our full model with survival ambiguity, we also target the empirical effect of survival ambiguity on the savings rate of ambiguity-averse individuals.[36] We exploit the joint information on individuals' subjective survival ambiguity and savings decisions in our data to estimate this association. We run an OLS regression for the savings rate on survival ambiguity, a dummy indicating whether the individual is ambiguity averse and the interaction between the two. The regression controls for a large set of demographics, health measures, sophistication scores, risk factors and preferences, as detailed in Section 4. To obtain an estimate for the effect of survival ambiguity on the savings rate for ambiguity-averse individuals, we compute the sum of the coefficients on survival ambiguity and its interaction with the ambiguity aversion dummy.

Identification Conditional on the values of the first-step parameters, the value of the discount factor in the baseline model is pinned down by the evolution of the wealth-to-income ratio over the life cycle. To identify the coefficient of relative ambiguity aversion ρ, we exploit the observed association between individuals' survival ambiguity and savings rate. As discussed in Section 5.2, a higher ambiguity aversion decreases the perceived survival probability, thereby reducing the accumulation of wealth for a given degree of ambiguity in survival beliefs. The identification of ρ exploits the circumstance that the model-predicted association between households' savings rate and their ambiguity in survival beliefs depends on the degree of ambiguity aversion.

[36]Note that the structural model with survival ambiguity assumes homogeneity in ambiguity preferences across households in the population. The data simulated by the economic model will then be informative on the effects of survival ambiguity for ambiguity-averse individuals.

5.4.3 Estimation results

The structural estimation results are reported in Table 3. The estimate for the time discount factor, β, in the baseline model without survival ambiguity (0.84), falls in the ballpark of previous estimates in the household finance literature using similar values for the coefficient of relative risk aversion. In the model with survival ambiguity, the estimate for the time discount factor increases slightly to $\simeq 0.89$. Because survival ambiguity decreases the perceived conditional survival probability (as discussed in Section 5.2), the model requires a greater discount factor to match the observed wealth accumulation over the households' life-cycle. We estimate a coefficient of relative ambiguity aversion equal to around 3.5. While this value falls in the ballbark of those used in the asset pricing literature (e.g., Izhakian and Yermack 2017; Augustin and Izhakian 2020), to the best of our knowledge we are the first to estimate the degree of individuals' ambiguity aversion when the role of ambiguity attitudes is considered separately from that of risk preferences and ambiguity in beliefs. Interestingly, although the structural estimation of the model with survival ambiguity targets an additional moment (the relationship between savings and survival ambiguity for ambiguity-averse individuals), it manages to produce a better overall fit with the data (see the SMM criterion reported in Table 3). Importantly, the relationship between savings rate and survival ambiguity for ambiguity-averse households in the data simulated by the economic model (-0.1725) is close to that observed in the actual data (-0.1511). This provides credibility to the model as a tool for studying the life-cycle effects of survival ambiguity on households' saving behavior.

Table 3: Estimated structural parameters

		W/out survival ambiguity	With survival ambiguity
Time discount factor	β	0.844	0.892
		(0.003)	(0.006)
Coefficient of relative ambiguity aversion	ρ		3.494
			(0.032)
SMM criterion		109.723	75.226

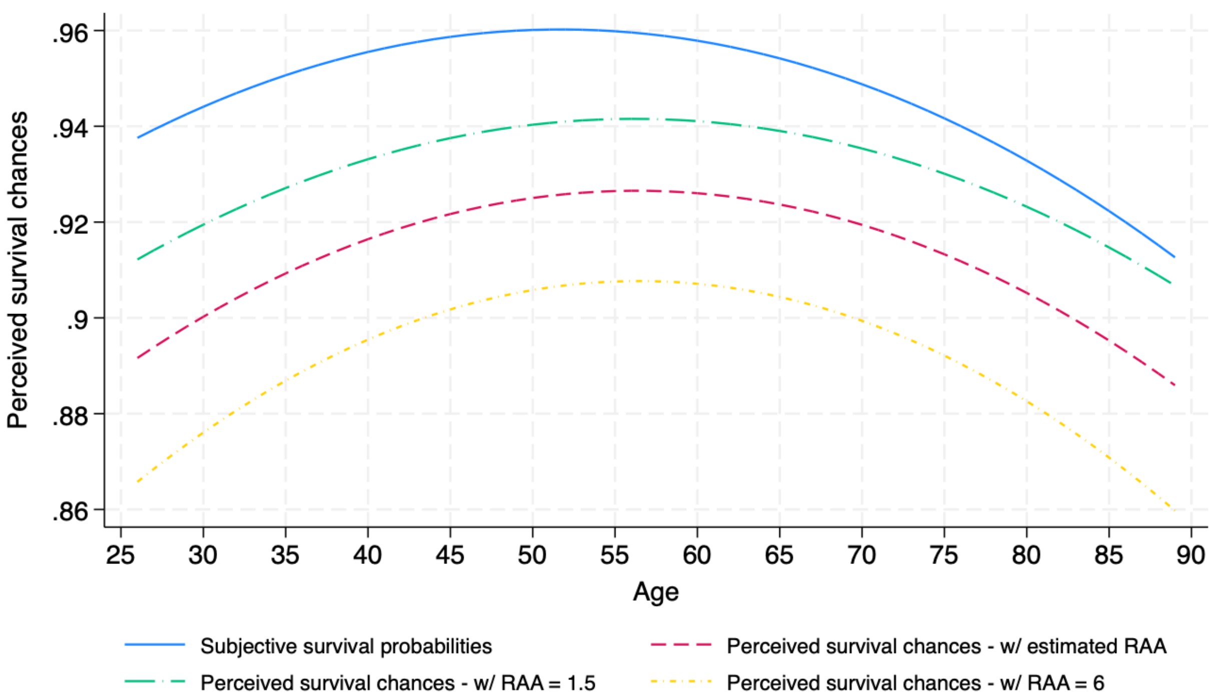
Notes: Estimates obtained using a SMM approach. Asymptotic standard errors are reported in parentheses.

To illustrate the role of survival ambiguity in the model, it is useful to compare the estimated effect of subjective survival probabilities on the individual's discount factor to that of perceived survival chances in the presence of survival ambiguity.[37] Figure 7 reports the model-implied 1-year survival chances (with and without survival ambiguity), based

[37] As discussed in Section 5.2, perceived survival chances in the presence of survival ambiguity depends on

on our estimates of s_t, $E[p_t]$, $Var[p_t]$ and ρ. The figure shows that the estimated model-implied perceived survival chances accounting for survival ambiguity (indicated by the red dashed line) are lower, at all ages, than those estimated using the elicited subjective point survival probabilities (indicated by the solid blue line). The effect of survival ambiguity is substantial (reducing perceived survival chances by around 3pp on average) and stronger at the beginning of the individuals' life cycle (due to the life-cycle dynamics of survival ambiguity documented above). The figure also illustrates the importance of the degree of ambiguity aversion in determining the effect of survival ambiguity on perceived survival chances. Perceived survival chances increase (as indicated by the green dashed line) when the coefficient of relative ambiguity aversion is reduced ($\rho = 1.5$) and decrease (as indicated by the yellow dashed line) when it is higher ($\rho = 6$).

Figure 7: Estimated perceived survival chances with and without survival ambiguity



Notes: The figure reports the subjective survival function estimated using the elicited subjective point survival probabilities, based on our estimates of s_t (solid blue line), the estimated model-implied perceived survival chances accounting for survival ambiguity, based on our estimates of $E[p_t]$, $Var[p_t]$ and ρ (red dashed line), as well as the perceived survival chances obtained setting the coefficient of relative ambiguity aversion to 1.5 (green dash line) or 6 (yellow dash line).

individual's survival ambiguity as well as their degree of ambiguity aversion (and therefore on the estimated value of the coefficient of relative ambiguity aversion ρ, given the parametrization of preferences).

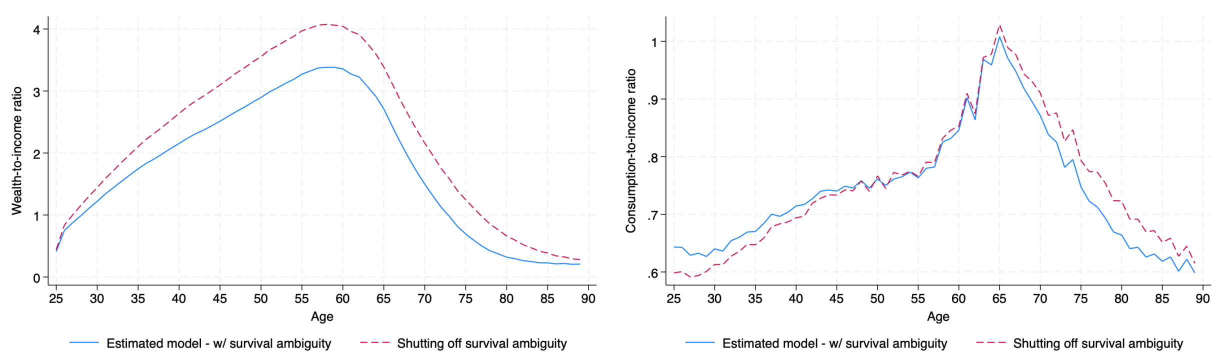
5.5 Model-predicted effects of survival ambiguity

To study the quantitative importance of survival ambiguity on savings behavior over the household life cycle, we start by conducting a counterfactual exercise that shuts down survival ambiguity in the estimated model. Therefore, we start by simulating the decisions of a cohort of households over their life-cycle using the estimated model, i.e., setting the degree of survival ambiguity to that observed in the data. We then simulate the estimated model setting $Var[p_t] = 0$ over the entire life cycle.

The estimated model shows that survival ambiguity has a large impact on the amount of wealth households accumulate before retirement (as shown in Figure 8, panel a). Specifically, the model predicts that survival ambiguity decreases the wealth accumulated at the age of 60 by around 18% on average. Panel (b) of Figure 8 shows the implications of survival ambiguity for consumption growth over the life cycle. The figure illustrates that ignoring survival ambiguity leads to a substantial understatement ($\simeq$ 10%) of the average propensity to consume out of permanent income at the beginning of the life cycle (up to about age 50), and a large overstatement after retirement. That is, because of its negative effect on accumulated retirement wealth, survival ambiguity decreases consumption by around 5.6% during retirement on average. Remarkably, the model predicts that survival ambiguity reduces savings during the accumulation phase of the households' life cycle and not during retirement, consistent with the empirical evidence documented in Section 4.

Figure 8: Model-predicted effect of survival ambiguity on households' wealth and consumption over their life cycle.

(a) Wealth (b) Consumption



Notes: Panel (a) compares the age-profile of wealth-to-permanent income ratio predicted by the estimated model with survival ambiguity (blue solid line) and the counterfactual age-profile of wealth accumulation generated when we shut down the contribution of survival ambiguity (red dashed line). Panel (b) reports the same comparison for the consumption-to-permanent income ratio.

To quantify the policy implications of our results, we conduct a second counterfactual exercise consisting in a 10% reduction of the individuals' degree of survival ambiguity. This exercise can be thought of as capturing the effects of an information campaign about group-specific objective survival chances (that we have indeed shown above to have an effect of similar magnitude on the extent of subjective survival ambiguity). We simulate the estimated model decreasing the individuals' degree of survival ambiguity from the beginning of their working life (e.g., the information campaign takes place in school). The estimated model predicts that a 10% decrease in survival ambiguity increases retirement wealth (at the age of 65) by around 4% (see Figure A12).

Together, these results suggest that survival ambiguity is an important determinant of households' savings behavior over their life cycle. On the one hand, the model provides a rationalization for the robust association between subjective survival ambiguity and savings behavior presented in the previous section. On the other, it provides an additional explanation–beyond the effect of subjective survival probabilities shown in Heimer et al. (2019)–for the long-standing observation that young households save "too little" compared to the predictions of a traditional life-cycle model, while older dis-save "too slowly".

6 Conclusion

To the best of our knowledge, this paper is the first to document the extent of individual subjective survival ambiguity, experimentally examine its determinants, and study its importance on savings behavior both empirically and in a realistically calibrated life cycle framework.

We find a strong and robust negative association between individuals' survival ambiguity and savings, using alternative measures of savings and uncertainty about survival probabilities. Remarkably, while the association between subjective survival probabilities and savings is no longer significant after controlling for a broader set of covariates beyond standard demographic characteristics, survival ambiguity remains a robust predictor of the savings rate. For individuals below the age of 60, survival ambiguity explains more of the variation (adjusted R^2) in savings behavior than subjective survival probabilities do.

While we do not interpret a causal relationship from reduced-form regressions, we attempt to limit concerns of omitted variable bias showing that the strong negative association remains after controlling for a long list of individual and household characteristics that include demographics, preferences, detailed health conditions, individuals' financial sophistication and cognition, exposure to (causes) of death and the weight assigned to different life risks when assessing their own survival chances. In addition, we find that the negative relationship between survival ambiguity and savings rate is driven entirely by ambiguity averse respondents. That is, any omitted variables would have to drive this association between survival ambiguity and saving behavior only for ambiguity averse people in order to bias our estimate. Moreover, implementing the coefficient stability test proposed by Oster (2019), we show that omitted variable bias is unlikely to confound the empirical relationship we find between measures of savings and survival ambiguity. To address concerns about cognitive skills affecting our estimate of survival ambiguity, we show that our results are robust not only to controlling for various measures of sophistication and cognition, but also to the analysis of different patterns of the distribution of subjective survival beliefs, and to an analysis carried out among highly sophisticated subgroups.

By quantifying the effect of survival ambiguity on saving decisions in a realistically calibrated life-cycle model, we contribute to the literature that has provided explanations for the accumulation of preretirement savings. Further, our findings provide an additional explanation for a long-standing puzzle in household finance - that is the observation of young saving "too little". While much of the recent literature on financial well-being has focused on the role of financial literacy, our findings suggest that survival ambiguity presents an additional - previously unexplored - determinant of financial well-being and retirement security. In addition to distorted survival beliefs (Heimer et al., 2019), the uncertainty around subjective survival probabilities provide another mechanism through which mortality considerations affect financial decision making. Because we show that informing individuals about their survival prospects decreases their degree of survival ambiguity, our results provide further support to information campaigns about objective survival chances to improve individuals' retirement preparedness.

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A Appendix - Additional Tables and Figures

Table A1: Respondent Characteristics

	N	Mean	SD	Median
Demographics				
Age	12833	46.313	16.438	45
Female	12833	0.521	0.500	0
Married	12833	0.551	0.497	1
Unemployed	12833	0.206	0.405	0
Retired	12833	0.204	0.403	0
Number of household members	11752	2.751	1.672	2
Number of kids	12267	1.501	1.476	1
Hispanic	12833	0.103	0.304	0
Race: White	12785	0.779	0.415	1
Race: Black or African-American	12785	0.129	0.335	0
Race: American Indian or Alaska Native	12785	0.012	0.110	0
Race: Asian	12785	0.045	0.207	0
Race: Native Hawaiian or Pacific Islander	12785	0.003	0.057	0
Race: Other	12785	0.031	0.175	0
Optimism	12833	2.195	0.803	2.1667
Education				
Primary school or high school	12767	0.344	0.475	0
College	12767	0.232	0.422	0
Bachelor	12767	0.228	0.419	0
Master or PhD	12767	0.196	0.397	0
Financials				
Household income	12100	80270.893	265076.672	50000
(Log) Household income	12100	10.426	1.922	10.8198
Past Saving rate	9282	0.206	0.245	.1
Planned Saving rate	9124	0.259	0.249	.2
Wealth-to-income ratio	10750	193.069	9807.138	1.1333
Political Orientation				
Democrat	12091	0.460	0.498	0
Republican	12091	0.320	0.466	0
Other	12091	0.220	0.414	0
Sophistication				
Financial literacy score	12833	1.715	1.056	2
Cognitive ability score	12833	0.373	0.737	0
Probability numeracy score	12833	1.906	1.299	2
Mortality probability numeracy	12833	0.696	0.460	1
Has studied economics or finance in high school	12264	0.427	0.495	0
Preferences				
Subjective risk aversion: 1	11322	0.239	0.427	0
Subjective risk aversion: 2	11322	0.237	0.425	0
Subjective risk aversion: 3	11322	0.359	0.480	0
Subjective risk aversion: 4	11322	0.165	0.371	0
Patience: Very Patient	12222	0.212	0.409	0
Patience: Patient	12222	0.507	0.500	1
Patience: Impatient	12222	0.201	0.401	0
Patience: Very Impatient	12222	0.080	0.272	0
Ambiguity averse	12833	0.592	0.491	1
Ambiguity neutral	12833	0.169	0.375	0
Ambiguity seeking	12833	0.239	0.427	0

Note: This table presents summary statistics on control variables for the full sample. For continuous variables, we show mean and standard deviation; for binary variables we show the share.

Table A2: Descriptive statistics of subjective survival probabilities and survival ambiguity

	N	Mean	SD	Median
Subjective one year survival probability	12833	87.233	19.832	98.4
Subjective ten year survival probability	12833	78.263	24.856	86.5
One year survival ambiguity	12805	0.062	0.070	.0343475
Ten year survival ambiguity	12812	0.064	0.065	.0428836

Note: This table presents summary statistics on subjective survival probabilities and survival ambiguity variables for the full sample.

Table A3: Correlation matrix for 1-year, 2-year and 10-year survival ambiguity

	1-year survival ambiguity	2-year survival ambiguity	10-year survival ambiguity
1-year survival ambiguity	1.00		
2-year survival ambiguity	0.73	1.00	
10-year survival ambiguity	0.61	0.73	1.00
N	12,795		

Table A4: Respondent Health Characteristics

	N	Mean	SD	Median
Subjective health state				
Excellent	12645	0.181	0.385	0
Very good	12645	0.282	0.450	0
Fair	12645	0.177	0.382	0
Poor	12645	0.048	0.213	0
Health related behavior				
Currently smoking: yes	12627	0.301	0.459	0
Ever smoked: yes	12557	0.530	0.499	1
BMI				
Underweight	12833	0.057	0.233	0
Normal	12833	0.171	0.377	0
Overweight	12833	0.320	0.466	0
Obese	12833	0.452	0.498	0
Diagnoses				
High blood pressure	12833	0.286	0.452	0
Hypertension	12833	0.132	0.338	0
Diabetes	12833	0.146	0.353	0
High blood sugar	12833	0.079	0.269	0
Cancer	12833	0.042	0.201	0
Lung disease	12833	0.043	0.203	0
Heart issue	12833	0.064	0.245	0
Stroke	12833	0.026	0.160	0
Psychiatric problems	12833	0.132	0.338	0
Depression	12833	0.184	0.387	0
Alzheimer	12833	0.005	0.073	0
Dementia	12833	0.009	0.095	0
Arthritis	12833	0.142	0.349	0
Weakened immune system	12833	0.052	0.222	0
Cholesterol	12833	0.143	0.350	0
Osteoporosis	12833	0.038	0.191	0
Other	12833	0.098	0.297	0
Good health (obj)	12833	0.372	0.483	0
Health related experiences				
Mother alive	12472	0.602	0.490	1
Father alive	12240	0.499	0.500	0
Grandmother alive	12367	0.224	0.417	0
Grandfather alive	11939	0.206	0.405	0

Note: This table presents summary statistics on health-related control variables for the full sample. For continuous variables, we show mean and standard deviation; for binary variables we show the share. Good health (obj) is a dummy variable that is equal to one if no diagnoses of the aforementioned health conditions has been made, and zero otherwise

Table A5: Determinants of (1-Year and 10-Year) Survival Ambiguity

	(1) 1-Year survival ambiguity		(3) 10-Year survival ambiguity	
1-Year survival probability	-0.000***	(0.000)		
3-Year survival probability			-0.000***	(0.000)
Age 45+	-0.010***	(0.002)	-0.009***	(0.001)
Female	0.002	(0.001)	0.003*	(0.001)
Above-median income	-0.006***	(0.002)	-0.003*	(0.001)
Some college	-0.003	(0.002)	-0.002	(0.001)
Financially literate	-0.000	(0.002)	0.004*	(0.001)
High cognitive skills	-0.004*	(0.002)	0.002	(0.001)
High prob. numeracy	-0.004**	(0.002)	0.002	(0.001)
High mortality prob. numeracy	-0.002	(0.002)	-0.002	(0.001)
Optimistic	-0.005***	(0.001)	-0.004***	(0.001)
In good health (subj.)	-0.002	(0.002)	0.000	(0.002)
In good health (obj.)	-0.006***	(0.001)	-0.008***	(0.001)
Hispanic	-0.004	(0.002)	-0.002	(0.002)
Race: White	0.002	(0.002)	0.002	(0.002)
Race: Black or Afr.-Americ.	0.004	(0.003)	0.000	(0.003)
Married	-0.001	(0.002)	-0.003*	(0.001)
Number of HH members	0.000	(0.000)	0.001	(0.000)
Number of kids	0.000	(0.000)	0.000	(0.000)
Retired	0.003	(0.002)	-0.001	(0.002)
Unemployed	-0.001	(0.002)	-0.001	(0.002)
Region	Yes		Yes	
Constant	0.083***	(0.008)	0.082***	(0.016)
N	11,037		11,043	
r2	0.036		0.022	

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: T-tests for Test of Random Allocation to Treatment Arms

	(1) Baseline vs. Treatment 2	(2) Baseline vs. Treatment 3	(3) Baseline vs. Treatment 4	(4) Baseline vs. Treatment 5	(5) Baseline vs. Treatment 6
Female	0.0172	-0.00390	0.0207	-0.0123	-0.00518
	(1.36)	(-0.25)	(1.36)	(-0.81)	(-0.34)
Age	0.635	0.112	0.882*	0.197	-0.0225
	(1.52)	(0.22)	(1.75)	(0.39)	(-0.04)
Race: White	0.00660	0.0111	-0.00718	-0.0145	-0.0153
	(0.62)	(0.86)	(-0.57)	(-1.15)	(-1.22)
Race: Black or African-American	-0.00227	0.00491	0.00278	0.0187*	0.00414
	(-0.26)	(0.47)	(0.27)	(1.85)	(0.40)
Race: American Indian or Alaska Native	-0.00326	0.00130	0.00143	-0.000784	0.000978
	(-1.11)	(0.39)	(0.44)	(-0.23)	(0.30)
Race: Asian	0.000179	-0.0184***	0.00399	-0.00490	0.00884
	(0.03)	(-2.75)	(0.65)	(-0.78)	(1.47)
Race: Native Hawaiian or Pacific Islander	-0.000566	0.000419	0.000457	0.000519	0.00172
	(-0.36)	(0.23)	(0.26)	(0.29)	(1.04)

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Logit Regressions for Test of Random Allocation to Treatment Arms

	(1) Control	(2) Treatment 1	(3) Treatment 2	(4) Treatment 3	(5) Treatment 4	(6) Treatment 5
Female	0.0260	-0.0738	0.0462	-0.0853	0.0730	0.0463
	(0.63)	(-1.79)	(0.86)	(-1.60)	(1.38)	(0.87)
Age	0.00178	-0.00148	0.00143	-0.00309	0.000175	0.000993
	(1.37)	(-1.14)	(0.85)	(-1.84)	(0.11)	(0.60)
Race: White	-0.0135	-0.0209	-0.00332	-0.00665	0.0632	0.00421
	(-0.11)	(-0.18)	(-0.02)	(-0.04)	(0.41)	(0.03)
Race: Black or African-American	0.0424	0.0334	0.0178	-0.0434	-0.0955	-0.0112
	(0.33)	(0.26)	(0.10)	(-0.26)	(-0.56)	(-0.07)
Race: American Indian or Alaska Native	-0.0427	0.266	-0.144	-0.225	0.0755	-0.147
	(-0.19)	(1.28)	(-0.48)	(-0.76)	(0.27)	(-0.50)
Race: Asian	-0.0340	-0.0619	0.408*	-0.180	0.138	-0.296
	(-0.22)	(-0.41)	(2.17)	(-0.91)	(0.71)	(-1.45)
Race: Native Hawaiian or Pacific Islander	0.111	0.292	-0.0271	-0.117	-0.0544	-0.659
	(0.30)	(0.83)	(-0.05)	(-0.23)	(-0.11)	(-1.07)
Constant	-1.227***	-0.996***	-2.054***	-1.723***	-1.999***	-1.970***
	(-9.49)	(-7.81)	(-12.17)	(-10.53)	(-11.96)	(-11.95)
N	12785	12785	12785	12785	12785	12785
chi2	2.813	9.242	13.19	7.423	6.573	7.852

Note: This table reports marginal effects from Logit regressions. The overall test statistic for the joint hypothesis that all coefficients in each column are zero provides a test of randomness. t statistics in parentheses. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively. The respective p-values (including all variables) are 0.0289, 0.0614, 0.4997, 0.5056, and 0.6991 for columns 1, 2, 3, 4, and 5, respectively.

Table A8: Robustness of the Measure: Effect of Survival Ambiguity Measured as the Coefficient of variation on Savings

	Past savings rate		Planned savings rate		Wealth-to-income ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Survival ambiguity	-0.103***		-0.0634*		-5.957*	
	(0.0336)		(0.0357)		(3.372)	
CV SA		-0.0572***		-0.0421**		-3.441**
		(0.0189)		(0.0201)		(1.729)
Survival Probability	-0.0000529	-0.000108	0.0000735	0.0000287	-0.0134	-0.0168
	(0.000142)	(0.000144)	(0.000148)	(0.000151)	(0.0166)	(0.0171)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Health indicators	Yes	Yes	Yes	Yes	Yes	Yes
Sophistication scores	Yes	Yes	Yes	Yes	Yes	Yes
Life/death experiences	Yes	Yes	Yes	Yes	Yes	Yes
Risk factors	Yes	Yes	Yes	Yes	Yes	Yes
Preferences	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,890	6,890	6,742	6,742	7,542	7,542

Note: This table presents results from OLS regressions of individuals' past savings rate, planned savings rate and wealth-to-income ratio on survival ambiguity in columns 1, 3, and 5 and on the coefficient of variation as an alternative measure of uncertainty of subjective survival probabilities in columns 2, 4, and 6. In all models, we control for an extensive list of characteristics, including individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence; health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other; sophistication scores, such as probability numeracy, financial literacy, and cognitive ability; dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle; *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood as well as preferences, such as risk preferences, ambiguity preferences, and patience. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table A9: Effect of Standardized Survival Probability and Standardized Survival Ambiguity on Savings

	(1)	(2)
	Savings as shareA of HH income	
Stand. survival ambiguity	-0.00649**	-0.00706***
	(0.00253)	(0.00231)
Stand. survival probability	0.000387	-0.00101
	(0.00268)	(0.00271)
Demographics	No	Yes
Health indicators	No	Yes
Sophistication scores	No	Yes
Life/death experiences	No	Yes
Risk factors	No	Yes
Preferences	No	Yes
Observations	8,505	6,890

Note: This table presents results from OLS regressions of individuals' past savings rate on standardized measures survival ambiguity and subjective survival probabilities, that is *Stand. survival ambiguity* is equal to *survival ambiguity* divided by the measures standard deviation (0.0686268) and *Stand. survival probability* is equal to *survival probability* divided by the measures standard deviation (19.07346). Column (1) presents unconditional results. The model in column (2) controls for individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence; for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other; for sophistication scores, such as probability numeracy, financial literacy, and cognitive ability; for dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle; for *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood; and for preferences, such as risk preferences, ambiguity preferences, and patience. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table A10: Effect of Survival Ambiguity on Savings by Level of Sophistication

	Past savings rate		Past savings rate		Past savings rate	
	Cognitive Ability==1	Cognitive Ability ==0	Financial Literacy==1	Financial Literacy==0	Probability Numeracy==1	Probability Numeracy==0
	(1)	(2)	(3)	(4)	(5)	(6)
Survival ambiguity	-0.187***	-0.0839*	-0.134***	-0.112**	-0.114***	-0.142**
	(0.0559)	(0.0454)	(0.0406)	(0.0518)	(0.0372)	(0.0579)
Survival probability	-0.0000949	0.000105	0.000296	0.000184	0.000287	0.000364*
	(0.000232)	(0.000169)	(0.000198)	(0.000177)	(0.000183)	(0.000187)
Observations	2,438	6,067	3,040	5,465	3,859	4,646

Note: This table presents results from OLS regressions of individuals' past savings rate on survival ambiguity by subgroups of sophistication. Columns (1) and (2) split the sample by cognitive ability, where the dummy for *Cognitive Ability* equals 1 if *Cognitive ability score*$\geq$ 1 and 0 otherwise. Columns (3) and (4) split the sample by financial literacy, where the dummy for *Financial Literacy* equals 1 if *Financial literacy score*==3 and 0 otherwise. Columns (5) and (6) split the sample by probability numeracy, where the dummy for *Probability Numeracy* equals 1 if *Probability numeracy score*$\geq$ 3 and 0 otherwise. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table A11: Effect of Survival Ambiguity on Savings by Ambiguity Preference

	Past savings rate			Planned savings rate		
	Ambiguity averse	Ambiguity neutral	Ambiguity seeking	Ambiguity averse	Ambiguity neutral	Ambiguity seeking
	(1)	(2)	(3)	(4)	(5)	(6)
Survival ambiguity	-0.118***	-0.0175	-0.0882	-0.125***	0.0274	0.00791
	(0.0428)	(0.0860)	(0.0770)	(0.0454)	(0.0874)	(0.0809)
Survival probability	0.0000224	-0.000311	0.000456	-0.0000961	-0.000137	0.000456
	(0.000182)	(0.000415)	(0.000294)	(0.000190)	(0.000413)	(0.000294)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Health indicators	Yes	Yes	Yes	Yes	Yes	Yes
Sophistication scores	Yes	Yes	Yes	Yes	Yes	Yes
Life/death experiences	Yes	Yes	Yes	Yes	Yes	Yes
Risk factors	Yes	Yes	Yes	Yes	Yes	Yes
Preferences	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,393	845	1,625	4,314	803	1,625

Note: This table presents results from OLS regressions of individuals' past savings rate on survival ambiguity (columns 1, 2, and 3) and of individuals' planned savings rate on survival ambiguity (columns 4, 5, and 6) by ambiguity preferences. "Ambiguity averse" individuals are identified having revealed a matching probability below 50%, "ambiguity averse" individuals have a matching probability of 50%, and "ambiguity seeking" individuals have a matching probability above 50%. In all models, we control for an extensive list of characteristics, including individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence; health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other; sophistication scores, such as probability numeracy, financial literacy, and cognitive ability; dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle; *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood as well as preferences, such as risk preferences, ambiguity preferences, and patience. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table A12: Test for Selection on Unobservables

	Savings rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Survival ambiguity coef.	-0.0765	-0.0637	-0.0718	-0.1020	-0.1004	-0.0983	-0.1028
δ		4.847	18.320	-12.216	-14.024	-16.648	-15.431
R^2	0.0004	0.2833	0.3495	0.3808	0.3882	0.3945	0.4035
Observations	6,890	6,890	6,890	6,890	6,890	6,890	6,890

Note: This table presents the results of the test for selection on unobservables in regression estimates proposed by Oster (2019). The Table reports OLS estimates for the relationship between savings and survival ambiguity, including different sets of controls, as well as the estimates of δ. Estimates of δ greater than 1 or less than 0 suggest that unobservables would need to be implausibly strongly–or even oppositely–selected relative to observables to fully explain away the estimated relationship, indicating robustness to omitted variable bias. We set R^2_{max} equal to $1.3\widetilde{R}^2$, where $\widetilde{R}^2$ denotes the R-squared from the controlled (i.e., including all controls) regression. The baseline (uncontrolled) model in Column (1) regresses the savings rate only on survival ambiguity. The specification in column (2) controls for basic individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence. The specification in column (3) also controls for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other. Specification (4) controls also for sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. In addition, specification (5) controls for dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle. To the list of controls, specification (6) adds *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, specification (7) controls additionally for preferences, such as risk preferences, ambiguity preferences, and patience.

Table A13: Relationship between Survival Ambiguity and Annuity Ownership

	(1) Annuity	(2) Annuity	(3) Annuity
Survival ambiguity	-29492.6***	-18612.2**	-16424.1
	(7891.4)	(8896.4)	(11160.4)
Survival probability		79.44***	32.01
		(22.49)	(29.88)
Demographics	No	Yes	Yes
Health indicators	No	No	Yes
Sophistication scores	No	No	Yes
Life/death experiences	No	No	Yes
Risk factors	No	No	Yes
Preferences	No	No	Yes
Observations	11,399	9,875	8,206

Note: This table presents results from OLS regressions of the market value / account balance of individuals' annuities. In specifications (2) and (3), we control for individuals' demographics, that is subjective 1-year survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence. The specification in column (3) also controls for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other, as well as sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. In addition, these specifications control for dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle. Further, they control for *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, specification (3) also controls for preferences, such as risk preferences, ambiguity preferences, and patience. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table A14: Relationship between Survival Ambiguity and Ownership of Long-Term Care Insurance

	(1) LTC	(2) LTC	(3) LTC
Survival ambiguity	-7665.1	-108.2	1779.4
	(6836.6)	(7870.0)	(9265.6)
Survival probability		36.76**	38.23*
		(17.66)	(19.79)
Demographics	No	Yes	Yes
Health indicators	No	No	Yes
Sophistication scores	No	No	Yes
Life/death experiences	No	No	Yes
Risk factors	No	No	Yes
Preferences	No	No	Yes
Observations	11,399	9,875	8,206

Note: This table presents results from OLS regressions of the market value of individuals' long-term care insurance in Columns. In specifications (2) and (3), we control for individuals' demographics, that is subjective 1-year survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence. The specification in column (3) also controls for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other, as well as sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. In addition, these specifications control for dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle. Further, they control for *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, specification (3) also controls for preferences, such as risk preferences, ambiguity preferences, and patience. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table A15: Relationship between Survival Ambiguity and Ownership of Universal Life Insurance

	(1) Life Insurance	(2) Life Insurance	(3) Life Insurance
Survival ambiguity	-29388.1***	-16577.7*	-17315.3*
	(7860.9)	(8674.8)	(10260.3)
Survival probability		39.47	-28.18
		(31.25)	(41.17)
Demographics	No	Yes	Yes
Health indicators	No	No	Yes
Sophistication scores	No	No	Yes
Life/death experiences	No	No	Yes
Risk factors	No	No	Yes
Preferences	No	No	Yes
Observations	11,399	9,875	8,206

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

Note: This table presents results from OLS regressions of the market value of individuals' universal life insurance in Columns. In specifications (2) and (3), we control for individuals' demographics, that is subjective 1-year survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence. The specification in column (3) also controls for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other, as well as sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. In addition, these specifications control for dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle. Further, they control for *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, specification (3) also controls for preferences, such as risk preferences, ambiguity preferences, and patience.

Table A16: Effect of 10-Year Survival Ambiguity on Savings

	Savings as share of household income						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10-Year survival ambiguity	-0.119***	-0.0909**	-0.0610*	-0.0543	-0.0372	-0.0356	-0.0548
	(0.0421)	(0.0373)	(0.0354)	(0.0349)	(0.0360)	(0.0359)	(0.0379)
10-year Survival probability		0.000620***	0.000142	0.000155*	0.0000964	0.0000442	0.0000106
		(0.0000901)	(0.0000917)	(0.0000931)	(0.0000963)	(0.0000979)	(0.000106)
Demographics	No	Yes	Yes	Yes	Yes	Yes	Yes
Health indicators	No	No	Yes	Yes	Yes	Yes	Yes
Sophistication scores	No	No	No	Yes	Yes	Yes	Yes
Life/death experiences	No	No	No	No	Yes	Yes	Yes
Risk factors	No	No	No	No	No	Yes	Yes
Preferences	No	No	No	No	No	No	Yes
Observations	8,511	7,985	7,946	7,946	7,518	7,518	6,895

Note: This table presents results from OLS regressions of individuals' past savings rate, planned savings rate and wealth-to-income ratio on 10-year survival ambiguity. The first column reports unconditional results. The specification in column (2) controls for individuals' demographics, that is subjective 10-year survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence. The specification in column (3) also controls for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other. Specification (4) controls also for sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. In addition, specification (5) controls for dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle. To the list of controls, specification (6) adds *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, specification (7) controls additionally for preferences, such as risk preferences, ambiguity preferences, and patience. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Figure A1: Timeline of survey and experiment

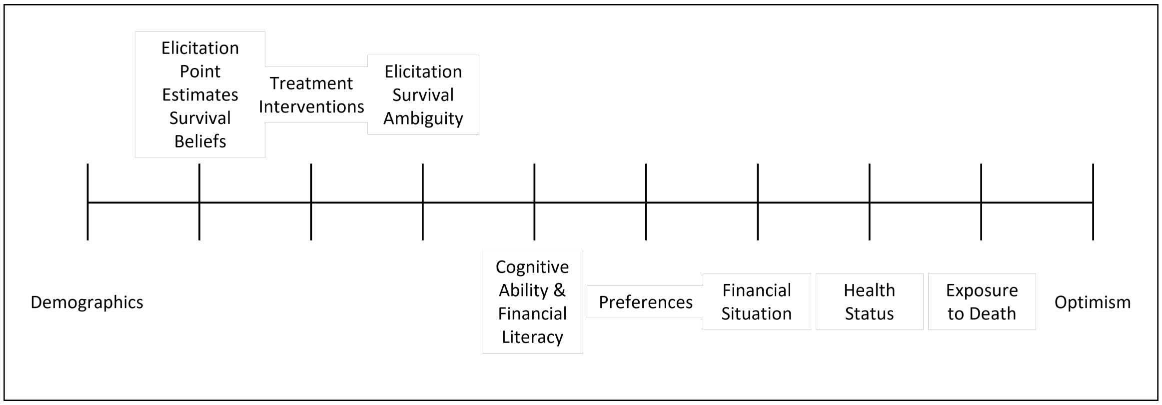


Figure A2: Kernel Density

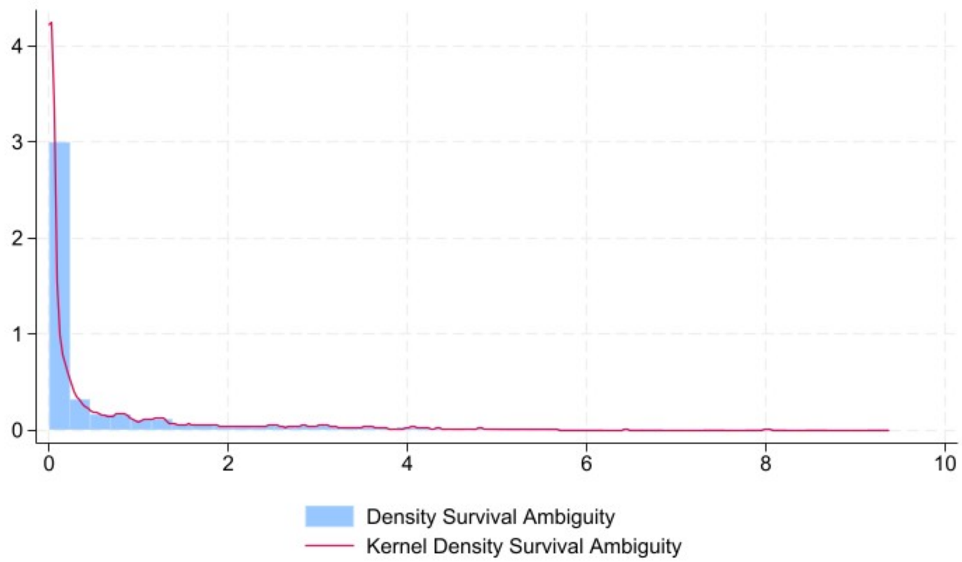


Figure A3: Determinants of Survival Ambiguity: Demographics

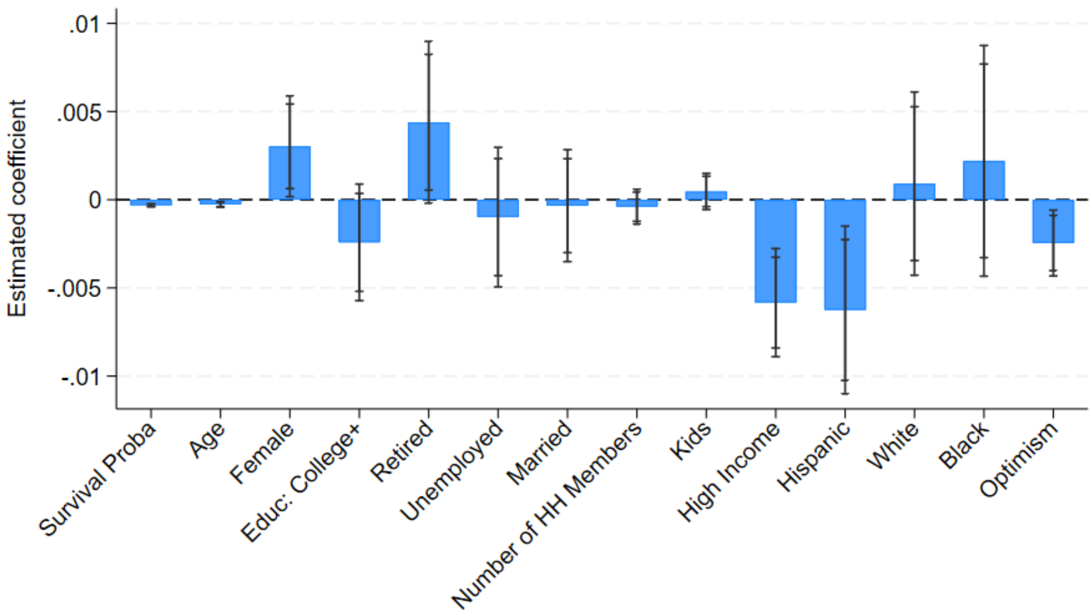


Figure A4: Determinants of Survival Ambiguity: Health (1)

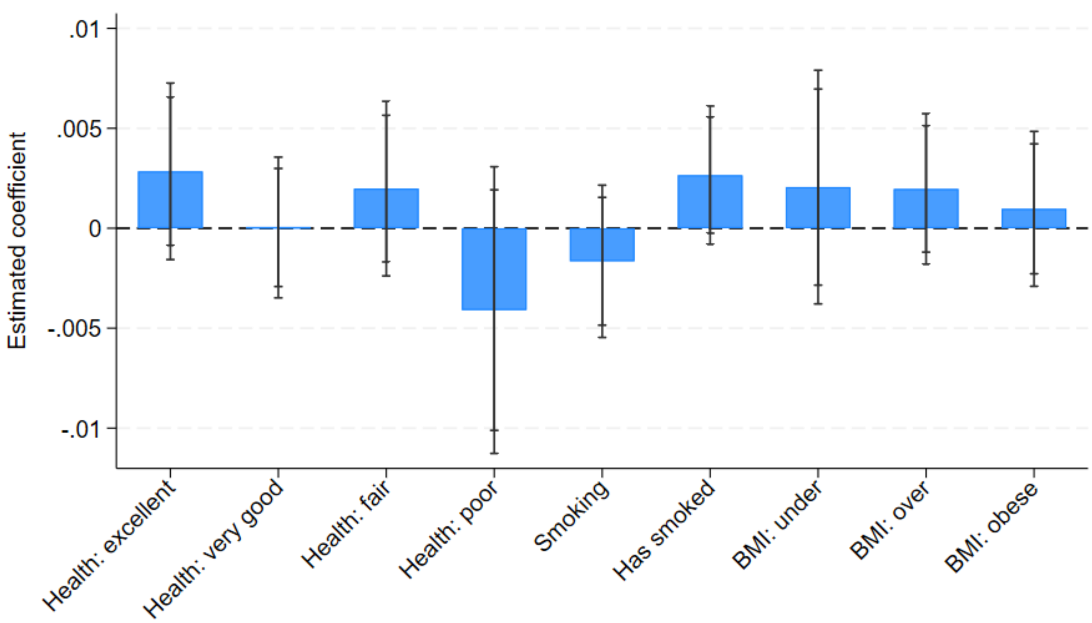


Figure A5: Determinants of Survival Ambiguity: Health (2)

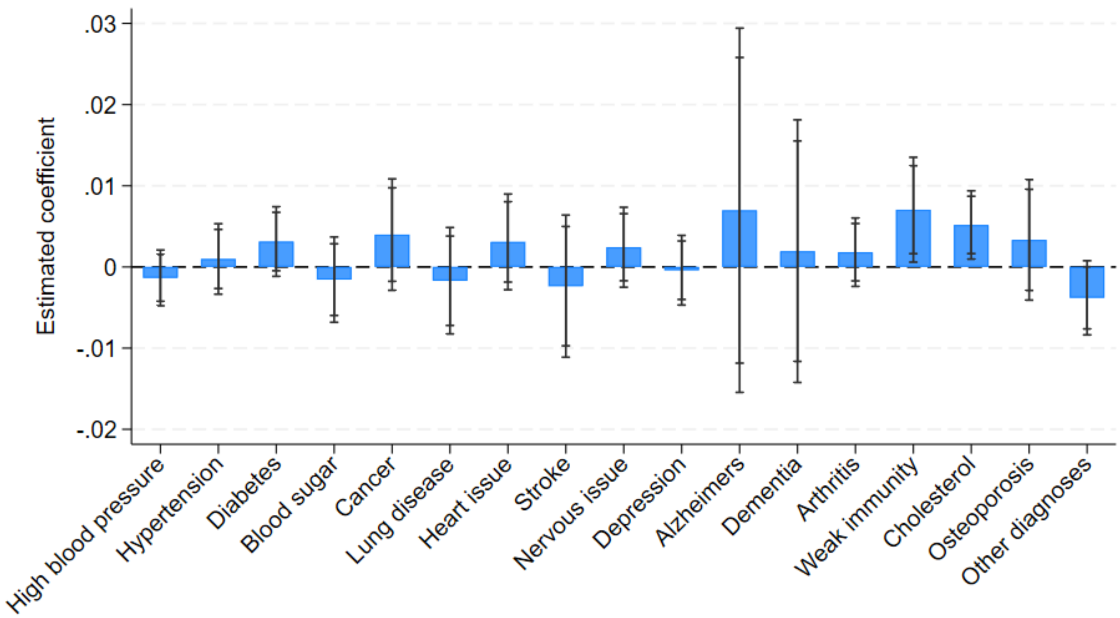


Figure A6: Determinants of Survival Ambiguity: Experiences

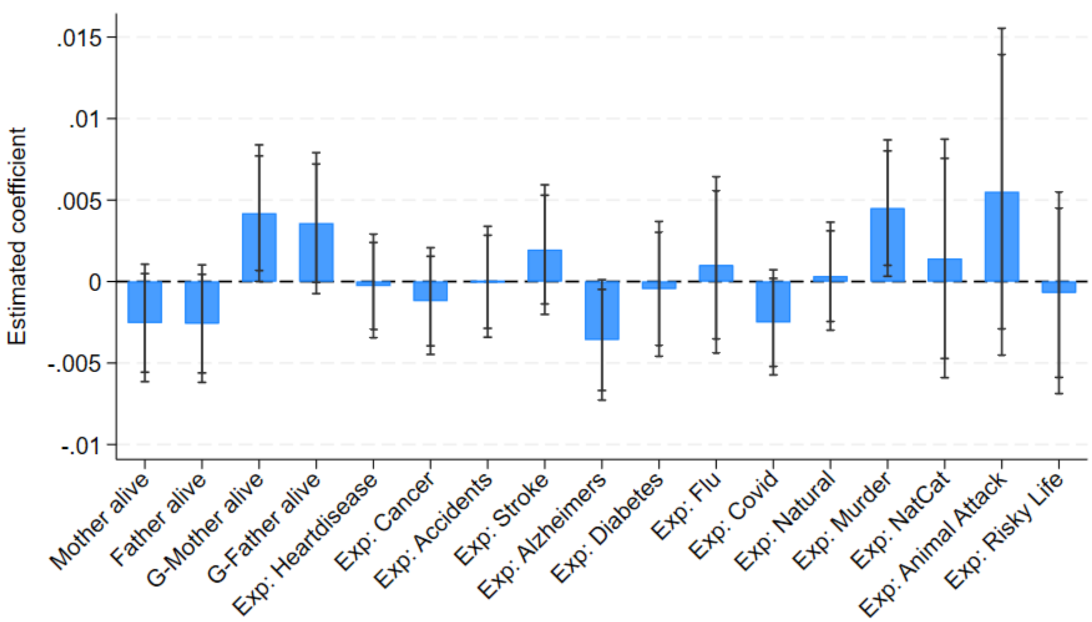


Figure A7: Determinants of Survival Ambiguity: Sophistication

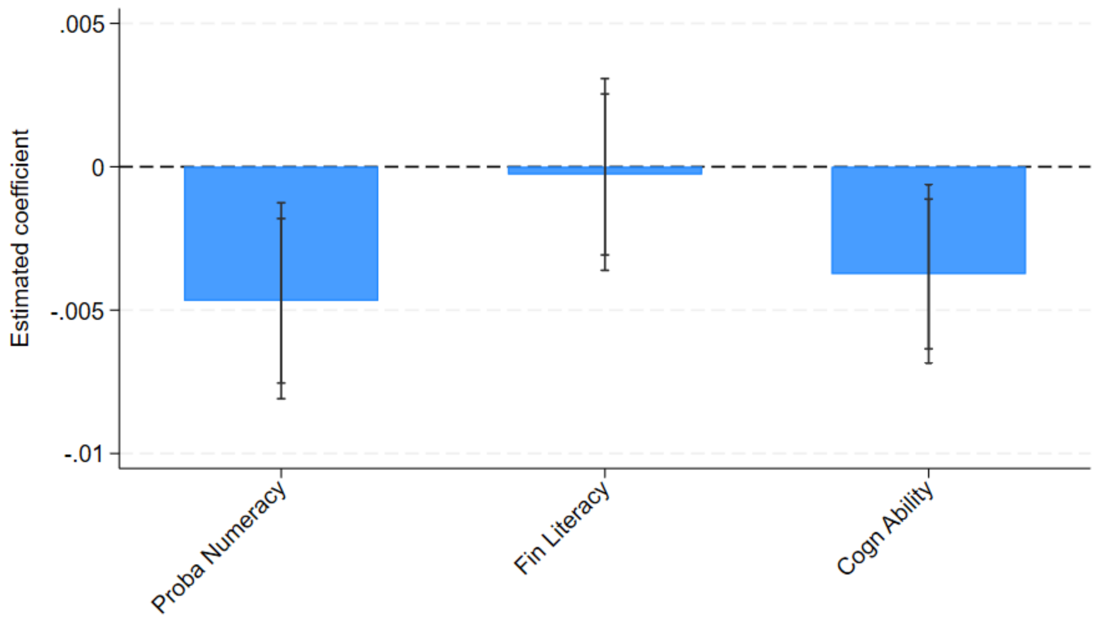


Figure A8: Treatment Effects for 4 groups

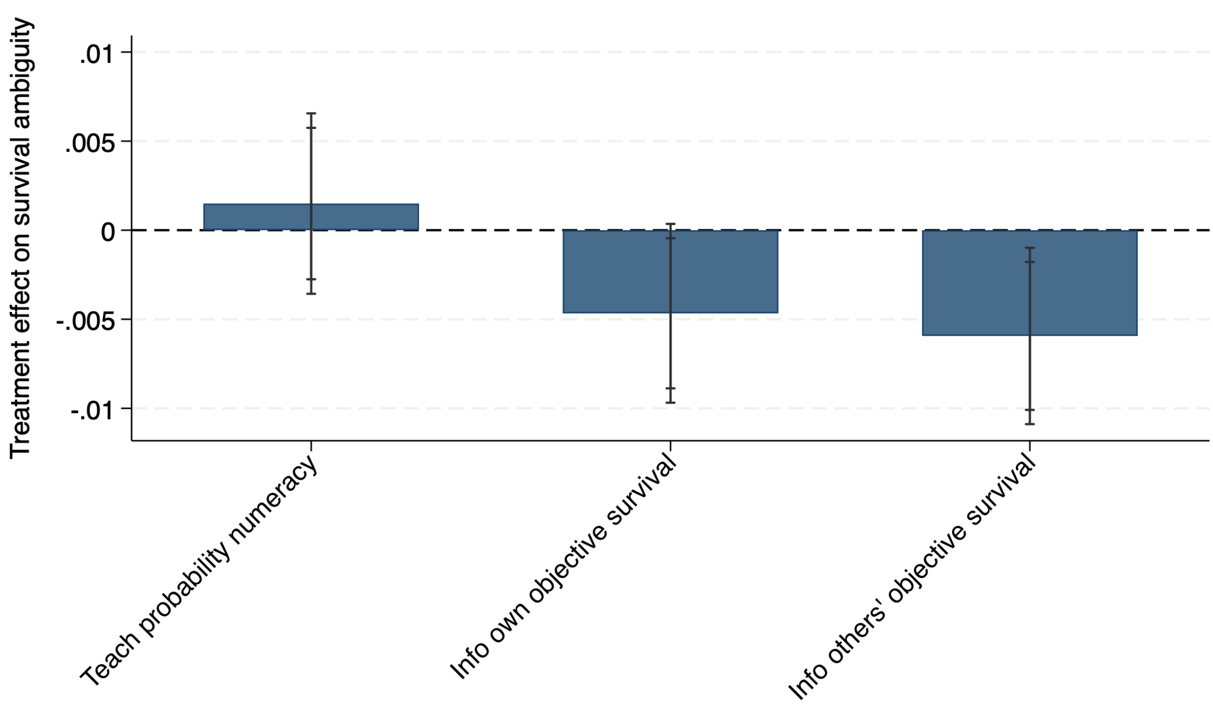


Figure A9: Treatment Effects for 6 groups

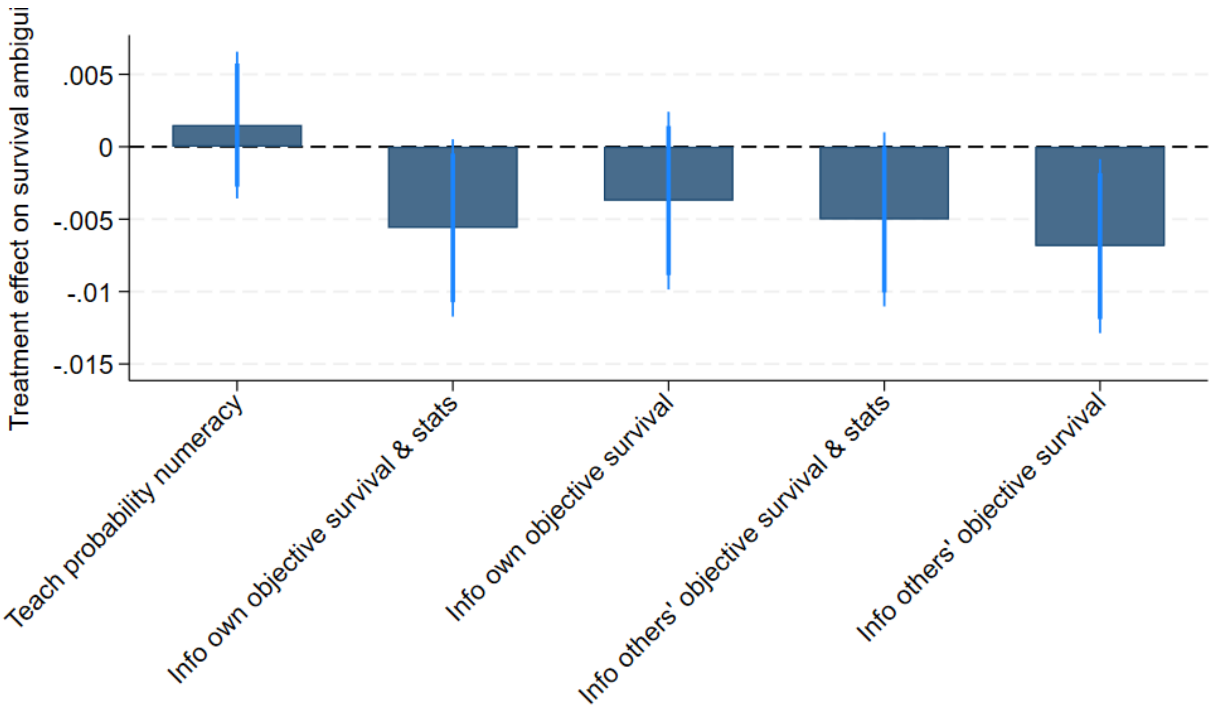


Figure A10: Treatment Effects on 10-Year Survival Ambiguity

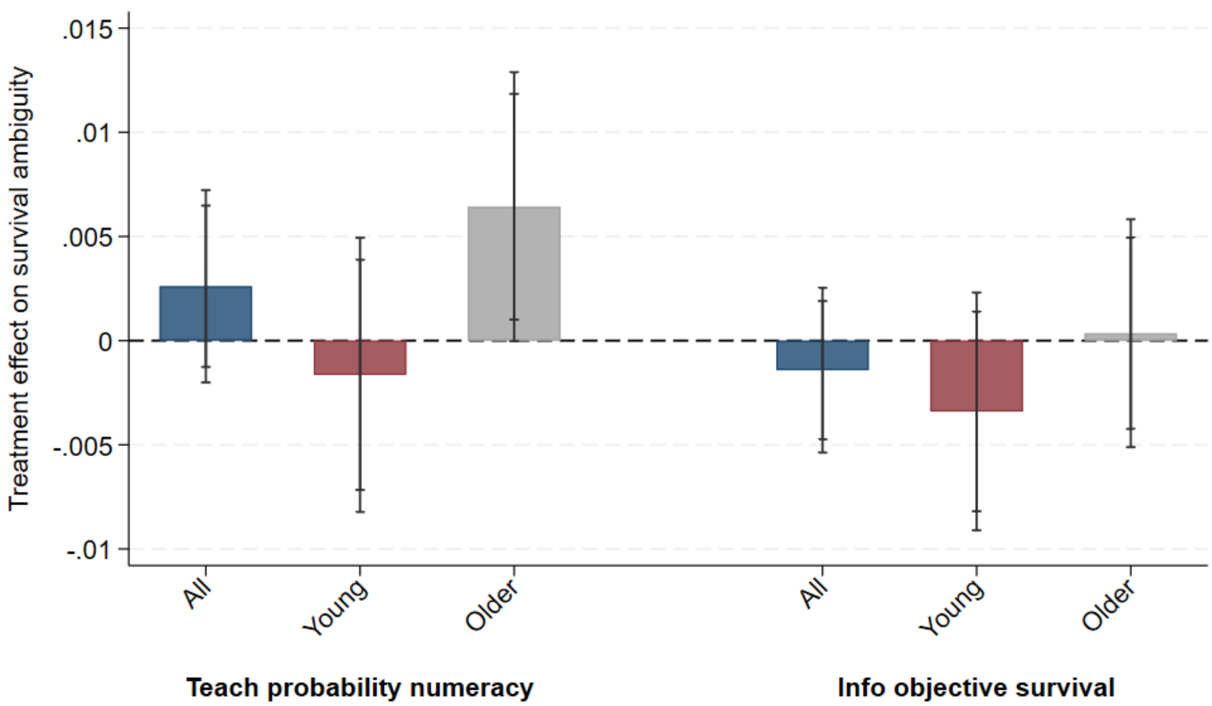
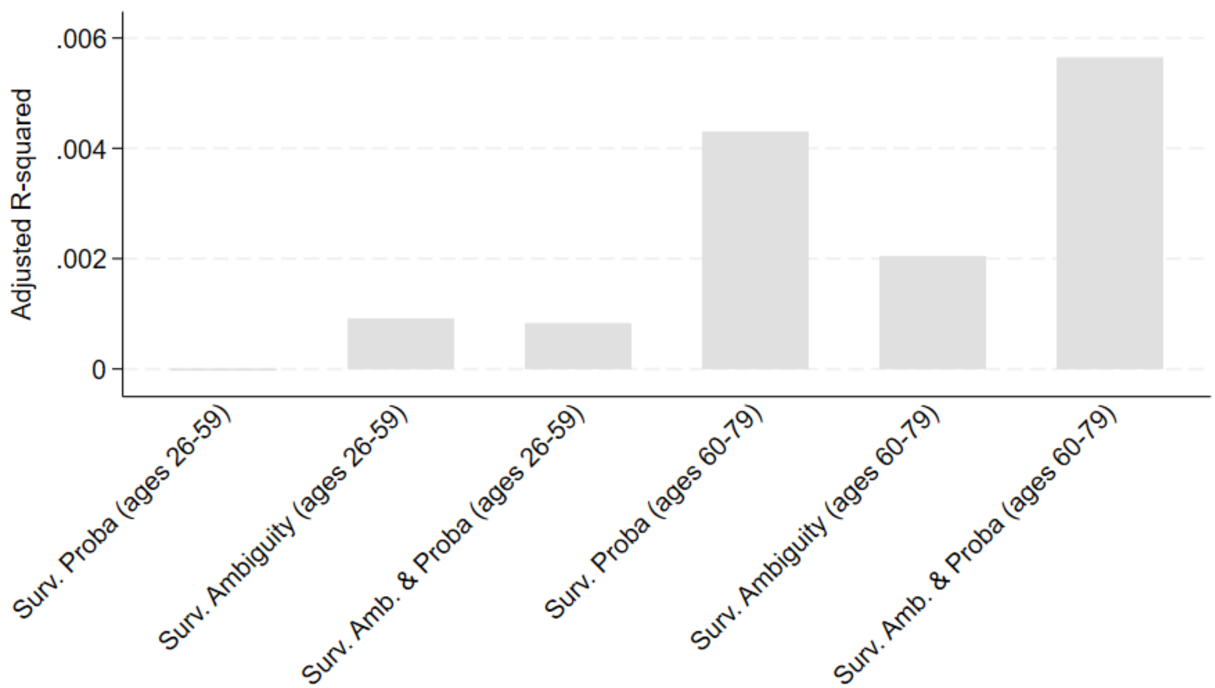
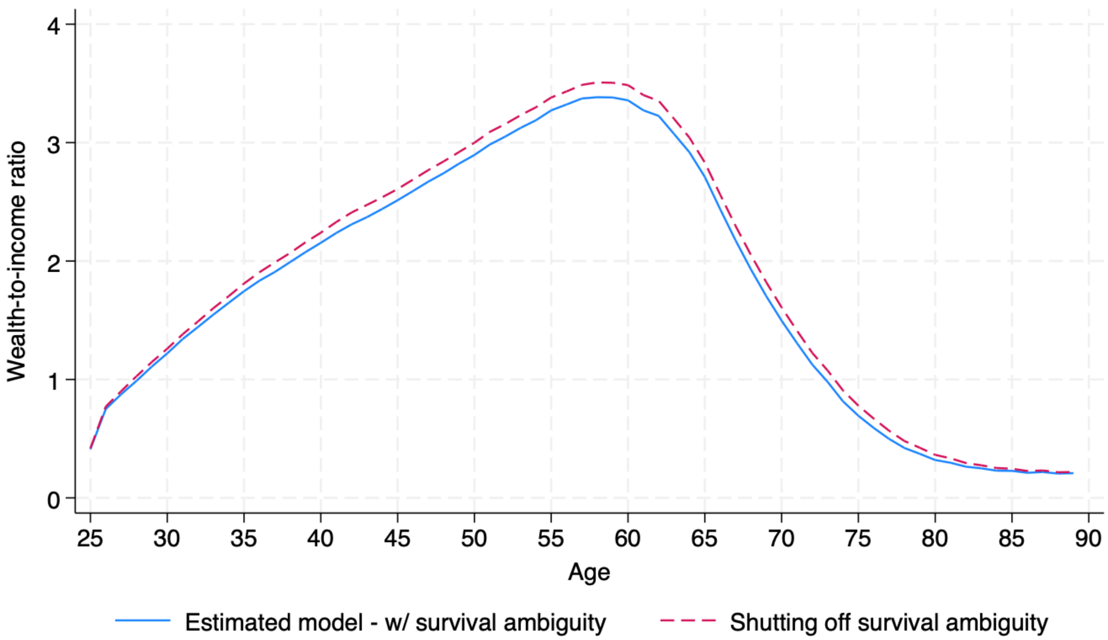


Figure A11: Comparison of R-squared Across Regression Models of Savings Rate



Note: This graph compares the R-squared across regression models of the savings rate on survival ambiguity (bars 1, 2, and 3) and survival probability (bars 4, 5, and 6) for different age groups. All regressions do not control for any other respondent characteristics.

Figure A12: Model-predicted effect of reducing survival ambiguity on households' wealth and consumption over their life cycle.



Notes: The figure compares the age-profile of wealth-to-permanent income ratio predicted by the estimated model with survival ambiguity (blue solid line) and the counterfactual age-profile of wealth accumulation generated when we reduce survival ambiguity by 10%.

B Appendix - Survey Management

Participants' compensation All participants received a baseline compensation for responding to the entire survey. No individual question was incentivized. We paid Qualtrics for data collection, quality checks including attention filters and survey timings as well as participants' compensation. When we inquired about the amount of individual compensation, we received the following response: "Respondents are reimbursed by the specific partner that we use for this project. Respondents will receive an incentive based on the length of the survey, their specific panelist profile, and target acquisition difficulty, amongst other factors. The specific type of rewards vary and may include cash, airline miles, gift cards, redeemable points, and vouchers, all rewards are in line with the US State minimum wage. All our panels are part of ESOMAR, MRS and other internationally recognised bodies and incentives are in line with best practice."

Data collection and randomization The survey was fielded in two waves. As part of the data collection process, Qualtrics was responsible for the random assignment of participants into the treatment group. After the initial fielding with 6,930 respondents in August 2022 (wave 1), we could not confirm the allocation of participants in the treatment group was random. Therefore, we revisited the randomization algorithm together with the Qualtrics team and re-fielded the survey with 5,903 participants in October 2022 (wave 2). Since the issue with the randomization algorithm is only relevant for the analysis of the experimental module, we use both waves (12,833 participants) for the non-experimental analyses of determinants of survival ambiguity as well as the analyses of the relationship between survival ambiguity and savings behavior. The analyses of the experimental module is based on wave 2, for which we can confirm that the random allocation into the treatment group was implemented correctly (see Table A6).

C Appendix - Validation of the Measure of Survival Ambiguity

Table C1: Patterns in the distributions of subjective 1-year survival probabilities

Pattern	N	Definition
AllMin	364	equals 1 if all mass is in the lowest interval
AllMax	1,947	equals 1 if all mass is in the highest interval
Bimodal 1 (”Schroedinger’s cat”)	161	equals 1 if all mass in lowest and highest interval
Bimodal 2	1,150	equals 1 if there is more mass in the 1st or the 2nd interval than in the 3rd interval and there is more mass in the 4th or the 5th interval than in the 3rd interval
Bimodal 3	1,501	equals 1 if the average mass per interval is higher in intervals 1 and 2 than in interval 3 and the average mass per interval is higher in interval 4 and 5 than in interval 3

Table C2: Determinants of Survival Ambiguity

	Survival Ambiguity	
	(1) Full Sample	(2) Full Sample Excluding All Patterns
1-Year survival probability	-0.000***	-0.000***
	(0.000)	(0.000)
Age 45+	-0.010***	-0.006***
	(0.002)	(0.002)
Female	0.002	0.004*
	(0.001)	(0.002)
Above-median income	-0.006***	-0.008***
	(0.002)	(0.002)
Some college	-0.003	-0.005*
	(0.002)	(0.002)
Financially literate	-0.000	-0.002
	(0.002)	(0.002)
High cognitive skills	-0.004*	-0.005*
	(0.002)	(0.002)
High prob. numeracy	-0.004**	-0.005*
	(0.002)	(0.002)
High mortality prob. numeracy	-0.002	0.001
	(0.002)	(0.002)
Optimistic	-0.005***	-0.002
	(0.001)	(0.002)
In good health (subj.)	-0.002	-0.002
	(0.002)	(0.002)
In good health (obj.)	-0.006***	-0.004*
	(0.001)	(0.002)
Hispanic	-0.004	-0.004
	(0.002)	(0.003)
Race: White	0.002	0.000
	(0.002)	(0.003)
Race: Black or Afr.-Americ.	0.004	0.001
	(0.003)	(0.004)
Married	-0.001	-0.000
	(0.002)	(0.002)
Number of HH members	0.000	0.000
	(0.000)	(0.001)
Number of kids	0.000	0.001
	(0.000)	(0.001)
Retired	0.003	0.006*
	(0.002)	(0.002)
Unemployed	-0.001	0.001
	(0.002)	(0.002)
Region	Yes	Yes
Constant	0.084***	0.055***
	(0.008)	(0.009)
N	11,037	7,693
r2	0.036	0.036

Note: This table presents results from OLS regressions of individuals' survival ambiguity on participants' characteristics. Column (1) considers the full sample, and the results in column (2) are based on a sample that excludes the patterns in the distribution of survival probabilities identified in Table C1. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table C3: Determinants of Survival Ambiguity

	Survival Ambiguity					
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Allmin	Allmax	Bimodal 1	Bimodal 2	Bimodal 3
1-Year survival probability	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age 45+	-0.010***	-0.009***	-0.009***	-0.009***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	0.002	0.002	0.003	0.002	0.003*	0.003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Above-median income	-0.006***	-0.006***	-0.008***	-0.006***	-0.005***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Some college	-0.003	-0.003	-0.005*	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Financially literate	-0.000	-0.001	-0.002	0.000	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
High cognitive skills	-0.004*	-0.004**	-0.006**	-0.004*	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
High prob. numeracy	-0.004**	-0.005**	-0.003	-0.005**	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
High mortality prob. numeracy	-0.002	-0.002	-0.001	-0.002	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Optimistic	-0.005***	-0.005***	-0.003*	-0.004**	-0.004**	-0.004**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
In good health (subj.)	-0.002	-0.003	-0.001	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
In good health (obj.)	-0.006***	-0.006***	-0.005**	-0.006***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Hispanic	-0.004	-0.005*	-0.005	-0.004	-0.003	-0.004
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Race: White	0.002	0.002	0.000	0.002	0.002	0.002
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Race: Black or Afr.-Americ.	0.004	0.003	0.004	0.004	0.001	0.002
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Married	-0.001	-0.001	-0.001	-0.001	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of HH members	0.000	0.000	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Number of kids	0.000	0.000	0.001	0.000	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Retired	0.003	0.004*	0.004	0.003	0.004*	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Unemployed	-0.001	-0.000	0.000	-0.001	-0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Region	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.084***	0.085***	0.093***	0.075***	0.056***	0.108***
	(0.008)	(0.008)	(0.026)	(0.013)	(0.007)	(0.017)
N	11,037	10,728	9,364	10,892	10,130	9,808
r2	0.036	0.038	0.035	0.037	0.033	0.032

Note: This table presents results from OLS regressions of individuals' survival ambiguity on participants' characteristics. The regression in column (1) is based on the full sample. Regressions in columns (2), (3), (4), (5), and (6) consider the full sample excluding individuals with a distribution of subjective survival probabilities that follows the "AllMin" pattern, the "AllMax" pattern, the "Bimodal 1" pattern, the "Bimodal 2" pattern or the "Bimodal 3" pattern, respectively. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table C4: Effect of Survival Ambiguity on Savings

	Savings as share of household income	
	(1)	(2)
	Full Sample	Full Sample Excluding All Patterns
Survival ambiguity	-0.103***	-0.117***
	(0.0336)	(0.0381)
Survival probability	-0.0000529	0.000140
	(0.000142)	(0.000168)
Demographics	Yes	Yes
Health indicators	Yes	Yes
Sophistication scores	Yes	Yes
Life/death experiences	Yes	Yes
Risk factors	Yes	Yes
Preferences	Yes	Yes
N	6,890	4,924

Note: This table presents results from OLS regressions of individuals' past savings rate on survival ambiguity. In all models, we control for individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, state of residence. We also control for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other. Further, we control for sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. Finally, we control for a dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle, as well as *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, we control for preferences, such as risk preferences, ambiguity preferences, and patience. Column (1) considers the entire sample, and the results in column (2) are based on a sample that excludes the patterns in the distribution of survival probabilities identified in Table C1. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table C5: Effect of Survival Ambiguity on Savings

	Savings as share of household income					
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Excl. Allmin	Excl. Allmax	Excl. Bimodal 1	Excl. Bimodal 2	Excl. Bimodal 3
Survival ambiguity	-0.103***	-0.105***	-0.103***	-0.105***	-0.0637*	-0.0891**
	(0.0336)	(0.0339)	(0.0336)	(0.0338)	(0.0358)	(0.0360)
Survival probability	-0.0000529	-0.0000172	-0.0000529	-0.0000370	-0.0000533	-0.0000402
	(0.000142)	(0.000145)	(0.000142)	(0.000142)	(0.000148)	(0.000150)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Health indicators	Yes	Yes	Yes	Yes	Yes	Yes
Sophistication scores	Yes	Yes	Yes	Yes	Yes	Yes
Life/death experiences	Yes	Yes	Yes	Yes	Yes	Yes
Risk factors	Yes	Yes	Yes	Yes	Yes	Yes
Preferences	Yes	Yes	Yes	Yes	Yes	Yes
N	6,890	6,718	6,890	6,805	6,361	6,141

Note: This table presents results from OLS regressions of individuals' past savings rate on survival ambiguity. In all models, we control for individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, state of residence. We also control for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other. In addition, we control for sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. Finally, we control for a dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle, as well as *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, we control for preferences, such as risk preferences, ambiguity preferences, and patience. The regression in column (1) is based on the full sample. Regressions in columns (2), (3), (4), (5), and (6) consider the full sample excluding individuals with a distribution of subjective survival probabilities that follows the "AllMin" pattern, the "AllMax" pattern, the "Bimodal 1" pattern, the "Bimodal 2" pattern or the "Bimodal 3" pattern, respectively. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table C6: Determinants of Patterns in Distribution of Survival Probabilities

	(1) Allmin		(2) Allmax		(3) Bimodal 3	
1-Year survival probability	-0.000	(0.000)	0.002***	(0.000)	-0.001***	(0.000)
Age	0.001*	(0.000)	0.002***	(0.000)	-0.000	(0.000)
Female	-0.007	(0.004)	0.003	(0.008)	0.002	(0.008)
Educ: College	0.004	(0.005)	0.005	(0.011)	-0.013	(0.009)
Educ: Bachelor	0.001	(0.005)	-0.050***	(0.011)	0.003	(0.010)
Educ: Master/Phd	-0.001	(0.005)	-0.064***	(0.012)	0.005	(0.011)
log(HH Income)	0.000	(0.001)	-0.002	(0.002)	-0.002	(0.002)
Hispanic	-0.005	(0.005)	0.012	(0.014)	0.006	(0.013)
Race: White	-0.002	(0.007)	-0.054***	(0.016)	0.004	(0.013)
Race: Black	-0.010	(0.008)	-0.041*	(0.019)	0.016	(0.017)
Health: excellent	-0.003	(0.006)	0.041**	(0.013)	-0.004	(0.011)
Health: very good	-0.003	(0.004)	0.014	(0.010)	0.006	(0.009)
Health: Fair	0.003	(0.006)	-0.014	(0.012)	-0.008	(0.011)
Health: Poor	0.029*	(0.013)	0.025	(0.021)	0.000	(0.021)
Proba numeracy	-0.004*	(0.002)	0.007	(0.004)	-0.013***	(0.004)
Financial literacy	-0.002	(0.002)	-0.005	(0.005)	-0.007	(0.004)
Cognitive ability	-0.006**	(0.002)	-0.020***	(0.005)	-0.008	(0.004)
Mortality prob numeracy	0.001	(0.004)	0.016	(0.009)	-0.027**	(0.009)
Optimism	0.002	(0.003)	0.024***	(0.006)	-0.003	(0.005)
Mother alive	0.004	(0.005)	0.016	(0.010)	-0.013	(0.009)
Father alive	-0.002	(0.005)	-0.001	(0.010)	-0.004	(0.009)
Grandmother alive	0.005	(0.005)	-0.018	(0.011)	0.009	(0.012)
Grandfather alive	-0.009	(0.005)	0.007	(0.011)	0.009	(0.012)
Exp: Risky lifestyle	0.013	(0.009)	-0.046***	(0.013)	-0.030	(0.015)
Ambiguity averse	-0.006	(0.004)	-0.011	(0.008)	0.005	(0.007)
Impatient: 2	-0.011*	(0.005)	-0.034**	(0.011)	-0.017	(0.009)
Impatient: 3	-0.004	(0.006)	-0.039**	(0.013)	-0.004	(0.012)
Impatient:4	-0.010	(0.008)	-0.047**	(0.015)	-0.018	(0.016)
Democrat	-0.001	(0.004)	-0.008	(0.008)	0.002	(0.007)
_cons	-0.017	(0.020)	0.028	(0.122)	0.280**	(0.099)
Demographics	Yes		Yes		Yes	
Health indicators	Yes		Yes		Yes	
Sophistication scores	Yes		Yes		Yes	
Life/death experiences	Yes		Yes		Yes	
Risk factors	Yes		Yes		Yes	
Preferences	Yes		Yes		Yes	
N	8,893		8,893		8,893	
r2	0.025		0.065		0.036	
chi2						

Note: This table presents results from OLS regressions of dummy variables that indicate whether a respondent created a pattern in the distribution of subjective survival probabilities according to the definition of "Allmin" (column 1), "Allmax" (column 2), or "Bimodal 3" (column 3), respectively. The patterns are identified in Table C1. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table C7: Determinants of Survival Ambiguity

	Survival Ambiguity	
	(1) Full Sample	(2) Full Sample Including Min-Max
1-Year survival probability	-0.000***	-0.000***
	(0.000)	(0.000)
Age 45+	-0.010***	-0.009***
	(0.002)	(0.002)
Female	0.002	0.003
	(0.001)	(0.001)
Above-median income	-0.006***	-0.006***
	(0.002)	(0.001)
Some college	-0.003	-0.003*
	(0.002)	(0.001)
Financially literate	-0.000	-0.000
	(0.002)	(0.002)
High cognitive skills	-0.004*	-0.004*
	(0.002)	(0.002)
High prob. numeracy	-0.004**	-0.004**
	(0.002)	(0.002)
High mortality prob. numeracy	-0.002	-0.002
	(0.002)	(0.002)
Optimistic	-0.005***	-0.005***
	(0.001)	(0.001)
In good health (subj.)	-0.002	-0.002
	(0.002)	(0.002)
In good health (obj.)	-0.006***	-0.006***
	(0.001)	(0.001)
Hispanic	-0.004	-0.004
	(0.002)	(0.002)
Race: White	0.002	0.002
	(0.002)	(0.002)
Race: Black or Afr.-Americ.	0.004	0.004
	(0.003)	(0.003)
Married	-0.001	-0.001
	(0.002)	(0.002)
Number of HH members	0.000	0.000
	(0.000)	(0.000)
Number of kids	0.000	0.000
	(0.000)	(0.000)
Retired	0.003	0.003
	(0.002)	(0.002)
Unemployed	-0.001	-0.001
	(0.002)	(0.002)
Region	Yes	Yes
Constant	0.084***	0.094***
	(0.008)	(0.023)
N	11,037	11,055
r2	0.036	0.036

Note: This table presents results from OLS regressions of individuals' survival ambiguity on participants' characteristics. The sample used for the regression results in column (2) consists of the full sample used in the main analysis, and in addition it includes participants who report the same number for their minimum survival probability and their maximum survival probability. For these individuals, we assign a survival probability of 0. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.

Table C8: Effect of Survival Ambiguity on Savings Rate (with min=max probabilities)

	Savings rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Survival ambiguity	-0.0996***	-0.0714**	-0.0711**	-0.0909***	-0.0782**	-0.0773**	-0.104***
	(0.0365)	(0.0332)	(0.0314)	(0.0311)	(0.0323)	(0.0320)	(0.0335)
Survival probability		0.000237*	-0.000151	0.0000515	0.0000336	0.00000689	-0.0000562
		(0.000133)	(0.000131)	(0.000130)	(0.000132)	(0.000132)	(0.000142)
Demographics	No	Yes	Yes	Yes	Yes	Yes	Yes
Health indicators	No	No	Yes	Yes	Yes	Yes	Yes
Sophistication scores	No	No	No	Yes	Yes	Yes	Yes
Life/death experiences	No	No	No	No	Yes	Yes	Yes
Risk factors	No	No	No	No	No	Yes	Yes
Preferences	No	No	No	No	No	No	Yes
N	8,522	7,996	7,957	7,957	7,528	7,528	6,904

Note: This table presents results from OLS regressions of individuals' past savings rate, planned savings rate and wealth-to-income ratio on survival ambiguity. The underlying sample consists of the full sample used in the main analysis, including also participants who report the same number for their minimum survival probability and their maximum survival probability. For these individuals, we assign a survival probability of 0. The first column reports unconditional results. The specification in column (2) controls for individuals' demographics, that is subjective survival probability, (linear, squared, and cubic) age, gender, education, employment status, marital status, number of household members, number of kids, household income, race, and state of residence. The specification in column (3) also controls for health indicators, i.e., subjective health status, smoking behavior, BMI as well as past diagnoses of several conditions, such as high blood pressure, hypertension, diabetes, high blood sugar levels, cancer, lung diseases, heart problems, strokes, issues with the nervous system, depression, Alzheimer, dementia, arthritis, weak immune system, high cholesterol, osteoporosis and other. Specification (4) controls also for sophistication scores, such as probability numeracy, financial literacy, and cognitive ability. In addition, specification (5) controls for dummy variables that indicate whether the individual's mother, father, grandmother and grandfather, respectively, are still alive as well as for whether the individually personally knew someone who died of diseases of the heart, cancer, accidents, cerebrovascular diseases, Alzheimer disease, Diabetes, Influenza and pneumonia, COVID-19, the natural course of life and aging, physical violence, natural disasters, animal attacks, or risky lifestyle. To the list of controls, specification (6) adds *risk factors*, that measure to what extent the individual placed weight on the risk factors heart disease, cancer, accidents, strokes, Alzheimer, diabetes, influenza, COVID-19, violence, natural catastrophes, animal attacks, and risky lifestyle when assessing their survival likelihood. Finally, specification (7) controls additionally for preferences, such as risk preferences, ambiguity preferences, and patience. All regressions are based on the full sample used in the main analysis, additionally including participants who report the same number for their minimum survival probability and their maximum survival probability. For these individuals, we assign a survival probability of 0. Robust standard errors for the estimated coefficients are reported in parenthesis. Three stars, two stars and one star indicate statistical significance at the 1 percent, 5 percent and at the 10 percent confidence level, respectively.