Survival and Financial Literacy in Investment Decisions Later in Life*

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Abstract

We study how survival beliefs and financial literacy jointly shape saving and portfolio decisions later in life. A randomized survey experiment shows that survival information updates longevity beliefs, while financial literacy increases risky-asset participation by attenuating participation costs. We embed these mechanisms in a heterogeneous-agent life-cycle model disciplined by the experimental estimates. Survey-informed, revenue-neutral counterfactuals show that financial literacy primarily drives market entry, while survival literacy complements financial literacy in raising the share of wealth invested in risky assets; only survival literacy, however, delivers positive welfare gains once financing costs are taken into account.

JEL: D15, E21, G53, H31, J14

Keywords: Aging, survival expectations, financial literacy, longevity risk, portfolio choice

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1 Introduction

Financial preparedness later in life is a major challenge in rapidly aging societies, and it rests on two broad dimensions. The first is longevity: subjective survival beliefs determine the effective horizon over which households plan consumption, saving, and investment. The second is financial sophistication: households differ in their ability to evaluate the long-run risk–return trade-offs that make risky assets worth holding over that horizon. Empirically, older individuals often report survival beliefs that depart systematically from life-table probabilities, and participation in risky financial markets remains limited throughout the older population. Crucially, the two channels need not operate independently: understanding the long-run returns to risky assets matters less when the perceived investment horizon is short, while expecting to live longer may have limited effects on portfolio choice when financial-market frictions remain binding.

This interaction is particularly relevant around retirement. At these ages, households must decide how rapidly to decumulate wealth, whether to enter or remain in financial markets, and how much risk to bear while facing uncertainty about longevity, income, returns, and long-term-care needs. Policies aimed at improving financial preparedness later in life typically focus on financial literacy, while the accuracy of perceived longevity receives much less attention. Whether financial education is effective may nevertheless depend on whether households correctly perceive the horizon over which its benefits accrue. Conversely, information about longevity may affect financial behavior only when households understand the relevant risk–return trade-offs and can overcome the costs of market participation.

This paper studies how survival literacy and financial literacy interact in shaping investment decisions later in life. We use a randomized information experiment to identify how these two forms of human capital operate and interact at the extensive and intensive margins of portfolio choice. We then use the experimentally identified mechanisms to discipline an estimated life-cycle model that translates short-run treatment effects into their long-run behavioral, welfare, and policy consequences.

We begin by documenting two empirical facts in the English Longitudinal Study of Ageing (ELSA). Individuals tend to underestimate their survival probabilities until approximately age 80, after which the pattern gradually reverses. Moreover, individuals whose subjective survival probabilities fall further below the corresponding life-table probabilities are significantly less likely to hold risky financial assets. These facts are consistent with survival beliefs shaping perceived investment horizons. Observational data alone, however, cannot establish whether information about population survival changes individuals' own survival beliefs, whether such updating affects portfolio decisions, or how the survival-belief channel interacts with financial-market frictions.

To identify these mechanisms, we conduct a randomized online survey of 3,600 UK residents aged

50–70. Respondents are assigned to one of four arms in a 2×2 factorial design: control, survival literacy, financial literacy, or both. The survival-literacy intervention provides age- and gender-specific population survival probabilities from official UK life tables, while the financial-literacy intervention explains compound returns, return volatility, and the risk–return trade-off over different investment horizons. Respondents then make portfolio recommendations in a hypothetical allocation problem in which the presence of an annual participation cost is independently randomized. We elicit population survival beliefs before treatment and respondents' own survival probabilities after treatment, allowing us to link prior longevity knowledge, subsequent belief updating, and portfolio choice within the same design.

The experiment identifies two distinct mechanisms. Survival information reduces the discrepancy between subjective and life-table survival probabilities by approximately 30 percent relative to the sample mean. Updating is entirely concentrated among respondents whose prior beliefs about population survival lie below the corresponding life-table probabilities. Information about population mortality therefore changes respondents' own survival expectations precisely when their prior population beliefs are inaccurate. This result implies that the discrepancy between subjective and objective survival probabilities cannot be attributed solely to private information about individual mortality risk: imperfect knowledge of population longevity is an important component.

Financial literacy operates through a different channel. The treatment increases risky-asset participation by approximately six percentage points and raises the share allocated to risky assets. Randomized participation costs sharply reduce participation, but financial literacy attenuates this deterrent effect by roughly one half. Financial literacy therefore reduces the behavioral relevance of participation frictions. The factorial design further reveals that the interaction between the two forms of literacy differs across margins. For participation, the combined treatment has essentially the same effect as financial literacy alone. For the risky portfolio share, instead, the combined treatment produces a larger response than financial literacy alone, indicating complementarity along the intensive margin. Finally, using assignment to survival literacy as an instrument, we show that reductions in survival-belief discrepancy increase both risky-asset participation and the risky portfolio share. Together, these results show that survival literacy operates through belief updating and the perceived planning horizon, whereas financial literacy primarily operates by attenuating participation frictions.

The survey identifies these mechanisms and their short-run behavioral effects but cannot quantify how they cumulate over the life cycle or interact with saving, mortality, long-term-care risk, and fiscal financing. We therefore develop and estimate a heterogeneous-agent life-cycle model in which households choose consumption, saving, and risky asset holdings using individual-specific subjective survival probabilities. Households differ in initial wealth, cognitive ability, discount factors, and

expected risky returns and face income, financial-market, and long-term-care risk. The model also features participation costs that are lower for incumbent investors than for new entrants. We estimate it to match ELSA life-cycle profiles of wealth, financial market participation, and risky portfolio shares separately by cognitive group.

We use the estimated model to implement three survey-informed policy counterfactuals: (i) a survival literacy intervention that reduces the gap between subjective and objective survival probabilities by 30 percent, matching the experimental belief response; (ii) a financial literacy intervention that reduces effective participation costs by 50 percent, matching the experimental reduction in sensitivity to randomized costs; (iii) a combined intervention that implements both changes. Unlike the survey, these interventions are revenue neutral: their implementation costs are financed through proportional adjustments in labor and capital income taxes.

The counterfactuals reveal substantial differences across margins. Financial and survival literacy are complementary for wealth accumulation, with the combined intervention generating gains larger than the sum of the two separate interventions. Financial literacy is instead the dominant driver of market entry: it induces an entry rate of 15 percent among baseline non-participants and increases participation duration by almost three years, while adding survival literacy produces little additional effect. Along the intensive margin, the pattern reverses: survival literacy amplifies the response of risky portfolio shares to financial literacy. Importantly, these interactions are not targeted in the structural estimation. The model therefore endogenously reproduces the experimental distinction between the extensive and intensive margins, providing an untargeted validation of its transmission mechanisms.

The welfare implications differ sharply from the behavioral effects. Financial literacy generates zero or negative welfare effects across the wealth distribution: its fiscal costs are borne broadly, while the benefits of lower participation costs accrue mainly to households with sufficient wealth to exploit them. Survival literacy, instead, generates positive welfare gains for most households, both through longer-horizon saving and portfolio choices and because households value future consumption and life itself. Thus, an intervention can substantially change financial behavior without generating broad welfare gains when households differ in their ability to act on the information provided.

We further use the model to study how two central features of late-life decision making shape these mechanisms. Counterfactuals without bequest motives show that bequests attenuate the response to survival-belief updating at older ages, when mortality risk makes the value of wealth in the death state quantitatively important. Counterfactuals without long-term-care risk show that this risk shapes the response to financial literacy through the precautionary wealth it generates, which allows older households to exploit lower participation costs.

Overall, our results characterize survival and financial literacy as two distinct forms of human capital: the former determines the horizon households perceive, while the latter affects their ability to act over that horizon. Their interaction shapes saving and portfolio decisions, but their welfare consequences differ once fiscal costs are taken into account. The results point to low-cost longevity-information interventions as a potential complement to the financial-education programs that currently dominate policy attention. More broadly, the effectiveness of these interventions depends on the institutional environment, in particular on the strength of bequest motives and the degree of public insurance against long-term-care risk.

Relative to the existing literature, the paper makes three main contributions. First, we provide causal evidence that imperfect knowledge of population longevity contributes to individual survival-belief distortions and that correcting these beliefs changes portfolio choice. Second, we identify survival and financial literacy as distinct but interacting determinants of investment behavior, operating through perceived horizons and participation frictions. Third, we combine experimental identification with an estimated life-cycle model to quantify how these mechanisms accumulate over time and translate into distributional, welfare, and policy consequences.

Our first contribution relates to the literature on subjective survival expectations and household economic behavior. Subjective probability data have become central to the analysis of decisions under uncertainty (Koşar, O'Dea 2023; Manski 2004; Van der Klaauw 2012). Subjective survival beliefs predict realized mortality and contain information beyond standard life tables (Hurd, McGarry 2002). They have also been linked to saving, bequests, annuitization, wealth accumulation, and portfolio choice (Foltyn, Olsson 2024; Gan et al. 2015; Heimer et al. 2019; O'Dea, Sturrock 2021; Spaenjers, Spira 2015). We provide causal evidence that population longevity information updates individual survival beliefs and that this updating affects risky-asset participation and portfolio shares.

Closely related is the literature on the formation of survival beliefs and longevity-information interventions. Subjective expectations respond to targeted information (Delavande 2008; Delavande et al. 2011), and mortality or life-expectancy information can update longevity beliefs and affect health or retirement-related outcomes (Ciancio et al. 2024; Hurwitz, Mitchell, Sade 2022). Responses to information also depend on its content, framing, and salience (Molinari 2020). We show that belief updating is concentrated among respondents whose priors understate population survival, providing evidence against a purely private-information explanation for the gap between subjective and life-table survival probabilities.

Our second contribution relates to the literature on financial literacy, cognitive skills, and household portfolio choice. Financial literacy and cognitive ability are strongly associated with stockholding,

portfolio quality, and wealth accumulation (Christelis et al. 2010; Lusardi, Mitchell 2014; Van Rooij et al. 2012). Structural work treats financial knowledge as human capital that affects saving, participation costs, and wealth inequality (Jappelli, Padula 2017, 2013, 2015; Lusardi et al. 2017), while recent evidence emphasizes cognitive ability in expectation formation and financial decisions (D'Acunto et al. 2023), including survival beliefs (Grevenbrock et al. 2021). We extend this literature by studying financial and survival literacy jointly and identifying how they interact differently at the extensive and intensive margins of portfolio choice.

Finally, we contribute to the experimental literature on information provision, financial education, and behavior. Information interventions often improve knowledge, but generate smaller changes in financial choices (Billari et al. 2023; Carpena et al. 2019; Duflo, Saez 2003). We use experimentally identified mechanisms to discipline a structural life-cycle model that traces their effects on saving, portfolio behavior, and welfare over time. In this respect, the paper provides a bridge between information experiments, which offer clean identification of mechanisms, and life-cycle models, which are needed to evaluate their long-run policy consequences.

The rest of the paper proceeds as follows. Section 2 presents the ELSA evidence. Section 3 describes the survey experiment and its results. Section 4 introduces and estimates the life-cycle model. Section 5 presents the survey-informed counterfactuals and welfare analysis. Section 6 concludes.

2 Empirical Evidence

2.1 Data

We use data from the English Longitudinal Study of Ageing (ELSA)[1], a biennial longitudinal survey representative of the English population aged 50 and above. We focus on financial respondents and combine information on household portfolio holdings, subjective survival expectations, cognitive ability, and demographic characteristics. Details on sample construction and variable definitions are reported in Appendix A.

Our empirical analysis centers around three variables of interest: financial market participation, cognitive ability, and subjective survival beliefs. Financial market participation is measured using an indicator for whether the household holds risky financial assets. Cognitive ability is summarized using the first principal component of memory, numeracy, and financial-literacy measures. Subjective survival beliefs are constructed exploiting ELSA questions eliciting individuals' subjective probabilities of surviving to age-specific targets. Comparing these beliefs with official life-table probabilities allows us to derive a measure of survival belief distortions.

[1] Banks et al. (2025).

2.2 Subjective Survival Beliefs

ELSA elicits subjective survival beliefs using probabilistic questions that ask respondents to report their perceived probability of surviving to an age-specific target that varies with respondents' age. [2]. We compare these subjective probabilities with the corresponding survival probabilities from the Office for National Statistics (ONS) life tables[3] in Figure 1. Two patterns emerge. First, individuals systematically underestimate their survival probabilities until approximately age 80. Second, the pattern gradually reverses at older ages. These findings are consistent with previous evidence documenting systematic distortions in subjective longevity expectations (see Heimer et al. (2019) and Foltyn, Olsson (2024), among others).[4]

Figure 1: Subjective and objective survival probabilities by target age and gender.



Dots: ONS life tables (2012, 2014, 2016). Solid lines: ELSA (waves 6, 7, 8).

We construct a variable capturing the individual discrepancy between subjective and objective probabilities [5]. This measure takes larger values the higher is the underestimation of survival chances, and has value 0 if the respondent overestimate his/her own life expectation, relative to the

[2]Individuals younger than 70 complete two survival questions, differing in the corresponding age-target (the second question always targets age 85). See Appendix A.3 for more details.

[3]ONS life tables are available at https://www.ons.gov.uk/.

[4]This pattern is consistent with the well-documented "flattening bias" in probabilistic expectations elicitation (Hudomiet et al. 2023). The literature suggests that, despite this bias, the shape of subjective survival curves retains meaningful information.

[5]For respondents younger than 70, the discrepancy measure is based on their first survival answer.

objective ones. Discrepancy is formally defined as follows:

$$accuracy = \begin{cases} \frac{subjective_i}{objective_i} & \text{if } \frac{subjective_i}{objective_i} < 1 \\ 1 & \text{if } \frac{subjective_i}{objective_i} \geq 1 \end{cases} \tag{1}$$

$$discrepancy = \frac{1 - accuracy}{\sigma_{accuracy}}$$

where $subjective_i$ is subjective ELSA answer and $objective_i$ is the age and gender specific ONS survival.

2.3 Subjective Survival Beliefs and Financial Market Participation

We examine whether survival belief distortions are associated with household financial market participation. We estimate a linear probability model where the outcome is financial market participation ($Participation_i$) and the main independent variable is $discrepancy_i$, defined as in Equation 1. We additionally control for demographic characteristics, socioeconomic characteristics, and progressively richer sets of controls. Cognitive ability and dispositional optimism are established predictors of survival-belief formation (Grevenbrock et al. 2021), and we add them progressively to assess whether the discrepancy–participation relationship survives once these channels are accounted for; we further control for health-related habits, which proxy for private information about own health that is unobserved by the researcher.

Table 1: Participation (linear probability model).

	Dependent variable: Participation			
	(1)	(2)	(3)	(4)
discrepancy	-0.031***	-0.029***	-0.028***	-0.021**
	(0.008)	(0.008)	(0.008)	(0.008)
cognitive skills		0.043***	0.043***	0.039***
		(0.007)	(0.007)	(0.007)
disposition optimism			0.013	0.008
			(0.018)	(0.018)
habits				*yes*
Controls	*yes*	*yes*	*yes*	*yes*
Observations	3,311	3,311	3,311	3,260

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$*

Additional controls: age, age squared, gender, having a partner, having children, income quartiles, employment status, number of ADLs, education. *Habits*: smoking, sport activities, healthy eating.

Table 1 reports the estimates. Households whose household head's subjective survival beliefs lie below life-table probabilities are significantly less likely to participate in financial markets. Across specifications, the coefficient on survival belief discrepancy remains negative and statistically significant after controlling for cognitive ability, dispositional optimism, and health-related behaviors. Quantitatively, a one-standard-deviation increase in discrepancy reduces financial market participation by approximately three percentage points. The relationship is robust to alternative specifications controlling for focal responses to probabilistic questions and to alternative measures of cognitive ability reported in Appendix B. Appendix B.1 shows that the negative association is primarily driven by individuals with relatively high cognitive ability, who are more likely to participate in financial markets. These strong empirical relationships are consistent with previous evidence (Spaenjers, Spira 2015).

Observational evidence alone cannot establish whether correcting survival beliefs changes financial behavior or disentangle the respective roles of survival and financial literacy. The remainder of the paper addresses this identification problem. We first use a randomized survey experiment to isolate the causal effects of survival and financial literacy interventions on portfolio choices and then embed the experimentally identified mechanisms in a heterogeneous-agent life-cycle model to evaluate their long-run implications.

3 Survey Experiment

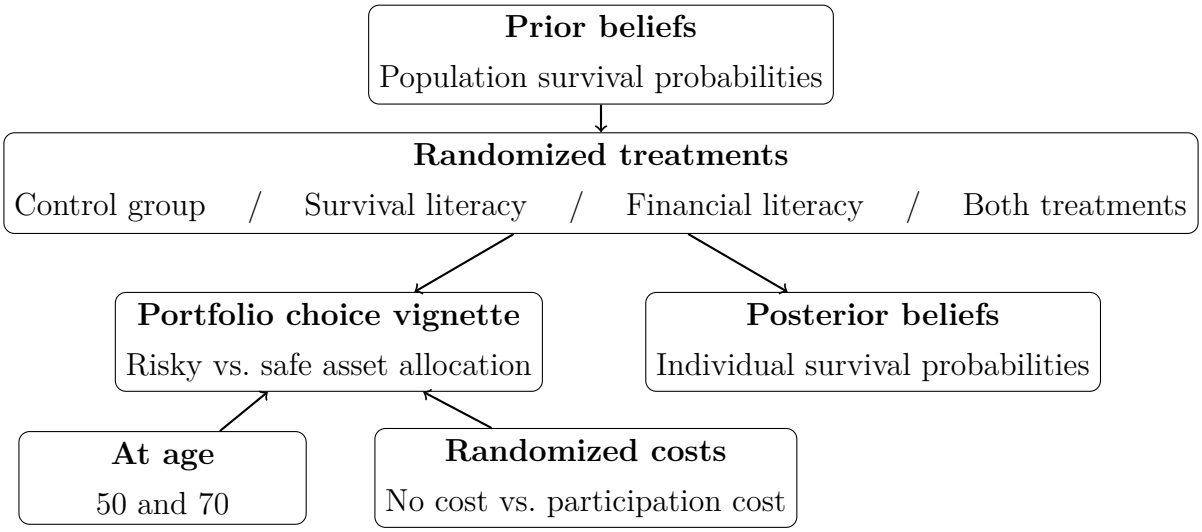
We conduct a randomized survey experiment designed to separately identify four channels through which survival and financial literacy may affect investment behavior. First, the effect of objective longevity information on the updating of subjective survival beliefs. Second, the direct effect of financial literacy information on portfolio choices. Third, the role of participation costs in shaping risky asset demand and the extent to which financial literacy mitigates these frictions. Finally, whether survival literacy and financial literacy interact in determining portfolio choices.

3.1 Survey Structure

We recruit 3,600 UK residents aged 50–70 through Prolific. Respondents are randomly assigned at the individual level to one of four treatment arms in a 2×2 factorial design: a control group, a survival literacy treatment (S), a financial literacy treatment (F), a combination of the two treatments (SF). This design separately identifies the effects of survival literacy, financial literacy, and their interaction on survival beliefs and portfolio choices.

Figure 2 summarizes the survey architecture. The survey consists of four stages. First, respondents report their prior beliefs about population survival probabilities. We elicit population rather

Figure 2: Survey architecture.



than individual survival beliefs before treatment to measure baseline longevity knowledge while minimizing the salience of respondents' own mortality. This choice is motivated by evidence that priming subjective longevity thoughts may itself affect subsequent survival beliefs (Hurwitz, Mitchell 2022), making it more difficult to isolate treatment-induced belief updating. Second, respondents receive the randomized information treatments. Third, they complete a hypothetical portfolio allocation task. Finally, respondents report their own subjective survival probabilities using the same elicitation employed in ELSA. This design allows us to jointly observe prior beliefs, belief updating, and portfolio choices within the same experimental environment.

The survival literacy treatment consists of a video that lasts 1:55 minutes and provides respondents with age- and gender-specific probabilities of surviving to ages 75 (or 80) and 85, based on official UK 2023 life tables. Its objective is to improve respondents' knowledge of population survival probabilities and, in turn, affect the perceived planning horizon.

The financial literacy treatment consists of a video that lasts 5:55 minutes and introduces key financial concepts, including interest rates, compound interest, and asset-return volatility, with particular emphasis on the differences in returns between safe and risky assets over short, medium, and long investment horizons.[6] Its objective is to improve respondents' understanding of long-run risk-return trade-offs and to reduce the behavioral relevance of participation costs. Details on the treatment materials are reported in Appendix D.1.

Following the information treatments, respondents complete a hypothetical portfolio allocation task. They are asked to advise a hypothetical individual on how to allocate £50,000 between a safe asset

[6]The control group receives a placebo video on payment methods which lasts 3:50 minutes.

(such as a savings account or government bonds) and a risky asset (such as a stock index fund). To isolate the role of investment horizons, each respondent evaluates two otherwise identical scenarios in which the individual's age is set to 50 or 70 years. The portfolio vignette is introduced as follows:

"Mr. Taylor has accumulated £50,000 in savings, which he can allocate between a safe asset (such as a savings account or government bonds) and a risky asset (such as a stock index fund). Suppose Mr. Taylor is 50 years old. How would you split his £50,000 between the safe asset and the risky asset? Please allocate the entire £50,000."

Independently of the age of the vignette's character, respondents are assigned to either a cost or a no-cost scenario. In the cost scenario, any positive investment in the risky asset requires paying an annual management fee of £400. This additional randomization allows us to identify the causal effect of participation costs on risky asset demand and to test whether financial literacy attenuates their deterrent effect.

Lastly, the survey collects a final set of information on respondents' financial asset holdings, financial literacy, cognitive ability, risk preferences, and demographic characteristics. Financial literacy is measured using the standard Big Five questions (Lusardi, Mitchell 2011), while cognitive ability is assessed through memory and numeracy tests adapted from the Health and Retirement Study (HRS). These variables are used to characterize the experimental sample, study treatment heterogeneity, and align the survey evidence with the heterogeneous-agent life-cycle model.

Table 2 summarizes the combination of treatment/control groups and vignette scenarios in the survey.

Table 2: Treatments and vignette combinations.

Ms/Mr	No Costs				Costs			
Taylor age	Control	Surv.Lit.	Fin.Lit.	Both	Control	Surv.Lit.	Fin.Lit.	Both
50	$C_{N,50}$	$S_{N,50}$	$F_{N,50}$	$SF_{N,50}$	$C_{C,50}$	$S_{C,50}$	$F_{C,50}$	$SF_{C,50}$
70	$C_{N,70}$	$S_{N,70}$	$F_{N,70}$	$SF_{N,70}$	$C_{C,70}$	$S_{C,70}$	$F_{C,70}$	$SF_{C,70}$

Notes: The treatment type is denoted with C: Control; S: Survival literacy; F: Financial Literacy; SF: Both Survival and Financial Literacy; the first subscript refers to the type of vignette (N: no participation costs, C: with participation costs). The second subscript indicates the age of Mr Taylor in the vignette.

3.2 Survey Results

The experiment was pre-registered in the AEA RCT Registry (AEARCTR-0018209) before data collection, together with a detailed analysis plan specifying outcomes, estimating equations and

sample restrictions.[7] Of the 3,600 respondents recruited on Prolific, 3,394 are retained in the final sample after excluding incomplete and returned submissions.Table D.2 in Appendix D.2 reports the balancing test. Observable characteristics are balanced across the four arms: of the forty comparisons reported, three are marginally significant, which is close to what would be expected by chance at conventional levels. All specifications include demographic controls.

Before turning to treatment effects, we verify that the two empirical patterns documented in Section 2 replicate in the experimental sample. Untreated respondents systematically underestimate their own survival probabilities relative to life-table benchmarks, and respondents whose subjective beliefs lie below the objective benchmark are significantly less likely to invest in risky assets. Despite the selected nature of the Prolific sample, these patterns closely mirror those observed in ELSA, supporting the external validity of the experimental environment. Details are reported in Appendix D.2.

Treatment effects are estimated using the following reduced-form specification:

$$Y_i = \alpha + \beta_S S_i + \beta_F F_i + \beta_{SF}(S_i \times F_i) + X_i'\gamma + \varepsilon_i,$$

where the outcomes are survival belief discrepancy, risky asset participation, and the share of wealth invested in risky assets.

3.2.1 Survival Literacy and Belief Updating

We first examine whether objective longevity information updates subjective survival beliefs. Table 3 reports the treatment effects on survival belief discrepancy.[8] Receiving the survival literacy treatment significantly reduces survival belief discrepancy by approximately one quarter of a standard deviation – or by 30% with respect to the average discrepancy in the sample. By contrast, financial literacy alone has no effect on survival beliefs. Respondents exposed to both treatments also revise their beliefs toward objective survival probabilities, although the effect is somewhat smaller than under the survival treatment alone, possibly reflecting the greater cognitive burden associated with receiving two information treatments.

[7]The analysis plan is available at https://doi.org/10.1257/rct.18209-1.1 . The main text reports the pre-registered primary outcomes; the remaining pre-specified analyses, together with a complete list of deviations from the plan, are collected in Appendix D.2.

[8]Results for the raw difference $m_{i,a}$ are in Tables D.3, D.4 and D.5. The first-target-age effect is confirmed in levels (-2.4 percentage points of underestimation); at age 85 it is zero in levels but precise on the index. The raw difference is two-sided while the index is censored at the benchmark, and the control-group gap turns from -7.9 to $+1.3$ percentage points between target ages, so offsetting revisions cancel out in levels. Hence our choice of belief measure in the IV specification.

In the third column of Table 3, we report heterogeneity with respect to prior beliefs. Respondents are classified according to whether their prior beliefs about population survival probabilities lie below the corresponding life-table probabilities. The estimated treatment effects are entirely driven by this group, while respondents whose priors are already close to or above life-table benchmarks display little or no updating. This pattern indicates that the intervention changes respondents' own survival expectations by updating their beliefs about population survival probabilities. If the initial discrepancy between subjective and objective survival probabilities were driven solely by respondents' private information about their own health, information on population mortality would have little reason to affect their beliefs. Instead, the selective updating among respondents whose priors are below the life-table benchmarks suggests that the intervention corrects distorted survival beliefs rather than mechanically shifting reported probabilities.

Table 3: Belief Updating

	discrepancy		
	(1)	(2)	(3)
Survival	-0.244***	-0.245***	-0.045
	(0.047)	(0.047)	(0.041)
Financial	0.024	0.023	0.050
	(0.052)	(0.052)	(0.046)
Both	-0.180***	-0.181***	0.024
	(0.050)	(0.050)	(0.047)
Survival × Below LT (Pop.)			-0.535***
			(0.104)
Financial × Below LT (Pop.)			-0.085
			(0.109)
Both × Below LT (Pop.)			-0.558***
			(0.108)
Below LT (Pop.)			1.079***
			(0.076)
Demographics	No	Yes	Yes
Obs	3394	3394	3378
Discrepancy (mean)	0.731		

Notes: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $BelowLT(pop)$: difference between subjective prior on population survival and LT in the first tertile.

Lastly, we investigate treatment heterogeneity by cognitive ability. Treatment effects are remarkably

similar across cognitive groups, suggesting that survival information is equally effective in updating beliefs. One possible explanation is that the Prolific sample is positively selected with respect to cognitive ability relative to the general population. Results are reported in Appendix D.2, Table D.6.

3.2.2 Financial Literacy, Participation Costs, and Portfolio Choice

We next turn to portfolio choices. Tables 4 and 5 report treatment effects on participation in the risky asset and on the share of wealth allocated to risky assets. Financial literacy has a substantial effect on participation. Respondents exposed to the treatment are approximately six percentage points more likely to suggest the vignette's character should invest in the risky asset than respondents in the control group. Randomized participation costs strongly reduce participation, confirming the importance of financial frictions in portfolio decisions. More importantly, the interaction between financial literacy and participation costs is positive and statistically significant, indicating that financial literacy attenuates the deterrent effect of participation costs by roughly 50%.

Table 4: Participation

	participation				
	(1)	(2)	(3)	(4)	(5)
Financial	0.059***	0.060***	0.048***	0.064***	0.029***
	(0.011)	(0.011)	(0.013)	(0.012)	(0.009)
Low cog.			-0.021		
			(0.022)		
Financial × Low cog.			0.038		
			(0.026)		
Low cog.(alt)				0.016	
				(0.026)	
Financial × Low cog.(alt)				-0.029	
				(0.033)	
Financial × Cost					0.057**
					(0.022)
Cost					-0.117***
					(0.019)
Demographics	No	Yes	Yes	Yes	Yes
Obs	1746	1746	1746	1746	1746
Part. (mean)	0.909				

Notes: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Cognitive score: PCA (financial literacy, numeracy, memory). *Lowcog.*: 1st tertile. The alternative Cognitive score is the sum of financial literacy (Big5), numeracy and memory scores. *Low cog. (alt)* is 1 if the cognitive score (alt) is in the first quintile. *Sample:* Control and Financial treatment only.

Financial literacy also increases the suggested share of wealth invested in risky assets, although the effect of participation costs on the intensive margin is considerably smaller than on the participation decision itself. Taken together, these findings suggest that participation costs primarily affect entry into risky asset markets, while conditional portfolio allocation is less sensitive to these frictions.

Treatment effects are similar across cognitive groups under the pre-specified classification. Under the alternative index, which isolates the bottom quintile rather than the bottom tercile, respondents in the lowest cognitive group increase their suggested risky share substantially less than others (Table 5, column 4). Since the alternative cut-off was chosen after inspecting the data, we treat this pattern as exploratory; it nonetheless suggests that the financial literacy intervention is least effective precisely among the respondents whom it is most intended to reach.

Table 5: Share

	risky share				
	(1)	(2)	(3)	(4)	(5)
Financial	0.092***	0.092***	0.092***	0.106***	0.089***
	(0.013)	(0.013)	(0.015)	(0.013)	(0.016)
Low cog.			-0.034		
			(0.022)		
Financial × Low cog.			0.005		
			(0.028)		
Low cog.(alt)				0.029	
				(0.029)	
Financial × Low cog.(alt)				-0.100***	
				(0.036)	
Financial × Cost					0.005
					(0.025)
Cost					-0.034*
					(0.019)
Demographics	No	Yes	Yes	Yes	Yes
Obs	1746	1746	1746	1746	1746
Share (mean)	0.379				

Notes: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Cognitive score: PCA (financial literacy, numeracy, memory). *Lowcog.*: 1st tertile. The alternative Cognitive score is the sum of financial literacy (Big5), numeracy and memory scores. *Low cog. (alt)* is 1 if the cognitive score (alt) is in the first quintile. *Sample:* Control and Financial treatment only.

The factorial design also allows us to investigate whether survival literacy and financial literacy reinforce each other in shaping portfolio decisions. Table 6 shows that, for financial market participation, the combined treatment does not increase participation beyond the effect of financial

literacy alone, suggesting that improving survival literacy adds little once respondents have acquired financial literacy. By contrast, for the share of wealth invested in risky assets, the combined treatment has a larger effect than the financial literacy treatment alone (p =0.028 for the test $\beta_{SF} = \beta_F$), suggesting complementarity at the intensive margin.[9]

Table 6: Participation and Share, combined treatments

	participation		risky share	
	(1)	(2)	(3)	(4)
Survival	0.033***	0.034***	0.040***	0.041***
	(0.013)	(0.012)	(0.013)	(0.013)
Financial	0.059***	0.060***	0.092***	0.093***
	(0.011)	(0.011)	(0.013)	(0.013)
Both	0.059***	0.060***	0.118***	0.118***
	(0.011)	(0.011)	(0.012)	(0.012)
Demographics	No	Yes	No	Yes
Obs	3490	3490	3490	3490

Notes: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The design also asks respondents to advise the same hypothetical investor at age 70. Here the financial literacy treatment has no detectable effect, either on participation or on the risky share (Table D.9). The contrast with the age-50 vignette is informative: the treatment explains how the risk–return trade-off improves over long investment horizons, so its content is largely irrelevant for an investor with a short remaining horizon. Respondents appear to apply the information selectively rather than as a general endorsement of risky assets, which supports a horizon-based interpretation of the financial literacy channel.

3.2.3 Survival Beliefs and Portfolio Choice Behavior

Finally, we investigate whether changes in survival beliefs translate into changes in investment behavior. To isolate the causal effect of survival beliefs, we instrument post-treatment survival belief discrepancy using randomized assignment to the survival literacy treatment. As shown in Table 7, the first stage is strong, confirming that the treatment generates substantial belief updating. The second-stage estimates show that respondents whose survival beliefs move closer to objective life-table probabilities become significantly more likely to suggest participation in risky financial

[9]We note that interaction effects in the 2×2 design were pre-specified as exploratory, since the planned sample size was powered to detect main effects rather than interactions.

markets and to allocate a larger share of wealth to risky assets. These estimates provide direct causal evidence that subjective survival beliefs affect portfolio choices. More importantly, they establish the mechanism through which survival literacy operates: objective longevity information changes investment behavior because it changes perceived planning horizons.

Table 7: Beliefs and Behavior

	discrepancy	participation	risky share
	(1)	(2)	(3)
	First Stage	IV	IV
Survival	-0.244***		
	(0.046)		
discrepancy		-0.114**	-0.173***
		(0.055)	(0.064)
F-stat (instrument)	27.57		
Obs	1708	1708	1708

Notes: Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Additional controls are cognitive level, costs in the vignette, age and gender. *Sample:* Control and Survival treatment only.

The identifying assumption is that random assignment to the survival literacy treatment affects portfolio choices only through its effect on subjective survival beliefs. This restriction is supported by the design: the instrument compares only the control and survival literacy arms, so respondents receive no financial information, and the portfolio task is framed in the third person, limiting emotional responses to respondents' own mortality.[10] Given random assignment and a strong first stage, the IV estimates identify a local average treatment effect for respondents whose survival beliefs are updated by the intervention. Appendix D.2 reports the pre-specified robustness checks, including alternative measures of post-treatment survival beliefs and the specification that conditions on beliefs rather than instrumenting them.[11]

[10]Two further points support this restriction: belief updating is concentrated among respondents whose priors about *population* survival lie below the life-table benchmark (Section 3.2.1), and the control group watches a placebo video, holding exposure and engagement constant across arms. We cannot rule out that priming affects portfolio choices independently of survival beliefs; the IV estimates should be read as the effect of belief revision under this restriction.

[11]We measure post-treatment beliefs using the standardized inaccuracy index at the first target age. The analysis plan specified the average deviation across the two target ages, which turns out to be a weak instrument (first-stage $F = 2.9$): as noted above, the control-group gap falls from -7.9 to $+1.3$ percentage points between target ages while its standard deviation rises from 17.2 to 23.9, so averaging halves the signal and raises the noise. Table D.8 reports all combinations of measure and aggregation. Since the second-stage

Overall, the survey identifies two distinct behavioral channels. Survival literacy affects portfolio choices through belief updating and longer perceived planning horizons, while financial literacy primarily increases risky investment by reducing the behavioral relevance of participation costs. These experimentally identified mechanisms provide the empirical foundation for the survey-informed counterfactual policy experiments developed in Section 5.

4 Life-Cycle Model

The survey experiment identifies the causal effects of survival literacy and financial literacy on beliefs and portfolio choices. However, it does not quantify the long-run implications of these behavioral responses for wealth accumulation, financial market participation, and welfare. We therefore embed the experimentally identified mechanisms in a heterogeneous-agent life-cycle model.

Household Problem. The household is the empirical counterpart of the ELSA benefit unit and its decision maker is the unit's financial respondent; Appendix E.1 sets out this choice and the measurement conventions that follow from it. In each period t, with $t = 1, \ldots, T$, households maximize their expected lifetime utility by choosing non-durable consumption, c_t, and the fraction invested in risky assets, f_t. They receive utility (U_t) from consumption and, when they die, they value bequest of wealth w_t according to a bequest function $b(w_t)$. The key departure from the standard life-cycle model is that households maximize expected lifetime utility using subjective, rather than objective, survival probabilities, as follows:

$$\max_{\{c_j, f_j\}_{j=t}^{T}} U(c_t) + E_t \left[\sum_{j=t+1}^{T+1} \beta^{j-t} \, \Pi^s(j-1, t) \left(\pi_j^s U(c_j) + (1 - \pi_j^s) b(w_j) \right) \right] \tag{2}$$

where β is the discount factor, $\Pi^s(j,t)$ is the probability of being alive at age j conditional on being alive at age t, and π_j^s is the probability of being alive at age j conditional on being alive at age $j-1$.[12]

The household maximization problem in equation (2) is solved under the following budget constraint:

$$s_t + a_t = (1 + r_t^s) s_{t-1} + (1 + r) a_{t-1} + y_t - T(y_t, s_{t-1}, a_{t-1}, r_t^s) - k(I_t, I_{t-1}) + tr_t - c_t. \tag{3}$$

where s_t and a_t are the amounts of wealth invested in risky and risk-free assets with returns r_t^s and r, respectively, c_t represents non-durable consumption, $k(.)$ captures per-period participation costs, y_t is labor income, and $T(.)$ denotes labor and capital income taxes.

estimate is the ratio of the reduced form to the first stage, and the reduced form does not depend on how beliefs are measured, this choice affects the units in which the effect is expressed but not its sign or significance.

[12]The two are linked by $\Pi^s(j,t) = \prod_{k=t+1}^{j} \pi_k^s$, with $\Pi^s(t,t) = 1$.

The model includes a consumption floor $\underline{c}$ that guarantees a minimum level of consumption in every period. When households are hit by a long-term-care shock, the consumption floor increases to reflect the additional resources required for care needs and assistance arrangements, $\underline{c}_{ltc}$. Households finance consumption using their own income and wealth whenever possible, while the government provides means-tested transfers tr_t whenever available resources are insufficient to attain the relevant consumption floor.

Wealth at the beginning of period t is

$$w_t = (1 + r_t^s)s_{t-1} + (1 + r)a_{t-1}. \tag{4}$$

Households additionally face borrowing and short-sale constraints, $a_t \geq 0$ and $s_t \geq 0$.

Preferences. The per-period utility is

$$U(c_t) = \frac{c_t^{1-\gamma}}{1-\gamma} + \bar{b},$$

where γ is the coefficient of relative risk aversion. Following Hall, Jones (2007) and De Nardi et al. (2024), we include a positive constant $\bar{b}$ to ensure that continuation utility from being alive always exceeds the value of death, independently of consumption.

Bequest motives. The bequest function is specified as

$$b(w_t) = \phi_B \frac{(w_t + \phi_K)^{(1-\gamma)}}{1-\gamma}.$$

The parameter ϕ_K, which is positive, regulates the curvature of the bequest function and allows the utility of a zero bequest to be finite. The parameter ϕ_B represents the intensity of bequest motives.

Risky Assets. The returns to the fraction of wealth invested in risky assets are stochastic and are given by $r_t^s = r + \mu_i^s + \eta_t$, where μ_i^s is excess return over that of risk-free assets and η_t is a shock with mean zero and variance σ_s^2.

We introduce heterogeneity across individuals in expected excess returns to risky assets, μ_i^s, relying on Fagereng et al. (2020) and Bach et al. (2020). These studies show that household portfolio returns display substantial cross-sectional heterogeneity that can be decomposed into two main components: a scale component related to wealth and a persistent type component capturing differences in investment ability, information, or financial sophistication. Since our data do not contain realized returns, we do not attempt to estimate this heterogeneity directly. Instead, we introduce heterogeneity in expected excess returns using a parsimonious functional form, while keeping the volatility of returns fixed across households. Specifically, we allow the expected excess return to vary with both

initial wealth and cognitive type. Initial wealth captures scale heterogeneity, reflecting the empirical finding that richer households tend to earn higher average returns, partly because they access higher yielding investment opportunities and bear more systematic risk. Cognitive type captures persistent differences in financial ability or sophistication, consistent with the evidence that households display stable investment styles over time.

Hence, the expected excess return is given by: $\mu_i^s = \bar{\mu} + \alpha\tilde{w}_i + \tau\mathbb{1}\left[\textit{high cognitive}\right]$, where $\tilde{w}_i = (w_i - w_{min})/(w_{max} - w_{min})$. This specification implies that expected excess returns increase linearly along the grid of initial wealth and differ by a constant shift between high- and low-cognitive households.

Lastly, we allow for the possibility of particularly negative realizations of the shock to returns to risky assets – financial market disaster scenario – that occur with probability p_{tail}.

Participation costs. Following Cocco (2005) and Alan (2012), households incur a participation cost in every period in which they invest in risky assets. Let $I_{t-1} \in \{0, 1\}$ denote an indicator equal to one if the household participated in the stock market in the previous period. The per-period participation cost is given by

$$k(I_t, I_{t-1}) = \begin{cases} 0, & \text{if } I_t = 0, \\ k^p, & \text{if } I_t = 1,\ I_{t-1} = 0, \\ \lambda k^p, & \text{if } I_t = 1,\ I_{t-1} = 1, \end{cases}$$

where $k^p > 0$ is the baseline participation cost as a fraction of current net labor income and $\lambda \in [0, 1]$ denotes the fraction of the baseline cost paid by households that already participated in the previous period. Hence, households incur the full participation cost when entering the stock market, while continuing participants pay only a fraction λ of this cost. This specification captures the idea that maintaining participation is less costly than entering the market for the first time, reflecting accumulated experience, familiarity with financial markets, and lower information and administrative costs.

Labor Income. Earnings from labor feature a deterministic and a stochastic component. The stochastic component is modeled as the combination of a transitory shock with variance σ_ϵ^2 and a permanent shock following an AR(1) process with persistence ρ and variance on the innovation σ_y^2. Moreover, with probability p_{w_0}, a zero earnings realization occurs. To allow for correlation between the uncertainty in the financial market and that in the labor market, we assume p_{w_0} to be higher in case of a financial disaster (Alan 2012). After retirement, which is set exogenously at age 65, households start to receive pension income which is modeled as a constant fraction of the last labor income realization.

Survival Probabilities. Households start making their consumption and financial decisions at age 50 and in each period they take into account their subjective survival expectations for the next period (π^s). These expectations – i.e. subjective survival curves – are obtained from the data and are individual specific, where the individual is assumed to be the financial respondent in the household. See Appendix C.1 for a detailed derivation of the subjective survival curves starting from respondents' answers to ELSA subjective survival questions.

Long Term Care. Starting at age 75, households face the risk, with probability p_{ltc}, of being hit by a health shock that generates long term care needs for the remaining part of their life (absorbing state). Once households enter the long term care state, they face lower survival chances and a higher minimum consumption need associated with care services and assistance arrangements (c_{ltc}). Households finance consumption and care expenditures using their own income and wealth whenever possible. However, if available resources are insufficient to attain the relevant consumption floor, the government provides transfers that cover the gap.

The Government. Households pay labor income taxes and taxes on returns to their investments to the government, captured by the function $T(.)$ in the budget constraint. We parameterize the labor and capital income tax schedules in the model to replicate the UK tax and transfer system in place in 2011 (our base year for all monetary values). In the counterfactual scenarios, we also allow for publicly-funded revenue-neutral financial and survival literacy interventions. Details on the tax function are in Appenix E.3.

Model Solution and Simulation. At the beginning of each period t, during working life, the household head observes the realization of the return of the risky investment r_t^s and the income realization y_t. Given the fraction invested in risky assets in period $t-1$, f_{t-1}, she/he has an initial wealth of w_t. Having this information she/he decides how much to consume c_t and the fraction of wealth to invest in risky assets f_t. This results in an amount a_t of wealth invested in risk-free assets and an amount s_t of wealth invested in risky assets. After retirement, the household receives a deterministic pension entitlement and it observes the realization of a long term care shock at the beginning of each period. If the long term care scenario occurs, then the household has to make consumption and investment decisions taking into account the need to spend an additional amount c_{ltc} in care services.

The model is solved backwards. The continuous state variables (w_t, y_t) are discretized on a grid. Additionally, we have two states for the ownership of risky assets in the previous period (I_{t-1}). The value function is evaluated at each point of the state space and we take expectations with respect to shocks on income by converting the persistent income component into a discrete Markov chain. The model is solved for approximately 600 individuals (i) and using individual specific subjective

survival curves (their derivation is reported in Appendix C.1).

The model reproduces the behavior of a specific cohort of individuals, those born between 1956 and 1964. We select household's financial head (that can be male or female) from ELSA data (waves 6 and 7).[13] For each individual solution i (that uses a specific subjective survival curve), we simulate 50 histories of mortality[14] and income shocks, and initialize wealth (w_0) and risky assets ownership (I_0) at their value in the data for individual i. Moreover, households are ex ante heterogeneous depending on their level of cognitive skills (high or low) which we assume to be constant over the part of the life cycle that we model. Households belonging to different cognitive skills types have different income processes.[15]

4.1 Calibration and Estimation

The parameters of the model are determined in two steps. We first determine parameters that can be calibrated or estimated independently of the full portfolio-choice problem. Conditional on these parameters, we estimate the remaining parameters governing portfolio behavior by matching simulated and empirical moments.

4.1.1 Parameters Determined Outside the Structural Estimation

The first step determines all parameters that do not require solving the full portfolio-choice problem. The coefficient of relative risk aversion, the risk-free return, the baseline equity premium, the volatility of risky returns, and the long-term care parameters are taken from the literature. The parameters governing subjective survival curves, the type-specific discount factors, labor income process parameters, and bequest parameters are estimated independently of the structural model as follows.

Subjective survival curves. Individual subjective survival curves are estimated outside the model from ELSA survival expectations. Following O'Dea, Sturrock (2021), we assume a Weibull distribution for subjective survival beliefs and estimate individual-specific Weibull parameters by nonlinear least squares. These estimated survival curves generate the year-by-year subjective survival probabilities entering the household optimization problem. Appendix C.1 describes the estimation

[13] Table E.1 in Appendix E.2 reports descriptive statistics for the sample used to initialize model simulations.

[14] The mortality probabilities faced by individuals when simulating from the model are consistent with the life tables, but re-weighted to account for heterogeneity between low and high cognitive individuals. See Appendix C.1 for details on the computation of life table survival probabilities conditional on cognitive level.

[15] We define the cognitive level of the individual i by using cognitive tests at age 50 to 55. There are two levels of cognition: "low" if the individual is in the first tertile of the cognitive score distribution, and "high" if he is in the second or third tertile.

procedure.

In addition, we calibrate the positive utility shifter, $\bar{b}$, following De Nardi et al. (2024) so as to match a statistical value of life (SVL) equal to £900,000 (in 2011). The SVL represents the monetary value corresponding to a marginal reduction in mortality risk and is defined as the marginal rate of substitution between wealth and survival probability. Appendix G.1 provides further details on the calibration.

Discount factor. To discipline discount-factor heterogeneity in the main model, we calibrate cognitive-type-specific discount factors using a parsimonious pre-50 savings block. The auxiliary model starts at age 20 and ends at age 50, when individuals enter the main life-cycle model. Before age 50, individuals face deterministic earnings profiles that vary by gender and cognitive type, save only in a risk-free asset, and face no mortality risk, medical or long-term-care shocks, treatment variation, or risky-asset participation decision. Initial assets at age 20 are set to zero. We calibrate two discount factors, one for low-cognitive and one for high-cognitive individuals, while allowing earnings profiles to differ across the four gender-by-cognitive types. For a given cognitive-type discount factor, we solve the deterministic savings problem separately by gender and cognitive type and compute model-implied wealth at age 50. The discount factor is chosen to match average wealth at age 50 by cognitive group, aggregating male and female model-implied wealth using the corresponding sample weights.

Since the main structural model starts at age 50, the auxiliary problem requires a terminal value. In the baseline calibration, we approximate the continuation value by assuming that age-50 wealth is converted into an annuity-equivalent consumption flow:

$$V_{50}(a_{50};\beta_c) = \frac{u\left(y_{50} + \kappa a_{50}\right)}{1-\beta_c},$$

where y_{50} is deterministic earnings at age 50 and κ is an annuity rate. We set $\kappa = 0.05$, corresponding to an annuity-equivalent flow of five percent of age-50 wealth per year. The resulting calibrated discount factors are then used as the low- and high-cognitive-type discount factors in the age-50-and-older model.

Allowing discount factors to differ by cognitive type is important for the interpretation of the survival-belief channel. Cognitive groups differ substantially in wealth at the point of entry into the main model, and these differences may reflect not only differences in expected longevity, but also persistent differences in patience, saving behavior, and lifetime economic opportunities. By calibrating discount factors to match pre-existing wealth differences at age 50, we avoid forcing the model to attribute all subsequent differences in saving and portfolio choices to survival chances alone. In this sense, discount-factor heterogeneity provides a conservative benchmark for the role of survival

beliefs: the estimated effects of subjective survival expectations are identified after accounting for baseline differences in the propensity to save across cognitive groups.

Labor income process. The labor income process is estimated separately for high- and low-cognitive households using a standard minimum-distance procedure. The estimation delivers the persistence and variances of the permanent and transitory income shocks. Details are reported in Appendix E.4.

Bequest. To calibrate the bequest parameters ϕ_B and ϕ_k, we compute the marginal propensity to bequeath (mpb) out of an extra pound and the consumption value of wealth at which the bequest motive becomes operative. We do it for a household head who starts period t with wealth $x^\star$ and dies next period with probability one. The two bequest parameters are calibrated in such a way that the marginal propensity to bequeath is equal to 0.93 and the bequest motive becomes operative when $x^\star$ is above £8,000 for both low and high cognitive types. These figures are in the range of values implied by the parameter estimates in De Nardi et al. (2010) and French (2005). The resulting calibrations of the bequest function parameters, ϕ_B and ϕ_k, are 34,262 (33,600 for high cognitive) and £108,411, respectively.

Table 8 summarizes the resulting parameter values with their respective sources.

Table 8: Parameters Determined Outside the Structural Estimation.

		Low cognitive	High cognitive	Source
β	discount factor	0.965	0.984	calibrated
γ	relative risk aversion	4	4	Love (2013)
$\underline{c}$	consumption floor	1,500	1,500	Capatina (2015)
mpb	marginal prop. to bequeath	0.93	0.93	De Nardi et al. (2010) and French (2005)
$x^\star$	bequest activation wealth	£8,000	£8,000	De Nardi et al. (2010) and French (2005)
r	return of risk-free asset	0.02	0.02	Love (2013)
$\bar{\mu}$	excess return of risky asset	0.025	0.025	Love (2013)
σ_s	sd of return of risky asset	0.2	0.2	Love (2013)
p_{tail}	prob. of financial disaster	0.02	0.02	Fagereng et al. (2017)
r_{tail}	return of risky asset (disaster)	- 0.485	- 0.485	Fagereng et al. (2017)
p_{ltc}	prob. of LTC shock	0.10	0.10	Barczyk, Kredler (2018)
$\underline{c}_{ltc}$	consumption floor if LTC shock	20,000	20,000	Banks et al. (2023)
ρ	persistency (income process)	0.956	0.904	estimated
σ_y	sd of persistent shock (income process)	0.038	0.060	estimated
σ_ϵ	sd of transitory shock (income process)	0.304	0.290	estimated
p_{w_0}	prob. of zero income	0.01	0.01	Alan (2012)

4.1.2 Structural Estimation

Conditional on the parameters determined in the first step, we estimate the remaining parameters governing households' portfolio decisions using the Method of Simulated Moments (MSM) (McFadden 1989; Pakes, Pollard 1989). Specifically, we estimate the vector:

$$\Theta = (k^p, \lambda, \alpha, \tau)\,,$$

where k^p denotes the per-period participation cost incurred by households entering the financial market, $\lambda \in (0, 1)$ scales the participation cost for households that already participated in the previous period, α captures the wealth-related (scale) component of heterogeneous risky returns, and τ captures the persistent return differential associated with cognitive ability (type). The parameter vector is obtained by minimizing the distance between empirical and simulated moments (Appendix E.5).

The estimation targets the average life-cycle profiles of total wealth, financial market participation, and the share of financial wealth invested in risky assets, computed separately for high- and low-cognitive households. These moments jointly identify the four portfolio parameters because each governs a distinct dimension of household financial behavior. The entry cost k^p primarily determines participation at the extensive margin, while the persistence parameter λ captures the lower effective costs faced by incumbent investors and therefore disciplines the persistence of financial market participation over the life cycle. The scale component α determines how expected returns vary with wealth and is mainly identified by the joint evolution of wealth accumulation and portfolio allocation. Finally, the type component τ captures persistent differences in investment opportunities across cognitive groups and is identified by the observed gaps in wealth accumulation, participation, and risky asset holdings between high- and low-cognitive households.

Table 9: Estimated Parameters.

Parameter		Estimate	S.E.
k^p	per-period costs	0.0212	0.0024
λ	scaler of per-period costs	0.4361	0.0210
α	heterogeneous risky returns – scale	0.0154	0.0015
τ	heterogeneous risky returns – type	0.0086	0.0009

Table 9 reports the estimated parameter values and the corresponding standard errors (Appendix E.5). Overall, the estimated parameters are economically plausible and broadly consistent with

the household finance literature. The estimated scale and type components of heterogeneous risky returns fall within the range of values documented by Bach et al. (2020). The estimated participation costs imply annual entry costs ranging approximately from £100 to £800, with a median close to £300, consistent with the estimates reported by Vissing-Jorgensen (2002) and Khorunzhina (2013). The estimated value of λ implies that households already participating in the financial market face substantially lower effective participation costs than new entrants, consistent with the empirical persistence of stock market participation documented in the data.

Figure 3: Total Wealth

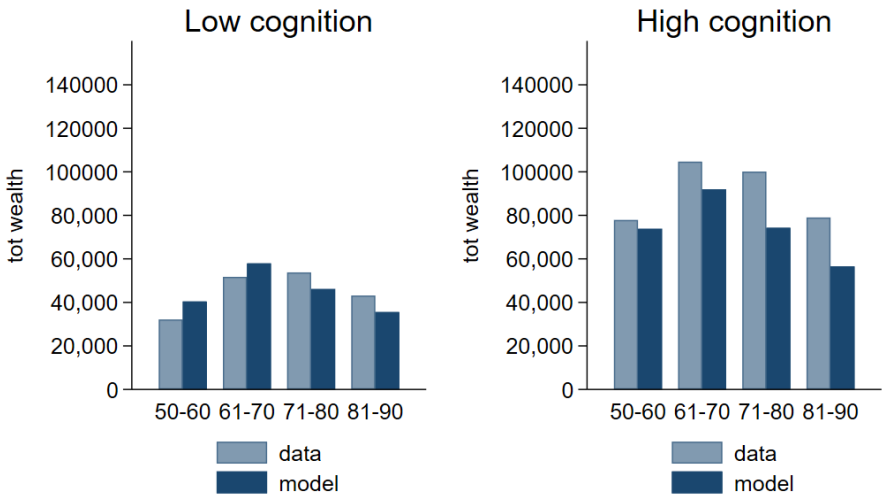


Figure 4: Participation

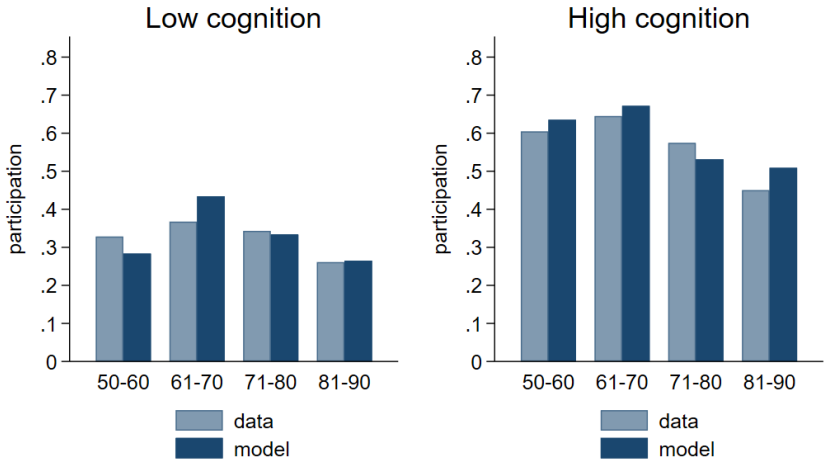
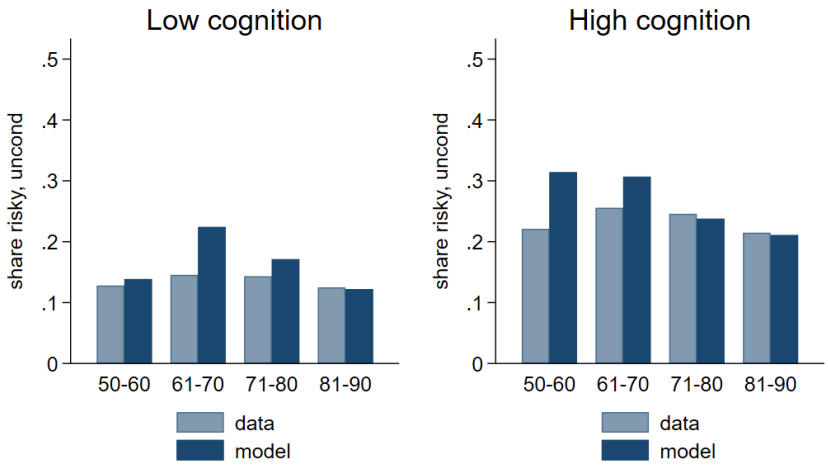


Figure 5: Share of Risky



Figures 3, 4, and 5 compare the empirical and simulated life-cycle profiles targeted in the estimation. The model successfully reproduces the main patterns of total wealth, participation, and share of wealth invested in risky assets observed in the data for low and high cognitive individuals.

5 Survey-Informed Counterfactuals

We then use the estimated life-cycle model to evaluate the long-run effects of information interventions motivated by the survey evidence of Section 3. The survey identified two distinct mechanisms: the survival literacy intervention primarily updates subjective survival beliefs, whereas the financial literacy intervention mainly reduces barriers to financial market participation. We discipline the model using these findings by considering three policy experiments: (i) a survival literacy intervention that reduces the discrepancy between subjective and objective survival probabilities by 30 percent, in line with results in Section 3.2.1; (ii) a financial literacy intervention that reduces participation costs by 50 percent, in line with results in Section 3.2.2; and (iii) a combined intervention that implements both changes simultaneously.

Unlike the survey experiment, these counterfactuals are evaluated under a revenue neutrality requirement. We assign a per-capita cost of £2 to the survival literacy intervention and £5 to the financial literacy intervention, with the combined intervention costing £7 per person. These costs capture the development, administration, and digital dissemination of the informational content[16].

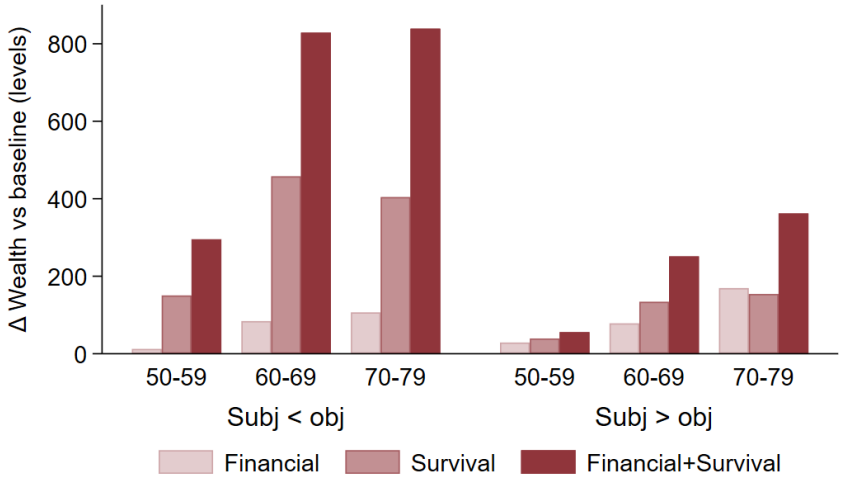
[16]These values should be interpreted as benchmark implementation costs. The £5 cost for the financial literacy intervention is conservative relative to the financial education literature (Frisancho 2020; Kaiser et al. 2020), while the lower £2 cost for the survival literacy intervention reflects its shorter, standardized digital

In each counterfactual, the intervention is financed through proportional adjustments in labor and capital income taxes that keep the government budget balanced. We evaluate the effects of these interventions on wealth accumulation, financial market participation, portfolio allocation, and welfare with respect to the baseline.

5.1 Wealth Accumulation

Figure 6 reports the effects of the three survey-informed interventions on life-cycle wealth accumulation by initial survival beliefs[17]. Consistent with the survey, financial literacy and survival literacy operate through distinct but complementary channels. Financial literacy encourages stock market participation by lowering participation costs, while survival literacy extends the perceived planning horizon through improved longevity beliefs. As a result, the combined intervention generates larger wealth gains than the sum of the two individual interventions, indicating that the effects of the two policies on wealth accumulation reinforce each other when implemented jointly.

Figure 6: Wealth change by survival beliefs and experiment



The effects are concentrated among individuals whose subjective survival probabilities initially lie below the corresponding life-table probabilities. For these households, updating pessimistic survival beliefs leads to longer investment horizons and stronger incentives to accumulate wealth, particularly during the transition into retirement, reaching a peak of approximately £800 under the combined

format and is consistent with the scalable online interventions described by Billari et al. (2023).

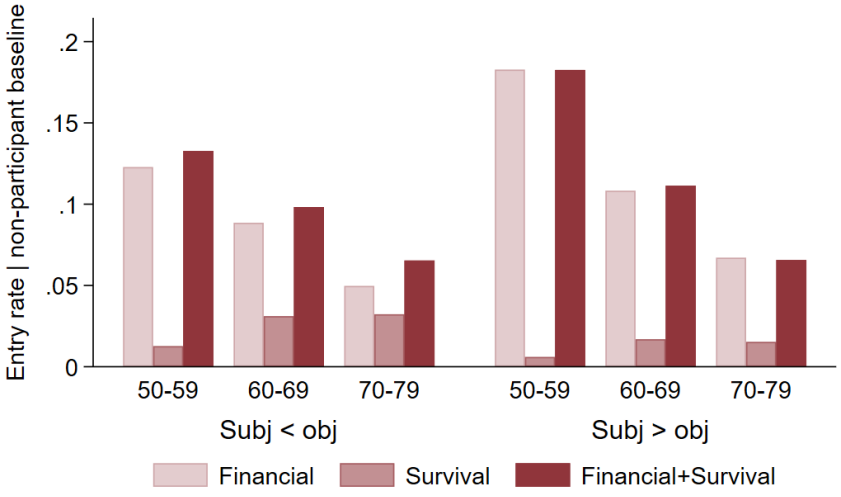
[17]Throughout the counterfactual analysis, households are classified according to their initial survival beliefs. Individuals are defined as pessimists (Subj $<$ obj) if their initial subjective survival probabilities lie below the corresponding life-table probabilities for at least 75% of the life-cycle periods, and as optimists (Subj $>$ obj) otherwise.

intervention. By contrast, the interventions have considerably smaller effects for individuals whose subjective survival probabilities already exceed the life-table benchmarks.

5.2 Financial Market Participation

Entry. Figure 7 reports the probability that households who do not participate into financial markets in the baseline scenario become participants under each policy intervention. Consistent with the survey experiment, financial literacy is the primary driver of market entry. Reducing participation costs substantially increases the probability of entering the stock market across all age groups, reaching an entry rate of almost 15% among baseline non-participants in the years before retirement. The effect is stronger among individuals whose subjective survival probabilities lie above the life tables (right panel), suggesting that once households perceive sufficiently long investment horizons, participation decisions are primarily governed by financial frictions. Moreover, the survival literacy intervention has only modest effects on entry. Importantly, the combined intervention produces entry rates that are nearly identical to those under the financial literacy intervention alone, indicating that adding survival literacy provides little additional incentive to enter the market once participation costs have been reduced. The model therefore endogenously reproduces the experimental finding that survival literacy does not add to financial literacy on the extensive margin (Table 6, column 2), despite this interaction not being targeted in the structural estimation.

Figure 7: Entry into financial markets by survival beliefs and experiment



Heterogeneity by initial wealth, reported in Appendix F, reinforces this result. The largest entry effects are observed among households in the upper-middle part of the wealth distribution, particularly

the third initial wealth quartile, who have greater scope to benefit from lower participation costs. These findings suggest that participation decisions are primarily driven by financial constraints. Households with sufficient financial resources are better positioned to exploit the reduction in participation costs, whereas limited wealth prevents poorer households from entering the market.

We then compute the average change, relative to the baseline, in the number of years spent in the stock market among households that enter at least once – a baseline that averages 12 years for households whose subjective survival probabilities lie below life-tables and 15 years for those whose beliefs lie above them. The financial literacy intervention increases participation duration by almost three years on average, compared with about one year under the survival literacy intervention, while the combined intervention yields almost the same increase as financial literacy alone. Thus, households not only enter financial markets more frequently than in the baseline, but also remain participants for substantially longer. This suggests that reducing participation costs has persistent effects on market participation rather than merely inducing temporary entry.

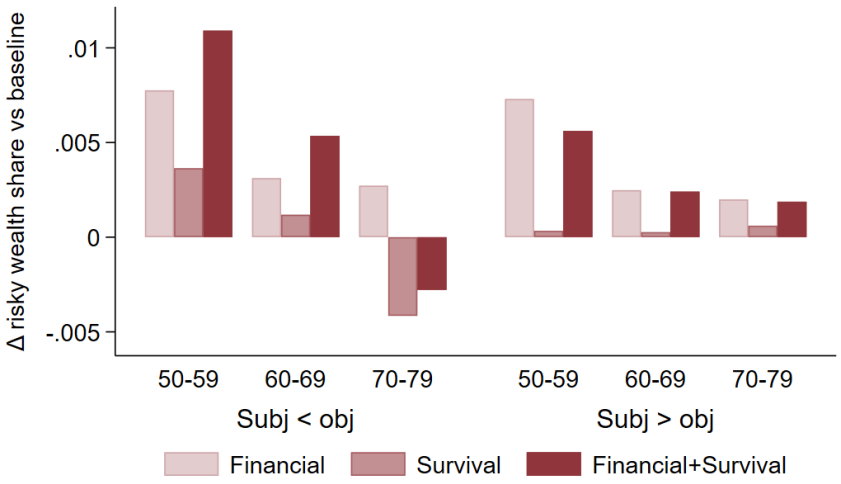
Exit responses provide complementary evidence (Appendix Figure F.2): they are substantially smaller than entry responses, concentrated at older ages, and more responsive to survival literacy, particularly among households with pessimistic survival beliefs. This pattern indicates that survival-belief updating primarily affects the timing of late-life portfolio decumulation rather than the decision to enter financial markets.

Portfolio shares. Finally, Figure 8 reports the effects of the interventions on the share of financial wealth invested in risky assets. To isolate changes along the intensive margin, the figure reports changes in risky portfolio shares conditional on households participating in the stock market in both the baseline and the corresponding counterfactual scenario. Unlike the entry results above, the intensive margin exhibits evidence of complementarity between survival and financial literacy, closely mirroring the survey evidence. While the financial literacy intervention increases risky portfolio shares by reducing participation frictions, the combined intervention generates consistently larger effects than the financial literacy intervention alone among individuals whose subjective survival probabilities initially lie below the life-table benchmarks (left panel). This suggests that once households overcome the barriers to stock market participation, improvements in survival literacy further affect portfolio allocation by extending the perceived investment horizon. Importantly, although these moments are not targeted in the structural estimation, the model endogenously reproduces the experimental evidence that survival literacy amplifies the intensive-margin response to financial literacy (Table 6, column 4).

Moreover, the survival literacy intervention also drives the decline in risky portfolio shares later in life for households whose subjective survival probabilities are below the life-table benchmarks,

consistent with the increasing importance of long-term care risk and wealth decumulation over the later stages of the life cycle.

Figure 8: Change in risky share by survival beliefs and experiment



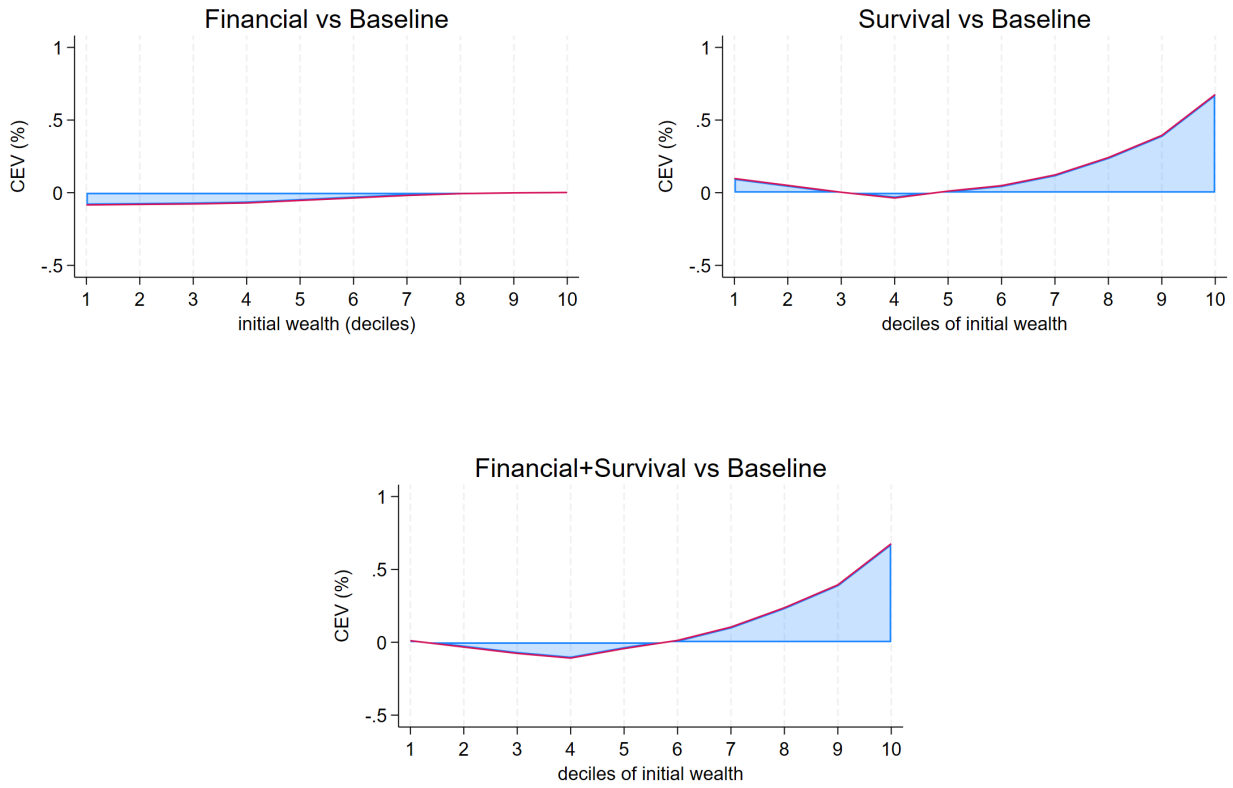
5.3 Welfare Analysis

We evaluate the welfare implications of the survey-informed policy interventions. Welfare changes are measured using consumption equivalent variation (CEV), defined as the proportional change in consumption that makes households indifferent between the baseline and the counterfactual scenario. Since the survival literacy intervention changes households' subjective survival beliefs, welfare comparisons require a generalized CEV measure that accounts for differences in perceived survival probabilities across scenarios. In addition, preferences include a utility shifter calibrated to match the statistical value of life (SVL), allowing households to derive utility from longer expected lives independently of consumption. Appendix G describes the calibration of the SVL and derives the generalized CEV measure.

Figure 9 reports the resulting CEV by initial wealth decile across the three counterfactual scenarios. The financial literacy intervention generates non-positive welfare effects throughout the wealth distribution. Although reducing participation costs encourages additional stock market participation and increases wealth accumulation, these benefits accrue primarily to households with sufficient financial resources to participate in risky asset markets. By contrast, the higher labor and capital income taxes required to finance the intervention are paid by all households. Consequently, for most individuals the tax burden outweighs the gains from improved portfolio decisions, resulting in zero or negative welfare effects. This finding highlights an important distributional consideration:

interventions that successfully increase financial market participation need not generate positive welfare once their financing is taken into account.

Figure 9: Consumption-equivalent variation (CEV) by deciles of initial wealth.



The survival literacy intervention produces a markedly different pattern. Welfare gains are positive for most of the wealth distribution and increase with initial wealth. These gains reflect two distinct mechanisms. First, by updating survival beliefs, the intervention induces households to adopt longer planning horizons, leading to improved saving and portfolio decisions over the life cycle. Second, because households revise upward their subjective survival probabilities, they place greater value on future consumption opportunities. Thus, part of the welfare gain reflects improved economic decisions, while part arises mechanically from changes in beliefs about expected lifetime utility. Together, these channels more than offset the modest tax burden required to finance the intervention.

Finally, the combined intervention delivers the largest welfare gains among wealthier households while mitigating the negative welfare effects associated with the financial literacy intervention alone. Welfare remains close to zero for the lowest wealth deciles, where the tax burden largely offsets the private benefits of improved financial decisions. However, from the middle of the wealth distribution

onward, the complementary effects of improved financial literacy and more accurate survival beliefs generate increasingly positive welfare gains. Overall, the results suggest that while financial literacy alone primarily benefits households already positioned to exploit financial market opportunities, combining it with survival literacy produces broader welfare improvements.

5.4 The Role of Bequest Motives and Long-Term-Care Risk

The counterfactuals of Section 5 are computed in an economy in which wealth is valued both as a source of future consumption and as a bequest, and in which surviving to old age exposes households to the risk of needing long-term care. Both features enter the household problem multiplicatively with the survival probability and therefore shape how a revision of subjective survival beliefs maps into saving and portfolio decisions. A bequest motive attaches value to wealth precisely in the states in which the household does *not* survive, so that becoming more optimistic about survival lowers the weight placed on that value. Long-term-care risk implies that surviving is not only an opportunity to consume for longer but also an exposure to a large, partially insured expenditure risk. We therefore re-solve and re-simulate the model with $\phi_B = 0$ and, separately, with $p_{ltc} = 0$, and repeat all three interventions in each economy. All remaining parameters are held at their baseline values.

Because the alternative economies differ from the baseline also in levels, we report a difference-in-differences statistic. For each outcome y, age group a, intervention p and belief group g, we compute

$$\mathcal{D}^{p}_{a,g} = \Big[\bar{y}^{\,p}_{a,g} - \bar{y}^{\,base}_{a,g}\Big]^{\text{alternative}} - \Big[\bar{y}^{\,p}_{a,g} - \bar{y}^{\,base}_{a,g}\Big]^{\text{baseline}}, \tag{5}$$

so that a positive value indicates that the intervention is more effective on that margin once the feature – bequest motive or LTC risk – is removed, i.e. that the feature dampens the response in the estimated model.

Bequest motives and the survival channel. Abstracting from participation costs and constraints, the Euler equation reads

$$c_t^{-\gamma} = \beta\, \mathbb{E}_t\Big[R_{t+1}\Big(\pi^{s}_{t+1}\, c_{t+1}^{-\gamma} + (1-\pi^{s}_{t+1})\, \phi_B \big(w_{t+1} + \phi_K\big)^{-\gamma}\Big)\Big], \tag{6}$$

so that the marginal benefit of saving is a survival-weighted average of the marginal utility of consumption if alive and of the marginal utility of the bequest if dead. Differentiating the right-hand side with respect to π^{s}_{t+1}, an upward revision of survival beliefs raises the incentive to save if and only if

$$w_{t+1} + \phi_K \;>\; \phi_B^{1/\gamma}\, c_{t+1}. \tag{7}$$

When bequest motives are strong, condition (7) can fail: wealth is then held largely to be transferred at death, and learning that one is more likely to survive lowers the probability of collecting that utility, offsetting or even reversing the standard horizon channel. Because the offsetting term carries weight $1-\pi^s_{t+1}$, it is negligible when survival is nearly certain and becomes relevant only as mortality risk rises: the bequest motive matters for the survival channel late, rather than early, in the life cycle. The two bequest parameters play distinct roles, since the marginal propensity to bequeath and the wealth level at which the bequest becomes operative are $mpb = \phi_B^{1/\gamma}/(1+\phi_B^{1/\gamma})$ and $x^\star = \phi_K/\phi_B^{1/\gamma}$: ϕ_B pins down the former, while ϕ_K shifts the operative threshold and hence determines how much of a luxury good the bequest is in the sense of De Nardi (2004). The economy with $\phi_B = 0$ is therefore a natural benchmark: it shuts down the second term in (6) and isolates the pure horizon channel. Appendix H reports the derivation.

Counterfactuals without bequest motives. Figure 10 is the quantitative counterpart of condition (7), and is expressed in the same units as the baseline wealth counterfactual of Figure 6 so that the two are directly comparable. Among households whose subjective survival probabilities initially lie below life-table probabilities, removing the bequest motive raises the wealth response to the survival-literacy intervention by approximately £1,000 at ages 70–79, with the combined intervention behaving almost identically and the financial-literacy intervention essentially unaffected. The magnitude is substantial: it exceeds the peak wealth gain of about £800 that the combined intervention generates in the estimated model, so that the bequest term offsets more than half of the old-age wealth response to correcting pessimistic beliefs. Differences among optimists are positive but roughly three times smaller, as expected given that the intervention moves beliefs mainly for pessimists. The positive survival–wealth gradient documented in the paper is attenuated by bequest at the ages at which mortality risk is high, which is precisely where the $1-\pi^s_{t+1}$ weight in (6) makes the offsetting term operative.

Before age 70 the differences are instead small and negative, of the order of $-$£200 to $-$£500. This reflects the luxury nature of the bequest. It is operative only in the upper part of the wealth distribution, where resources accumulated in the first two decades of the simulated life cycle serve a double purpose — financing consumption if alive and a bequest if not — so that the interventions amplify accumulation and removing the bequest removes that amplification[18]

[18]Appendix Figure H.1 confirms this reading: under the inverse hyperbolic sine (IHS) transformation, which downweights the tail, the pre-70 differences vanish while the amplification at 70–79 survives unchanged.

Figure 10: Role of Bequest Motives: Wealth

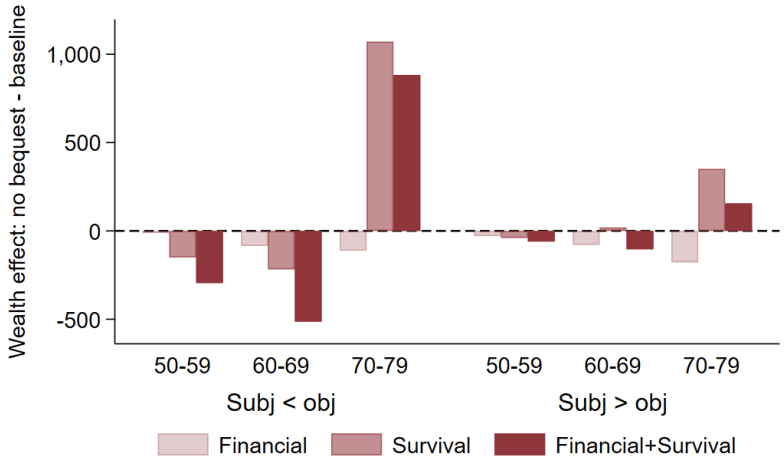


Figure 11: Role of Bequest Motives: Market Entry

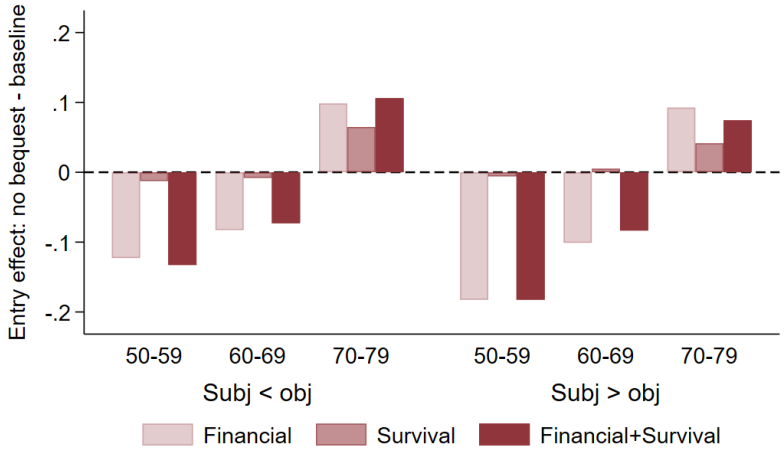


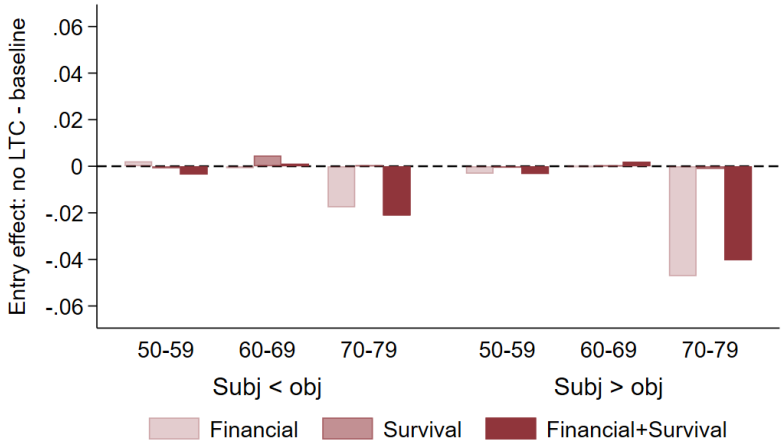
Figure 11 shows that bequest motives also shape the timing of participation decisions. Removing them lowers the entry response to the financial-literacy intervention by about 12 and 8 percentage points at ages 50–59 and 60–69 among pessimists (18 and 10 percentage points among optimists), and raises it by roughly 10 percentage points at 70–79 in both groups; the combined intervention behaves almost identically, while survival literacy plays a minor role on this margin, mirroring the baseline finding that entry is governed by financial frictions. Without bequests households target lower wealth early on and a larger pool of non-participants remains later in life. The participation response therefore shifts toward later ages.

Exit responses move consistently (Appendix Figure H.2): among pessimists aged 70–79, removing

bequests reduces the exit response to the survival-literacy intervention. In the estimated model, a pessimistic household learning that it will live longer faces two forces: its horizon lengthens, but the value of holding wealth into the death state falls because that state has become less likely, pushing toward faster decumulation and market exit. With $\phi_B = 0$ only the first force survives and treated households remain invested longer. Finally, risky shares (Appendix Figure H.3) show a uniformly negative difference for the financial-literacy intervention: a bequest motive extends the effective investment horizon beyond the household's own lifetime, and removing it attenuates the intensive-margin response to lower participation costs. The survival component moves in the opposite direction, so the complementarity documented in Section 5 survives, but its composition shifts away from financial and toward survival literacy.

Counterfactuals without long-term-care risk. LTC risk enters the model from age 75 onward as an absorbing state that raises the consumption floor from $\underline{c}$ to $\underline{c}_{ltc} > \underline{c}$. Eliminating it works in two opposite directions: households no longer need to self-insure against future care costs, which weakens the precautionary motive, but the asset-tested floor that implicitly taxed their wealth becomes less generous, which raises the return to saving (De Nardi et al. 2016; Hubbard et al. 1995).

Figure 12: Role of Long-Term-Care Risk: Market Entry



The former channel dominates the participation response to the financial literacy intervention. Figure 12 shows virtually no differences before age 70, but substantially weaker entry responses at ages 70–79. Among households with pessimistic survival beliefs, the entry response falls by 1.7 percentage points; among optimists, it falls by 4.7 percentage points. Relative to the baseline responses (4.9 and 6.8 percentage points, respectively; Figure 7), this corresponds to a reduction of roughly one third for pessimists and almost the entire response for optimists. Without LTC risk, households accumulate less wealth and are therefore less able to exploit lower participation costs.

Risky portfolio shares display a similar pattern (Appendix Figure H.7), whereas exit responses change little (Appendix Figure H.6).

The opposite pattern emerges for wealth accumulation. Despite lowering baseline wealth, removing LTC risk amplifies the incremental wealth response to the financial literacy intervention (Appendix Figures H.4 and H.5). Households also accumulate more wealth in response to the survival literacy intervention because a longer expected life no longer entails greater exposure to future LTC expenditures. The quantitative effects, however, remain modest, ranging from approximately £50 to £100—about one order of magnitude smaller than in the baseline model.

Taken together, these exercises show that the mechanisms identified in the baseline model are robust to alternative assumptions on bequest motives and LTC risk. Bequest motives primarily shape the transmission of survival-belief updating into late-life saving and portfolio decisions, while also affecting the timing and intensity of responses to lower participation costs. LTC risk mainly operates through the precautionary wealth it generates after age 70, determining the extent to which older households can exploit lower participation costs. Hence, the relative effectiveness of survival and financial literacy interventions depends on the strength of bequest motives and the degree of public insurance against long-term-care risk.

6 Conclusions

This paper shows that survival beliefs and financial literacy affect household financial decisions through distinct but complementary channels. Survival literacy extends the perceived planning horizon by updating longevity beliefs, whereas financial literacy primarily lowers participation frictions. Although the two interventions reinforce each other in increasing wealth accumulation and financial market participation, only survival literacy generates broad welfare gains once implementation costs are taken into account. These findings suggest that improving households' understanding of longevity is a cost-effective complement to traditional financial education. More generally, the paper shows how a randomized information experiment can discipline, rather than merely motivate, a structural life-cycle model – turning a short-run belief-updating treatment effect into a long-run, welfare-relevant policy estimate.

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A Sample Construction and Variable Definitions

This appendix describes the construction of the ELSA estimation sample and the variables used in Section 2.

A.1 Sample Selection

The cross-sectional analysis in Section 2.3 uses wave 8 of the English Longitudinal Study of Ageing (ELSA), which contains approximately 8,800 respondents.

ELSA records wealth at the level of the benefit unit, defined as a single adult or a couple together with any dependent children. We therefore combine benefit-unit portfolio outcomes and characteristics with the characteristics of the unit's financial respondent, defined as the person who completes the Income and Assets module. For readability we refer to the benefit unit as the household throughout the paper; at the ages we consider, the two coincide for the large majority of respondents. In one-person households the assignment of the financial respondent role is immediate. In couples, both partners may be recorded as the financial respondent, in the same or in different waves. We select the partner who is identified as the financial respondent most often across waves; ties are resolved first in favour of the older partner and then, if necessary, in favour of the male partner.

Of the respondents interviewed in wave 8, 4,864 are identified as household financial respondents. The empirical estimates retain only observations with non-missing values for the dependent variable and the covariates used in the main specifications. The largest sources of missingness are financial literacy and dispositional optimism, which are unavailable for 856 and 657 respondents, respectively. Additional observations are lost because participation, survival-belief discrepancy, or cognitive skills are missing. The resulting baseline sample contains 3,311 households. The specification that additionally controls for healthy-related habits uses 3,260 households.

A.2 Variable Definitions and Summary Statistics

Financial-market participation. The participation indicator equals one if the household holds any asset classified as risky in the empirical analysis. These risky assets follow the definition of ELSA and include stocks and shares, bonds and Premium Bonds, share Individual Savings Accounts (ISAs), and life-insurance ISAs (ISA are financial products that benefit from a generous tax exemption in the UK.).

Wealth. Wealth is measured by ELSA's derived variable for net total non-housing wealth of the benefit unit: the sum of savings, investments and physical wealth, net of financial debt, excluding the primary residence and the associated mortgage debt. This measure is the empirical counterpart

of the investable wealth $w_t = s_t + a_t$ in the model, which households allocate between a risky and a risk-free asset. Excluding owner-occupied housing avoids matching a model in which all wealth is freely reallocated each period to a stock that is largely illiquid and yields consumption services we do not model. Private pension wealth is likewise excluded, consistently with the model, in which pension entitlements enter as the post-retirement income flow rather than as a stock; counting them also as wealth would double-count the same resources. The measure retains physical wealth, which includes second homes, business property and other valuables. These components are small for the large majority of benefit units at the ages we consider. All monetary variables used in the empirical analysis, in the calibration, and in the structural estimation are deflated to 2011 prices. To adjust for differences in unit size we divide wealth by the household equivalence scale supplied in the ELSA–IFS derived variables file. It follows the modified OECD convention: a weight of 1 for the first adult, 0.5 for each additional adult and for dependent children aged 14 and over, and 0.3 for children below 14. We deflate by the household rather than the benefit-unit scale because the purpose of an equivalence scale is to adjust resources for the needs they must support, and the economies of scale in consumption that the scale summarises are realised among all individuals sharing a dwelling. The benefit unit is the administrative unit on which entitlement is assessed in the UK transfer system, not a consumption-sharing unit. The two scales coincide for 85% of the wave-8 sample; where they differ, the additional member is most commonly a co-resident adult child, and the household scale exceeds the benefit-unit scale by a median factor of 1.5. ELSA supplies equivalised measures for income but not for wealth, on the grounds that no single convention for adjusting wealth holdings to unit size is universally accepted. We apply the same modified OECD scale to wealth so that the equivalisation of resources is internally consistent across income and wealth, and so that unit-level wealth is commensurate with the individual-level earnings process and the individual-level survival curves used in the model.

Survival-belief measures. The survival-belief discrepancy is defined in equation (1). It equals zero for respondents whose subjective survival probability is at least as high as the corresponding life-table probability and increases with the extent of underestimation. The focal-response indicator equals one for subjective survival probabilities of 0, 50, or 100 and zero otherwise.

Cognitive skills and financial literacy. The composite cognitive score is the first principal component of memory, numeracy, and financial-literacy measures. In specifications that separate financial literacy from other cognitive skills, the latter score excludes the financial-literacy component.

Education. Education is coded in three ordered categories based on the age at which the respondent left full-time education: compulsory school leaver, between the compulsory school-leaving age and 18, and age 19 or above.

Dispositional optimism. Following Steptoe, Wardle (2017), the optimism indicator equals one if the respondent selects the highest response category (in a 1-4 scale) for both of the following CASP-19 items: "I feel that life is full of opportunities" and "I feel that the future looks good for me."

Health and health-related behaviours. The activities-of-daily-living (ADL) indicator equals one if at least one household member reports difficulty with at least one of the six ADLs. The behavioural controls are indicators for current smoking, mild exercise more than once a week, vigorous exercise at least once a week, and consumption of at least four portions of fruit and vegetables per day.

Table A.1 reports summary statistics for the baseline estimation sample, both overall and by financial-market participation status.

Table A.1: Descriptive statistics. Sample from regression Table 1.

Variables	All	Non-participants	Participants
Obs.	3,311	39,5%	60,5%
Males (%)	54.9	44.2	62.9
Age (mean)	69.4	69.2	69.5
Retired (%)	65.8	62.2	65.0
Education:			
compulsory school leaver (%)	38,9	57,2	26,7
between csl[a] age and 18 (%)	38,9	31,2	43,9
at age 19 or above (%)	22,3	11,2	29,5
HH Income (£ weekly)	493	374	570
HH Fin. Wealth (£ thousand)	33	5	74.1
ADL (%)	75.0	66.8	81.5
Optimism (%)	25.6	20.3	29.1
Cogn. Skill (mean)	0.31	-0.02	0.53
Discrepancy (mean)	0.84	1.01	0.72

[a]csl: compulsory school leave age.

A.3 ELSA subjective survival questions

ELSA elicits subjective survival beliefs by asking respondents:

What are the chances that you will live to be age X or more?

where the target age X depends on the respondent's current age, as shown in Table A.2.

Table A.2: Respondents age and Target age.

Age	Target Age (X)
≤ 65	75
66 - 69	80
70 - 74	85
75 - 79	90
80 - 84	95
85 - 90	100

Moreover, if the respondent's age is less than 70, then a follow-up question is asked:

*What are the chances that you will live to be **85** or more?*

Respondents younger than 70 receive an additional question about the probability of surviving to age 85. ELSA therefore provides one elicited survival probability for respondents aged older than 69 and two for respondents younger than 70.

B Additional Empirical Results

Figures B.1 and B.2 reproduce Figure 1 excluding respondents who report focal survival probabilities answers, 0, 50 and 100. Responses of 0 and 100 express certainty rather than an interior probability, while a response of 50 may indicate difficulty translating beliefs into probabilistic terms. Excluding these observations leaves the main pattern unchanged: respondents systematically underestimate survival probabilities over most of the age range.

We also examine whether respondents who report a survival probability of 50 are disproportionately more likely to answer 50 to subsequent ELSA expectation questions on unrelated outcomes. They are not, suggesting that the result is not driven by a general tendency to use 50 as a default response.

Figure B.1: Corresponds to Figure 1 in the main text, excluding individuals who report a subjective survival chance equal to 50.



Figure B.2: Corresponds to Figure 1 in the main text, excluding individuals who report a subjective survival chance equal to 50, 0 and 100.



B.1 Heterogeneity by Cognitive Skills

Tables B.1 splits the sample by cognitive skills, showing that the effect of *discrepancy* on participation is mainly driven by households with high cognition. Low-cognition respondents are those in the

bottom tertile of the cognitive-score distribution within age windows at their first ELSA interview; all other respondents are classified as high cognition. The negative association between survival-belief discrepancy and participation is concentrated in the high-cognition group.

Table B.1: Linear probability model. Table 1 estimates by high and low cognitive households.

	Dependent variable: Participation			
Cognition:	*low*	*high*	*low*	*high*
	(1)	(2)	(3)	(4)
discrepancy	−0.019	−0.026**	−0.019	−0.026**
	(0.013)	(0.010)	(0.013)	(0.010)
dispositional optimism	−0.006	0.008	−0.002	0.008
	(0.038)	(0.020)	(0.038)	(0.020)
cognitive skills			0.044**	0.007
			(0.019)	(0.012)
Observations	1,008	2,303	1,008	2,303

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$ *Controls*: age, age squared, gender, having a partner, having children, income quartiles, employment status, number of ADLs, education. Habits (Col. (4)): smoker (dummy), mild and intense sport (more than once a week, at least once a week respectively), healthy eating (at least 4 portions of fruit/vegetables per day).

Table B.2 presents the effect of discrepancy on participation using alternative definition of cognitive skills. In this case, we use the financial literacy score and the memory/numeracy tests score as separated variables. The coefficients of discrepancy are identical to Table 1, while both memory and numeracy skills and financial literacy are positively associated to participation. This association is stronger for financial literacy.

Table B.2: Linear probability model. Different definition of cognition: keeping financial literacy and math/memory test abilities separated.

	Dependent variable: Participation			
	(1)	(2)	(3)	(4)
discrepancy	−0.031***	−0.029***	−0.028***	−0.021**
	(0.008)	(0.008)	(0.008)	(0.008)
memory/numeracy skills		0.017**	0.017**	0.015**
		(0.007)	(0.007)	(0.007)
fin. literacy		0.058***	0.058***	0.053***
		(0.008)	(0.008)	(0.008)
Observations	3,311	3,311	3,311	3,260

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ *Controls*: age, age squared, gender, having a partner, having children, income quartiles, employment status, number of ADLs, education. Habits (Col. (4)): smoker (dummy), mild and intense sport (more than once a week, at least once a week respectively), healthy eating (at least 4 portions of fruit/vegetables per day).

C Life Tables by Cognitive Type

Life tables summarise age-specific mortality and survival patterns for a hypothetical cohort exposed to prevailing mortality rates, relative to a specific Country, gender and year. This Section describes life table's main components in details. We later use these quantities to construct and rescale survival probabilities by cognitive type.

m_x: is known as the central rate of mortality. That is the average number of deaths each year at age x last birthday in the relevant three-year period, divided by the average population at that age over the same period.

q_x: is the mortality rate between age x and *(x+1)*. That is, the probability that a person aged x exactly will die before reaching age *(x+1)*.

l_x: is the number of males or females surviving to exact age x of 100,000 live births who are assumed to be subject throughout their lives to the mortality rates experienced in the specified three-year period.

d_x: is the number of males or females dying between exact age x and $x+1$ described similarly to l_x, that is, $d_x = l_x - l_{x+1}$.

e_x: is the average period life expectancy at exact age x, which is the average number of further years that those aged x exactly will live based on the mortality rates experienced in the specified three-year period.

C.1 Subjective Survival Curves

The Weibull distribution has two parameters λ_i and k_i, the scale and the shape parameter, respectively. This distribution allows to compute the survival probability $S_i(\alpha)$ of an individual i of age z to the target age α as:

$$S(\alpha) = exp\Big[- \Big(\frac{\alpha - z}{\lambda_i} \Big)^{k_i} \Big] \quad : \quad \lambda_i, k_i > 0 \tag{C.1}$$

To estimate the Weibull parameters λ_i, k_i of each individual i, we follow O'Dea, Sturrock (2021) additional assumption that individuals are almost certain not to live beyond age 110, assuming that the agents' survival probability at age 110 years is the one provided by ONS life tables[19]. This assumption implies that individuals aged 70 years or more have two survival points, while those aged 69 years or less have three survival points.

In line with O'Dea, Sturrock (2021), we estimate λ_i and k_i Weibull parameters with nonlinear least squares. In particular, the estimation procedure minimizes:

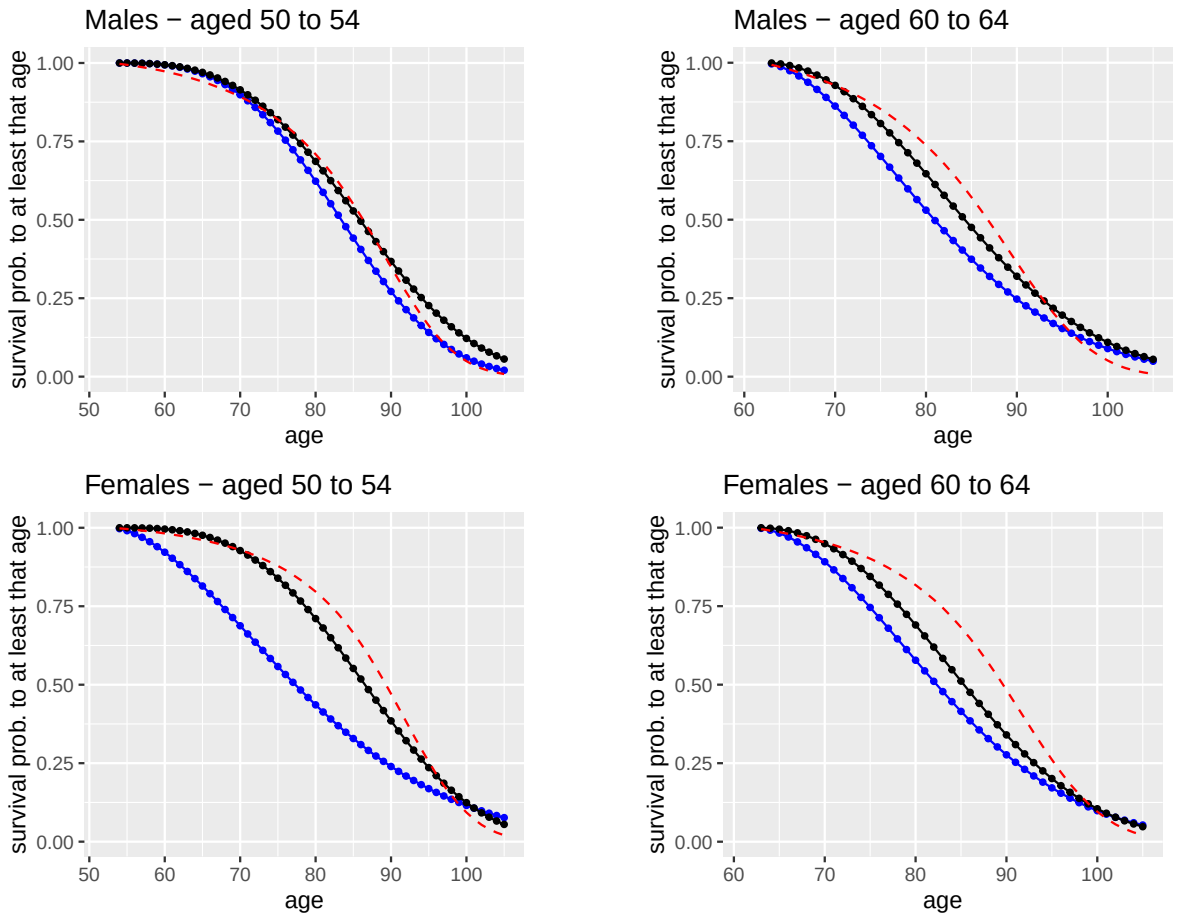
$$(\hat{\lambda_i}, \hat{k_i}) = arg\ min_{\lambda_i, k_i} \sum_{\alpha \in A_i} \left(S_i^{subjective}(\alpha) - exp\Big[- \Big(\frac{\alpha - z}{\lambda_i} \Big)^{k_i} \Big] \right)^2 \tag{C.2}$$

where $S_i^{subjective}(\alpha)$ is the subjective survival probability and $A_i = [75, 85, 110]$ or $A_i = [X, 110]$ is the vector composed by the three or two target ages (depending on the current age of the respondent, see Table A.2).

The fitted curves yield annual conditional survival probabilities and mortality rates. In Figure , we compare median subjective survival curves by age-cohort, gender and cognition, with objective life curves. All four figures show the degree of discrepancy: subjective curves lie below objective life tables. Moreover, low-cognitive individuals (and women) underestimate more their survival chances.

[19] $S_{i,110}^{objective} \in [0.001, 0.003]$.

Figure C.1: Subjective vs Objective survival curves by age, gender and cognition. The *black* lines represent the median high cognitive survival curves, the *blue* lines the median low cognitive subjective survival curve, the *red* lines represent the ONS objective life curve.



C.1.1 Year-To-Year subjective survival and mortality rates

Using l_x, $s_{x,x+t}$ (see Section C) and the Weibull distribution, we have (for $s_{50,51}$ and $s_{50,52}$):

$$\begin{cases} s_i(50,51) = exp\Big[- \Big(\frac{51-50}{\lambda_i}\Big)^{k_i} \Big] &= \frac{l^i_{51}}{l^i_{50}} \\ s_i(50,52) = exp\Big[- \Big(\frac{52-50}{\lambda_i}\Big)^{k_i} \Big] &= \frac{l^i_{52}}{l^i_{50}} \end{cases} \tag{C.3}$$

conditioning on survivorship to age 50, we can fix $l_{50} = 100000$. Then:

$$\begin{cases} l^i_{51} &= l^i_{50} \cdot s_i(50,51) &= 100000 \cdot s_i(50,51) \\ l^i_{52} &= l^i_{50} \cdot s_i(50,52) &= 100000 \cdot s_i(50,52) \end{cases} \tag{C.4}$$

from which we obtain:

$$l^i_{51,52} \;=\; \frac{l^i_{52}}{l^i_{51}} \;=\; \frac{s_i(50,52)}{s_i(50,51)} \tag{C.5}$$

where $l^i_{51,52}$ represents individual subjective *year-to-year survival probability* between age 51 and age 52, given that today agent i is 50 years old.
We then compute individual specific *subjective year-to-year mortality* as $m^i_{x,x+1} = 1 - l^i_{x,x+1}$.

C.1.2 Alternative Rescaling

We use objective mortality rates conditional on the level of cognition (high or low) for both men and women. To derive them, we use ELSA data linked to administrative death records which allow to know the exact year of death of any individual (including attriters) up until February 2013 (this information is available in the public data release of ELSA).

Data are biennial but, given the linkage with administrative death records, we construct a dummy variable taking value one if the individual dies by next year and zero otherwise. This allows us to estimate the probability of dying by $t+1$ conditional on being alive in t, for each age and cognitive level in t. We do it estimating a fixed effect regression and controlling for a four-grade polynomial in age interacted with a dummy for having a low cognitive level. Details on the procedure used to derive mortality rates are provided below.

1. We estimate the probability of being of cognition level i ($\hat{Pr}(Cogn_Skill_t = i)$) and of dying by $t+1$ conditional on cognition level i ($\hat{Pr}(death^D_{t+1}|Cogn_Skill_t = i)$) using all observations. To control for cohort effects, we estimate these probabilities using fixed-effect regressions. When we predict from the estimated regressions, we set the fixed effect equal to the average fixed effect for those born between 1956 and 1964 (the cohort of interest);

2. the probability of dying by $t+1$ at each age t is given by:

$$\hat{Pr}(death^D_{t+1}) = \sum_{i=1}^{4} \hat{Pr}(Cogn_Skill_t = i) * \hat{Pr}(death^D_{t+1}|Cogn_Skill_t = i); \tag{C.6}$$

3. We compare the estimated probability with the life tables for each age t:

$$\frac{\hat{Pr}(death^{LT}_{t+1})}{\hat{Pr}(death^D_{t+1})} = \alpha_t$$

4. We rescale each conditional probability in such a way that the unconditional probability matches the life tables:

$$\hat{Pr}(death^{LT}_{t+1}) = \sum_{i=1}^{4} \hat{Pr}(Cogn_Skill_t = i) * \hat{Pr}(death^C_{t+1}|Cogn_Skill_t = i)$$

with $\hat{Pr}(death^{C}_{t+1}|Cogn_Skill_t = i) = \alpha_t * \hat{Pr}(death^{D}_{t+1}|Cogn_Skill_t = i)$.

D Survey Experiment

D.1 Survey Materials

This Section provides additional detail on the survey materials described in Section 3. It presents representative frames from the survival and financial literacy treatments and the interface used to elicit respondents' portfolio choices.

Figure D.1 shows a representative frame from the survival literacy treatment. In the example, the video reports that, according to the official UK 2023 life tables, a 53-year-old man has a 75 per cent probability of surviving to at least age 75 and a 43 per cent probability of surviving to at least age 85. The same information is personalized by age and gender of the respondent, collected at the beginning of the survey.

Figure D.1: Survival literacy treatment video (screenshot)

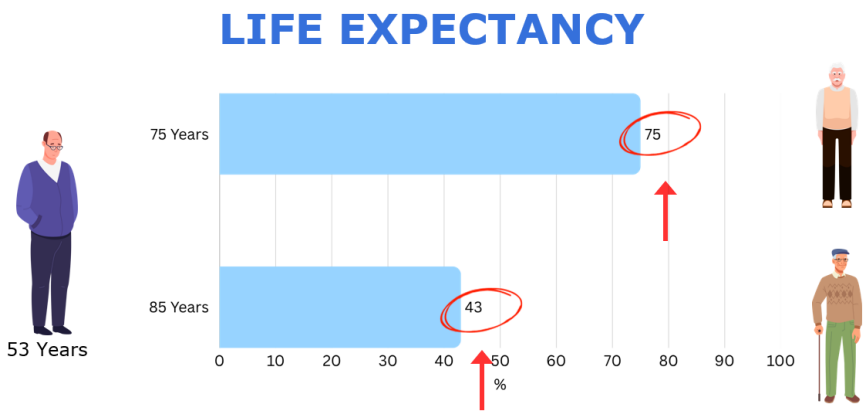


Figure D.2 shows a representative frame from the financial literacy video-treatment. This frame compares the value of £100 invested by two friends—Ms. Smith and Ms. Jones—in 1990 in the S&P 500 (Ms. SMith) with the value of the same amount invested in short-term government bonds (Ms. Jones) over horizons ranging from one to 20 years. The comparison illustrates differences in cumulative returns and volatility between risky and safe assets across investment horizons.

Figure D.2: Financial literacy treatment video (screenshot)

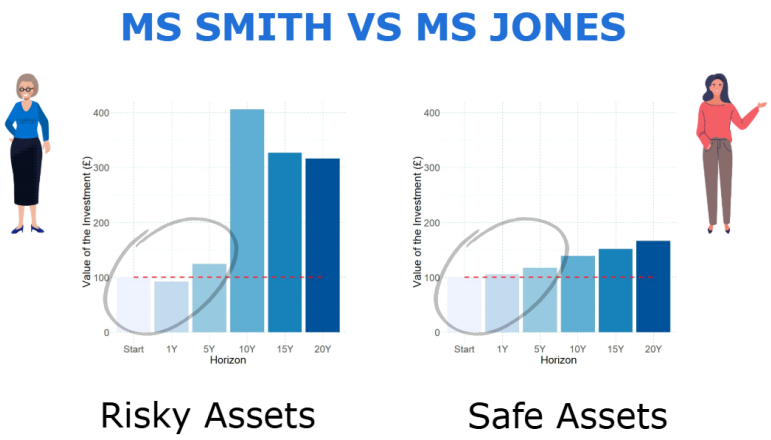
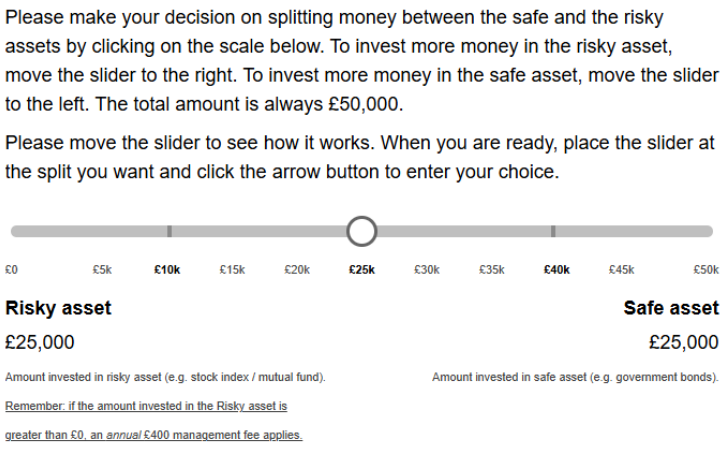


Figure D.3 shows the slider used to elicit portfolio allocations in the participation-cost condition described in Section 3.1. Respondents allocate £50,000 between risky and safe assets; moving the slider updates both amounts, which always sum to £50,000. The interface also reminds respondents that any positive allocation to the risky asset entails an annual management fee of £400.

Figure D.3: Portfolio choice vignette



D.2 Pre-registration, Pre-specified and Additional Analyses

The experiment and the analysis plan were registered in the AEA RCT Registry before data collection (AEARCTR-0018209[20]). This appendix reports the pre-specified analyses that are not included in the main text and documents all deviations from the analysis plan.

[20]Dal Bianco, Chiara et al. 2026. "Survival and Financial Literacy in Investment Decisions Later in Life." AEA RCT Registry. May 07. https://doi.org/10.1257/rct.18209-1.1

D.3 Deviations from the analysis plan

1. *Choice of primary belief measure.* The plan specifies two measures of survival misperception: the raw difference between subjective and life-table probabilities, $m_{i,a}$, and a standardized inaccuracy index. The main text reports the latter, which is comparable across target ages; results for $m_{i,a}$ are in Tables D.3, D.4 and D.5. The two measures agree at the first target age and diverge at the second, for the reason discussed in Section 3.2.1.

2. *Target ages.* The main text reports results for the first target age (75 or 80, depending on respondent age). Results for the second target age (85) and for the pooled specification with standard errors clustered at the individual level are in Tables D.4 and D.5.

3. *Definition of cognitive level.* The pre-specified measure is the first tercile of a principal-component index combining the Big Five financial literacy questions, a memory recall task and a serial subtraction task; this is the definition used throughout the main text. Tables D.6, 4 and 5 additionally report results for an alternative, non-pre-specified index defined as the simple sum of the three components, with low cognition defined by the first quintile. This alternative definition is motivated by the selected nature of the Prolific sample, whose respondents are more educated and score higher on the cognitive tests than the general population of the same age. In such a sample, the bottom tercile of the index need not correspond to genuinely low cognitive ability, and the pre-specified cut-off may therefore understate the extent of heterogeneity along this dimension. Restricting attention to the bottom quintile isolates the left tail of the distribution more sharply, at the cost of statistical power.

4. *Portfolio outcomes and the full factorial design.* The plan restricts the analysis of portfolio choices to the comparison between the control group and the financial literacy arm. Table 6, which reports effects for all four arms, is an additional exploratory analysis. As noted in the registered power calculations, the design is powered to detect main effects rather than interactions.

5. *Sample.* As pre-specified, all results in the main text use the full sample without exclusion criteria. Table D.11 reports the pre-specified robustness checks based on data-cleaning rules and sample restrictions.

D.4 Replication of the ELSA facts in the experimental sample

Figure D.4: Subjective and objective survival probabilities by target age and gender. Experimental data collected through Prolific and ONS life tables 2023.

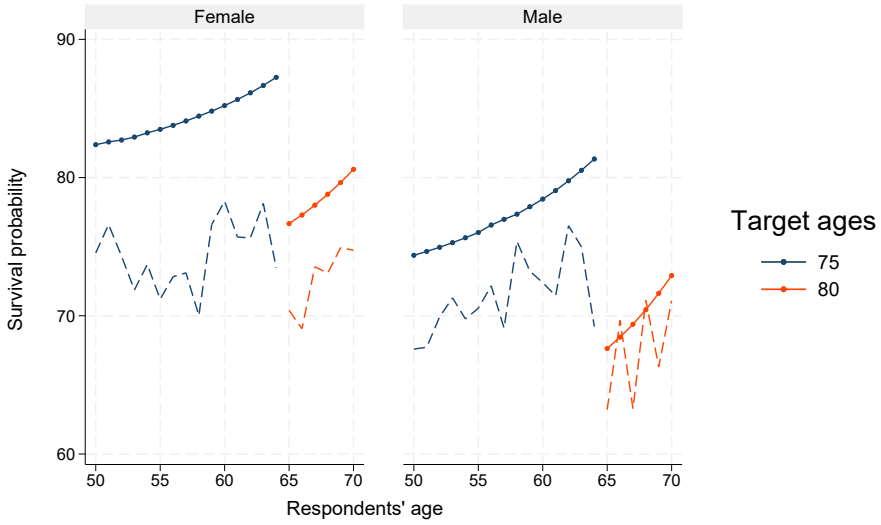


Table D.1: Participation (linear probability model). Experimental dataset.

	Participation			
	(1)	(2)	(3)	(4)
discrepancy	-0.037***	-0.031***	-0.032***	-0.026***
	(0.009)	(0.008)	(0.008)	(0.008)
cognitive skills		0.116***	0.115***	0.113***
		(0.007)	(0.007)	(0.007)
dispositional optimism			-0.001	-0.000
			(0.000)	(0.000)
Demographics	Yes	Yes	Yes	Yes
Habits	No	No	No	Yes
Obs	3326	3326	3284	3254

Notes: Replication of Table 1 using experimental data collected through Prolific. Controls include: age, age squared, gender, having a partner, having children, being employed, education, focal answers. *Habits:* smoking and physical activity. *Cognitive skills:* PCA (financial literacy, numeracy, memory). Dispositional optimism: probability that tomorrow will be raining 0-100. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.5 Additional pre-specified results

This appendix reports the pre-registered results not shown in the main text. We first present the balancing test across treatment arms (Table D.2). For survival beliefs, we report robustness of the belief-updating results to the second target age, to pooling target ages, and to alternative measures of the subjective–actuarial gap, together with heterogeneity by cognitive level (Tables D.3–D.6). For portfolio choices, we report the full pre-specified interaction between financial literacy, cognition, and participation costs, which the main text presents one margin at a time because the fully interacted specification proved too demanding for the data once implemented (Table D.7); robustness of the IV estimates of beliefs on participation and the risky share to alternative measures of the endogenous belief-discrepancy variable, holding the instrument – assignment to the survival literacy treatment – fixed (Table D.8); and, as a robustness check on the 50-year-old vignette results reported in the main text, portfolio choices in the 70-year-old vignette (Table D.9). We conclude with robustness to pre-specified sample restrictions and to multiple hypothesis testing (Tables D.11–D.12).

Finally, we consider a secondary pre-registered outcome: respondents' subjective probability of ever needing continuous professional care. The survival literacy treatment reduces this probability by approximately three percentage points, an effect that is similar across cognitive groups (Table D.10). The direction is worth noting. Information that extends the expected lifespan might be expected to raise perceived exposure to age-related care needs; what we observe is the opposite. One interpretation is that respondents who learn that survival to advanced ages is common also revise downward their association between old age and dependency. We report the result because it was pre-specified, but we do not build on it: the survey does not elicit the beliefs about disability that would be needed to distinguish this interpretation from

Table D.2: Balancing Test

	Treatment			
Variable	Control	Financial	Survival	Both
male	0.42	0.40	0.40	0.40
age	57.33	57.53	57.62	57.86**
educ2	0.26	0.25	0.24	0.26
educ3	0.58	0.54	0.56	0.54*
anystocks	0.51	0.53	0.54	0.50
empbinary	0.70	0.70	0.67	0.67
incouple	0.61	0.60	0.61	0.62
poorhealth	0.19	0.20	0.20	0.19
howner	0.77	0.78	0.80*	0.79
lowcogn	0.29	0.32	0.31	0.32

Notes: Significance refers to differences relative to the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.3: Treatment effects on the subjective–actuarial survival gap (levels)

	survival gap (levels)		
	(1)	(2)	(3)
Survival	2.372***	2.406***	-1.118
	(0.749)	(0.744)	(0.721)
Financial	-0.475	-0.424	-0.846
	(0.838)	(0.831)	(0.828)
Both	1.197	1.207	-2.296***
	(0.782)	(0.778)	(0.791)
Survival × Below LT (Pop.)			9.534***
			(1.556)
Financial × Below LT (Pop.)			1.365
			(1.611)
Both × Below LT (Pop.)			9.534***
			(1.579)
Below LT (Pop.)			-18.200***
			(1.140)
Demographics	No	Yes	Yes
Obs	3394	3394	3378
Survival gap (mean)	-7.701		

Notes: Outcome is $m_{i,a} = p_{i,a}^{subj} - p_{i,a}^{lt}$, measured in probability units. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4: Belief updating, second target age (85)

	survival gap (levels)		discrepancy	
	(1)	(2)	(3)	(4)
Survival	0.443	-4.762***	-0.325***	-0.107**
	(1.009)	(1.130)	(0.048)	(0.047)
Financial	0.039	-0.080	-0.010	0.001
	(1.163)	(1.296)	(0.055)	(0.054)
Both	-1.689*	-6.054***	-0.269***	-0.087*
	(1.012)	(1.146)	(0.049)	(0.049)
Survival × Below LT (Pop.)		14.297***		-0.595***
		(2.005)		(0.107)
Financial × Below LT (Pop.)		0.852		-0.048
		(2.203)		(0.118)
Both × Below LT (Pop.)		12.007***		-0.506***
		(1.949)		(0.109)
Below LT (Pop.)		-22.219***		0.918***
		(1.560)		(0.084)
Demographics	Yes	Yes	Yes	Yes
Obs	3380	3359	3380	3359
Outcome (mean)	0.686		0.641	

Notes: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.5: Belief updating, target ages pooled

	survival gap (levels)		discrepancy	
	(1)	(2)	(3)	(4)
Survival	1.441*	-2.910***	-0.285***	-0.076**
	(0.822)	(0.696)	(0.044)	(0.031)
Financial	-0.180	-0.461	0.007	0.026
	(0.939)	(0.802)	(0.049)	(0.035)
Both	-0.218	-4.148***	-0.225***	-0.031
	(0.839)	(0.720)	(0.046)	(0.034)
Survival × Below LT (Pop.)		11.882***		-0.565***
		(1.299)		(0.075)
Financial × Below LT (Pop.)		1.124		-0.067
		(1.397)		(0.080)
Both × Below LT (Pop.)		10.756***		-0.532***
		(1.279)		(0.077)
Below LT (Pop.)		-20.197***		0.999***
		(0.987)		(0.057)
Demographics	Yes	Yes	Yes	Yes
Obs	6774	6737	6774	6737
Outcome (mean)	-3.516		0.686	

Notes: Both target ages pooled; standard errors clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.6: Discrepancy by cognitive level

	discrepancy			
	(1)	(2)	(3)	(4)
Survival	-0.244***	-0.245***	-0.275***	-0.246***
	(0.047)	(0.047)	(0.053)	(0.049)
Financial	0.024	0.023	0.007	0.052
	(0.052)	(0.052)	(0.060)	(0.056)
Both	-0.180***	-0.181***	-0.210***	-0.177***
	(0.050)	(0.050)	(0.057)	(0.052)
Survival × Low cog.			0.093	
			(0.108)	
Financial × Low cog.			0.044	
			(0.117)	
Both × Low cog.			0.081	
			(0.113)	
Low cog.			0.074	
			(0.086)	
Survival × Low cog.(alt)				0.013
				(0.149)
Financial × Low cog.(alt)				-0.209
				(0.154)
Both × Low cog.(alt)				-0.028
				(0.158)
Low cog.(alt)				0.132
				(0.115)
Demographics	No	Yes	Yes	Yes
Obs	3394	3394	3394	3394
Discrepancy (mean)	0.731			

Notes: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Cognitive score: PCA (financial literacy, numeracy, memory). *Lowcog.*: 1st tertile. The alternative Cognitive score is the sum of financial literacy (Big5), numeracy and memory scores. *Low cog. (alt)* is 1 if the cognitive score (alt) is in the first quintile.

Table D.7: Financial literacy, cognition and participation costs (full interaction)

	participation		risky share	
	(1)	(2)	(3)	(4)
Financial	0.027***	0.018**	0.097***	0.096***
	(0.010)	(0.009)	(0.019)	(0.019)
Financial × Low cog.	0.007	0.010	-0.023	-0.009
	(0.019)	(0.018)	(0.037)	(0.037)
Financial × Cost	0.038	0.053**	-0.010	-0.005
	(0.026)	(0.026)	(0.030)	(0.030)
Financial × Cost × Low cog.	0.060	0.051	0.054	0.024
	(0.049)	(0.049)	(0.055)	(0.056)
Low cog.	0.003	0.000	-0.009	-0.020
	(0.019)	(0.017)	(0.029)	(0.030)
Cost	-0.105***	-0.118***	-0.020	-0.027
	(0.021)	(0.021)	(0.022)	(0.022)
Cost × Low cog.	-0.043	-0.039	-0.047	-0.027
	(0.043)	(0.043)	(0.043)	(0.044)
Demographics	Yes	Yes	Yes	Yes
Z_i	No	Yes	No	Yes
Obs	1746	1682	1746	1682
Outcome (mean)	0.909	0.730	0.379	0.259

Notes: Estimates of equation (8) of the analysis plan, including the *Financial* × *Low cog.* × *Cost* interaction. Control and financial literacy arms only. Column (2) and (4) additionally control for post-treatment survival beliefs (Z_i is the average deviation between subjective and benchmark survival probabilities across the two target ages) Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.8: Beliefs and behavior: alternative measures of survival beliefs

	(1) Avg. deviation	(2) Avg. inaccuracy	(3) Deviation (target 1)	(4) Inaccuracy (target 1)
Panel A. Reduced form: effect of survival literacy				
Participation	0.029**	0.029**	0.029**	0.029**
	(0.012)	(0.012)	(0.012)	(0.012)
Risky share	0.045***	0.045***	0.045***	0.045***
	(0.013)	(0.013)	(0.013)	(0.013)
Panel B. First stage: dependent variable in the column header				
Survival literacy	1.398*	-0.283***	2.442***	-0.248***
	(0.821)	(0.044)	(0.744)	(0.046)
F-statistic	2.90	41.34	10.77	28.56
Panel C. IV: risky asset participation				
Survival beliefs Z_i	0.021	-0.104**	0.012*	-0.118**
	(0.015)	(0.046)	(0.006)	(0.054)
Panel D. IV: share of wealth in risky assets				
Survival beliefs Z_i	0.032	-0.158***	0.018**	-0.179***
	(0.021)	(0.053)	(0.008)	(0.064)
Observations	1705	1705	1705	1705

Notes: Panel A reports the reduced form, i.e. the effect of assignment to the survival literacy treatment on risky asset participation and on the risky share. The reduced form does not depend on how post-treatment survival beliefs are measured and is therefore common to all columns of Panel C. Panel B reports first-stage coefficients and F-statistics for four definitions of the endogenous variable Z_i: (1) the average deviation between subjective and life-table probabilities across the two target ages (the definition in the analysis plan); (2) the average standardized inaccuracy index across target ages (the pre-specified robustness check); (3) the deviation at the first target age; (4) the standardized inaccuracy index at the first target age (the specification reported in Table 7). Panel C reports the corresponding second-stage estimates. Because the second-stage coefficient equals the reduced form divided by the first stage, the four columns differ only in the units in which the effect of beliefs is expressed, not in sign or in the underlying identifying variation. Where the first-stage F-statistic falls below conventional thresholds, we report Anderson–Rubin confidence sets, which remain valid under weak identification. Control and survival literacy arms only. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.9: Portfolio choices in the 70-year-old vignette

	participation		risky share	
	(1)	(2)	(3)	(4)
Financial	0.011	-0.014	-0.001	0.014
	(0.021)	(0.027)	(0.015)	(0.020)
Financial × Cost		0.045		-0.029
		(0.042)		(0.029)
Cost		-0.154***		0.004
		(0.029)		(0.021)
Demographics	Yes	Yes	Yes	Yes
Obs	1746	1746	1746	1746
Part. (mean)	0.730		0.259	

Notes: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.10: Survival literacy and subjective long-term care risk

	LTC risk	
	(1)	(2)
Survival	-2.921**	-2.902**
	(1.244)	(1.462)
Survival × Low cog.		-0.098
		(2.783)
Low cog.		0.344
		(2.006)
Demographics	Yes	Yes
Obs	1511	1511
Outcome (mean)	53	

Notes: Outcome is the self-reported probability (0–100) of ever needing professional care on a continuous basis, in a nursing home or at home, not provided by family or friends. Estimates of equation (12) of the analysis plan. Control and survival literacy arms only. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.11: Robustness to pre-specified data cleaning and sample restrictions

	(1) Full sample	(2) Duration trimmed	(3) Monotonic	(4) Non-focal	(5) All restrictions
Panel A. Survival belief discrepancy					
Survival literacy	-0.248***	-0.244***	-0.288***	-0.259***	-0.274***
	(0.046)	(0.047)	(0.048)	(0.047)	(0.049)
Observations	3394	3343	3126	3320	3111
Panel B. Risky asset participation					
Financial literacy	0.058***	0.057***	0.056***	0.055***	0.056***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
Observations	1746	1727	1525	1625	1603
Panel C. Share of wealth in risky assets					
Financial literacy	0.093***	0.094***	0.094***	0.095***	0.091***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Observations	1746	1727	1525	1625	1603
Panel D. IV: survival beliefs and risky share					
discrepancy	-0.179***	-0.168***	-0.164***	-0.174***	-0.154***
	(0.064)	(0.064)	(0.056)	(0.061)	(0.058)
F-statistic	28.56	26.98	35.15	30.92	31.33
Observations	1705	1673	1575	1664	1563

Notes: Each column re-estimates the baseline specification for the three primary outcomes applying, in turn: (i) trimming of the survey duration distribution at the 1st and 99th percentiles; (ii) exclusion of respondents whose reported survival probability to the earlier target age is not strictly greater than the probability of surviving to age 85; (iii) exclusion of respondents reporting 0, 50 or 100 at both target ages; (iv) all restrictions jointly. Restrictions are applied symmetrically across arms. Panel A is column (2) of Table 3. Panel B is column (2) of Table 4. Panel C if column (2) of Table 5. Panel D is column (3) of Table 7. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.12: Multiple hypothesis testing adjustment, primary outcomes

	Coefficient (s.e.)	Unadjusted p-value	Romano–Wolf p-value
Survival lit. → belief discrepancy	-0.245	0.000	0.000
	(0.047)		
Financial lit. → belief discrepancy	0.023	0.661	0.652
	(0.052)		
Financial lit. → participation	0.060	0.000	0.000
	(0.011)		
Financial lit. → risky share	0.092	0.000	0.000
	(0.013)		
Survival lit. → participation	0.029	0.018	0.050
	(0.012)		
Survival lit. → risky share	0.045	0.001	0.004
	(0.013)		
Survival lit. → nursing home risk	-2.921	0.019	0.050
	(1.244)		

Notes: Unadjusted p-values and Romano–Wolf stepdown p-values for the main effects of the two treatments on the pre-registered outcomes. The family comprises seven hypotheses, computed jointly with 2,000 bootstrap replications. Rows 1 and 2 correspond to column (2) of Table 3; row 3 to column (2) of Table 4; row 4 to column (2) of Table 5; rows 5 and 6 to Panel A of Table D.8; row 7 to column (1) of Table D.10.

E Life-Cycle Model

E.1 Unit of Analysis

The model is a unitary household model in which the decision maker is the household's financial respondent. Three features of the data motivate this choice. First, ELSA records assets at the level of the benefit unit — a single adult or a couple, together with any dependent children — and not at the level of the individual, so portfolio outcomes are only observed for the unit as a whole. Second, subjective survival expectations are elicited from individuals, and we assign to the household the expectations of the financial respondent, i.e. of the person who completes the Income and Assets module and is therefore the member most plausibly responsible for the unit's saving and investment decisions. Third, the UK tax unit is the individual (Appendix E.3), so modelling labour income at the individual level is consistent with the tax function we impose.

Two conventions follow. To make benefit units of different size comparable, and to render unit-level wealth commensurate with the individual-level earnings process, we express wealth in equivalised terms; the wealth measure and the equivalence scale are described in Appendix A.2. Throughout the paper we use "household" to refer to the ELSA benefit unit.

Because the problem terminates with the death of the financial respondent while the unit's wealth does not, the bequest function $b(w)$ is interpreted broadly, as capturing the continuation value accruing to a surviving partner as well as to other heirs. The model therefore abstracts from second-earner income, from within-couple risk sharing, and from the mortality risk of the partner.

E.2 Initial conditions

Table E.1 reports descriptive statistics of the sample of 672 individuals born between 1956 and 1964 used to intialize model simulation.

Table E.1: Initial conditions, by cognitive skills.

	All	Low cognition	High cognition
Initial wealth (£ thousand, mean) – w_0	44.6	21.1	53.8
Participants (fraction) – I_0	0.492	0.324	0.557
Male (fraction)	0.525	0.479	0.542
Obs.	671	188	483

E.3 Tax and Transfer Function

The model incorporates a parsimonious representation of the UK tax and transfer system, calibrated to the main tax parameters in place in 2011. The tax unit is the individual. The tax base includes earnings, pensions, and investment income, net of the applicable personal tax-free allowance. The main tax allowances used in the model are reported in Table E.3.

Earned and pension income is subject to a three-band income tax schedule. Investment income is taxed separately using a reduced-form schedule in which the applicable rate depends on total taxable income, including both earned or pension income and investment income. The corresponding tax rates and thresholds are reported in Table E.2.

For individuals below State Pension Age (SPA), the model also includes National Insurance contributions. The annual Primary Threshold is set at £7,176 and the Upper Earnings Limit at £42,484. The contribution rates are 12% up to the Upper Earnings Limit and 2% above it. National Insurance contributions are not levied after SPA.

Table E.2: Income tax schedule

Band	Rate on earned and pension income	Rate on investment income
£0–£2,560	0.20	0.10
£2,561–£35,000	0.20	0.20
£35,001–£150,000	0.40	0.40
Above £150,000	0.50	0.50

The standard personal allowance is £7,475. After SPA, the model applies an age-related allowance of £9,940 during the first ten years and £10,090 thereafter. When total income exceeds £24,000, the age-related allowance is reduced with income, subject to a lower bound equal to the standard personal allowance. Married couples' allowances and other tax credits are not modelled separately.

Table E.3: Personal tax allowances

Allowance	Amount per year
Standard personal allowance	£7,475
Age-related allowance: first ten years after SPA	£9,940, reduced when income exceeds £24,000, but not below £7,475
Age-related allowance: subsequent years	£10,090, reduced when income exceeds £24,000, but not below £7,475

The transfer system is represented in reduced form through a minimum-consumption floor. When household resources, consisting of available assets and after-tax income, are below the relevant floor, the government provides a transfer covering the shortfall. Transfers are therefore given by

$$Tr_t = \max\left\{0,\, \bar{c}(h_t) - \left(a_t + y_t^{net}\right)\right\}, \tag{E.1}$$

where a_t denotes available assets, y_t^{net} is income net of income tax and National Insurance contributions, and $\bar{c}(h_t)$ is the consumption floor associated with health state h_t. The annual consumption floor is set at £1,500 in the baseline health state and at £20,000 in the long-term-care state.

E.4 Labor Income Process

We estimate the labor income process using the longitudinal component of ELSA. The estimation sample includes financial respondents — the same individuals whose subjective survival curves enter the household problem — aged 50–69 with positive employment income. Weekly employment income is annualized and expressed in 2011 prices. To limit the influence of outliers, we trim the bottom and top percentiles of the log-income distribution. The entire procedure is carried out separately for individuals with high and low cognitive skills.

For each cognitive group $g \in \{H, L\}$, the earnings process has a deterministic component, $\omega_{e,g}(age_{it}, Male_i)$, specified as a third-order polynomial in age and a gender indicator. In estimating the deterministic component, we additionally control for school-leaving age, year of birth, and the unemployment rate. In the model, these additional controls are evaluated

at fixed reference values and absorbed into the cognitive-group-specific intercept. Thus,

$$\log e_{it} = \omega_{e,g}(age_{it}, Male_i) + \psi_{it}, \tag{E.2}$$
$$\omega_{e,g}(age_{it}, Male_i) = \alpha_g + \beta_{1g} age_{it} + \beta_{2g} age_{it}^2 + \beta_{3g} age_{it}^3 + \beta_{mg} Male_i.$$

The composite error term ψ_{it} is the sum of a persistent component, ϑ_{it}, and a transitory component, υ_{it}. Persistence in earnings is captured by an AR(1) process:

$$\begin{aligned} \psi_{it} &= \vartheta_{it} + \upsilon_{it}, \\ \vartheta_{i,t+1} &= \rho_{e,g}\vartheta_{it} + \nu^e_{i,t+1}, \qquad \nu^e_{it} \sim N(0, \sigma^2_{\nu^e,g}), \\ \upsilon_{it} &\sim N(0, \sigma^2_{\upsilon,g}), \qquad \vartheta_{i0} \sim N(0, \sigma^2_{0,g}). \end{aligned}$$

We assume that the persistent component ϑ_{it} is observed by the individual when making consumption and portfolio decisions, while future innovations are uncertain. The transitory component υ_{it} is treated as measurement error and does not constitute a state variable in the dynamic model.

For each cognitive group, the parameters of the stochastic process are estimated by GMM using individuals observed in at least two ELSA waves. Identification is based on the variances and autocovariances of the earnings residuals across survey waves. The moment conditions account for the approximately biennial frequency of ELSA interviews, and standard errors are clustered at the individual level. Table E.4 reports the resulting estimates.

Table E.4: Labor income process parameter estimates

	High cognition	Low cognition
Deterministic component		
α_g	-16.173	35.693
β_{1g}	1.212	-1.406
β_{2g}	-0.018	0.026
β_{3g}	8.41×10^{-5}	-1.57×10^{-4}
β_{mg}	0.457	0.551
Stochastic component		
$\rho_{e,g}$	0.904	0.956
	(0.039)	(0.053)
$\sigma^2_{\nu^e,g}$	0.060	0.038
	(0.028)	(0.029)
$\sigma^2_{\upsilon,g}$	0.290	0.305
	(0.041)	(0.042)
$\sigma^2_{0,g}$	0.285	0.184
	(0.054)	(0.045)

For the numerical solution of the model, the persistent component is approximated separately for each cognitive group by an age-dependent Markov chain with five states. The state values and transition probabilities are constructed using the corresponding estimates of $\rho_{e,g}$, $\sigma^2_{\nu^e,g}$, and $\sigma^2_{0,g}$. Labor income is received until State Pension Age, after which households receive pension income.

E.5 MSM Structural Estimation

The MSM objective function is the following:

$$\arg\min_{\Theta} \left(\hat{m} - m(\Theta)\right)' \left(\hat{m} - m(\Theta)\right),$$

where $\hat{m}$ denotes the vector of empirical moments and $m(\Theta)$ the corresponding model-implied moments. The weighting matrix is the identity matrix.

With an identity weighting matrix, $W = I$, the asymptotic covariance matrix of the MSM

estimator is given by the sandwich formula

$$\widehat{\mathrm{Var}}(\hat{\theta}) = (G'G)^{-1}G'\hat{S}G(G'G)^{-1},$$

where

$$G = \left.\frac{\partial g(\theta)}{\partial \theta'}\right|_{\theta=\hat{\theta}}$$

is the Jacobian of the moment conditions and $\widehat{S}$ is the estimated covariance matrix of the empirical moments.

The standard error of parameter $\hat{\theta}_j$ is

$$\mathrm{SE}(\hat{\theta}_j) = \sqrt{\left[\widehat{\mathrm{Var}}(\hat{\theta})\right]_{jj}}.$$

F Survey-Informed Counterfactuals

Figure F.1: Entry by Quartiles of Initial Wealth

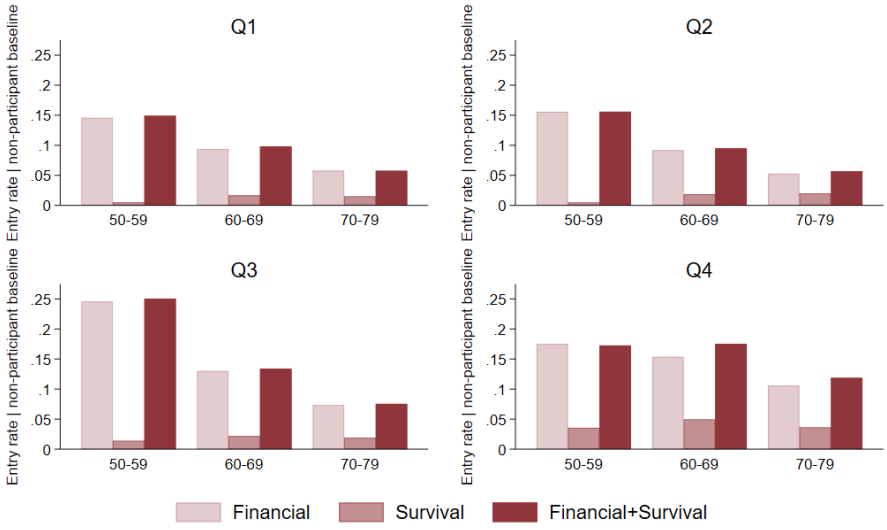
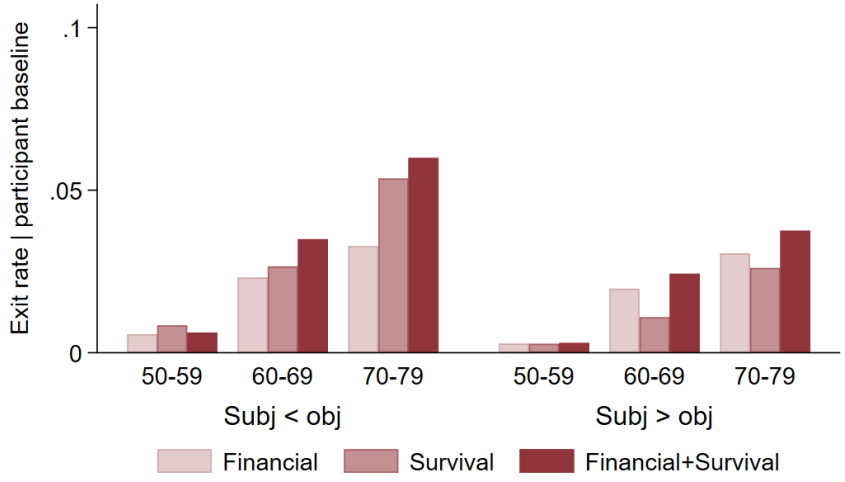


Figure F.2: Exit from financial markets by survival beliefs and experiment



G Welfare Analysis

G.1 Statistical Value of Life

The Statistical Value of Life (SVL) represents the monetary value associated with a marginal reduction in mortality risk that would prevent one statistical death. It can be interpreted as the marginal rate of substitution between wealth and survival probability.

In our model, the SVL is defined as:

$$\frac{dV_t/d\pi}{dV_t/dw}$$

where π denotes the survival probability and w denotes wealth.

The derivative of the value function with respect to survival probability is given by:

$$\frac{dV_t}{d\pi} = \beta \left(E_t V_{t+1} - \frac{\phi_B (w_{t+1} + \phi_K)^{1-\gamma}}{1-\gamma} \right),$$

which captures the discounted difference between the expected continuation value if the individual survives and the utility from leaving a bequest in the event of death.

The derivative of the value function with respect to wealth is given by:

$$\frac{dV_t}{dw} = (1+r) c_t^{-\gamma},$$

where $c_t^{-\gamma}$ is the marginal utility of consumption.

Remark. Since our model features two assets and stochastic returns on the risky asset, we approximate the marginal value of wealth using the deterministic risk-free return r. This simplification allows us to avoid carrying expectations over stochastic returns in the envelope condition.

Combining the two expressions, the SVL can be written as:

$$SVL_t = \frac{\beta}{1+r}\left(E_t V_{t+1} - \frac{\phi_B(w_{t+1}+\phi_K)^{1-\gamma}}{1-\gamma}\right)c_t^{\gamma}.$$

The SVL is state-dependent and varies across individuals depending on their consumption, wealth, and continuation value, which in turn reflect heterogeneity in income, portfolio choices, survival risk, and health status (long-term care risk).

For a given value of the utility shifter $\bar{b}$, we solve and simulate the model and compute the average SVL as a weighted average across the four cognitive skill–gender types. The weights are given by the relative numerosity of each type in the simulated population.

In the calibration, we target an empirical value of the SVL equal to £900,000. Importantly, this target is imposed over working ages, where empirical estimates of the value of life are most reliable and comparable to the model environment.

We then choose $\bar{b}$ such that the model-implied average SVL over working ages matches this target. Once identified, the utility shifter $\bar{b}$ is kept constant over the life cycle, allowing the model to generate age- and state-dependent variation in the SVL through changes in consumption, wealth, survival risk, and continuation values.

G.2 Consumption Equivalent Variation with Survival Risk

In this section we derive a generalized Consumption Equivalent Variation (CEV) measure that allows for differences in survival probabilities between the baseline and the counterfactual scenarios.

Let π_j^i denote the conditional probability of being alive at age j conditional on being alive at age $j-1$ in scenario $i \in \{1,2\}$. Let $\Pi^i(j-1,0)$ denote the probability of being alive at age $j-1$ conditional on being alive at the initial age 0. Hence,

$$\Pi^i(j,0) = \Pi^i(j-1,0)\pi_j^i.$$

In the presence of LTC risk, conditional survival probabilities depend on the LTC state. Therefore, $\Pi^i(j-1,0)$ should be interpreted as the unconditional probability of being alive at age $j-1$, obtained by integrating over the two possible LTC states.

The generalized CEV, μ, is defined as the uniform proportional change in consumption and bequeathed wealth along the counterfactual allocation (scenario 2) that makes the individual indifferent between the two scenarios:

$$E_0\left[\sum_{j=1}^{T+1}\beta^j\Pi^2(j-1,0)\left(\pi_j^2\left(\frac{((1-\mu)c_j^2)^{1-\gamma}}{1-\gamma}+\bar{b}\right)+(1-\pi_j^2)b\Big((1-\mu)w_j^2\Big)\right)\right]$$
$$=E_0\left[\sum_{j=1}^{T+1}\beta^j\Pi^1(j-1,0)\left(\pi_j^1\left(\frac{(c_j^1)^{1-\gamma}}{1-\gamma}+\bar{b}\right)+(1-\pi_j^1)b(w_j^1)\right)\right]. \tag{G.1}$$

Using the homotheticity of preferences,

$$\frac{((1-\mu)c)^{1-\gamma}}{1-\gamma}=(1-\mu)^{1-\gamma}\frac{c^{1-\gamma}}{1-\gamma},\qquad b\Big((1-\mu)w\Big)=(1-\mu)^{1-\gamma}b(w),$$

we can rewrite the indifference condition as

$$(1-\mu)^{1-\gamma}E_0\left[\sum_{j=1}^{T+1}\beta^j\Pi^2(j-1,0)\left(\pi_j^2\frac{(c_j^2)^{1-\gamma}}{1-\gamma}+(1-\pi_j^2)b(w_j^2)\right)\right]$$
$$+\bar{b}\,E_0\left[\sum_{j=1}^{T+1}\beta^j\Pi^2(j-1,0)\pi_j^2\right]$$
$$=E_0\left[\sum_{j=1}^{T+1}\beta^j\Pi^1(j-1,0)\left(\pi_j^1\frac{(c_j^1)^{1-\gamma}}{1-\gamma}+(1-\pi_j^1)b(w_j^1)\right)\right]+\bar{b}\,E_0\left[\sum_{j=1}^{T+1}\beta^j\Pi^1(j-1,0)\pi_j^1\right]. \tag{G.2}$$

Define

$$E_0\widetilde{W}^i\equiv E_0\left[\sum_{j=1}^{T+1}\beta^j\Pi^i(j-1,0)\left(\pi_j^i\frac{(c_j^i)^{1-\gamma}}{1-\gamma}+(1-\pi_j^i)b(w_j^i)\right)\right],$$

and

$$\widetilde{\Pi}^i\equiv E_0\left[\sum_{j=1}^{T+1}\beta^j\Pi^i(j-1,0)\pi_j^i\right].$$

Note that $\Pi^i(j-1,0)\pi_j^i = \Pi^i(j,0)$, so that $\widetilde{\Pi}^i$ can equivalently be written as

$$\widetilde{\Pi}^i = E_0\left[\sum_{j=1}^{T+1}\beta^j \Pi^i(j,0)\right].$$

Then,

$$(1-\mu)^{1-\gamma}E_0\widetilde{W}^2 = E_0\widetilde{W}^1 + \bar{b}\left(\widetilde{\Pi}^1 - \widetilde{\Pi}^2\right),$$

and therefore the generalized CEV is

$$\mu = 1 - \left[\frac{E_0\widetilde{W}^1 + \bar{b}\left(\widetilde{\Pi}^1 - \widetilde{\Pi}^2\right)}{E_0\widetilde{W}^2}\right]^{\frac{1}{1-\gamma}}.$$

When survival probabilities are identical across scenarios, $\pi_j^1 = \pi_j^2$ for all j, then $\widetilde{\Pi}^1 = \widetilde{\Pi}^2$ and the term involving $\bar{b}$ cancels out, so the expression reduces to the standard CEV formula.

Computation of survival probabilities. The unconditional survival probability is constructed from conditional survival probabilities. Let π_j^i denote the probability of being alive at age j conditional on being alive at age $j-1$ in scenario $i \in \{1,2\}$. Then, in the absence of LTC risk, the probability of being alive at age j conditional on being alive at the initial age is given by

$$\Pi^i(j,0) = \prod_{k=1}^{j}\pi_k^i.$$

In the presence of LTC risk, survival probabilities depend on the health state. Let $P_t^{H,i}$ and $P_t^{L,i}$ denote the probabilities of being alive and not in LTC (healthy), and alive and in LTC, respectively, at age t. The unconditional survival probability is then given by

$$\Pi_t^i = P_t^{H,i} + P_t^{L,i}.$$

These probabilities evolve recursively according to the transition probabilities implied by the model. In particular, before the onset of LTC risk, all individuals are in the healthy state and Π_t^i coincides with the product of conditional survival probabilities. After the age at which LTC risk arises, the evolution of $P_t^{H,i}$ and $P_t^{L,i}$ reflects both survival and transitions into the LTC state, which is absorbing and characterized by lower survival probabilities.

H Alternative Model Specifications

H.1 Bequest Motives and the Survival Channel: Derivation

Equation (6) follows from combining the first-order condition for consumption with the envelope condition $V'_{t+1} = c_{t+1}^{-\gamma}$, abstracting from participation costs and constraints, where R_{t+1} is the gross portfolio return. Differentiating the right-hand side of (6) with respect to π^s_{t+1} gives $\mathbb{E}_t\Big[R_{t+1}\Big(c_{t+1}^{-\gamma} - \phi_B(w_{t+1} + \phi_K)^{-\gamma}\Big)\Big]$, which is positive if and only if condition (7) holds. The expressions for *mpb* and $x^\star$ used in Section 4.1 are obtained from the first-order condition of a household that starts period t with wealth x and dies next period with probability one.

H.2 Additional results

This appendix reports the remaining difference-in-differences statistics defined in equation (5) for the no-bequest and no-long-term-care economies.

Figure H.1: Role of Bequest Motives: Wealth (IHS)

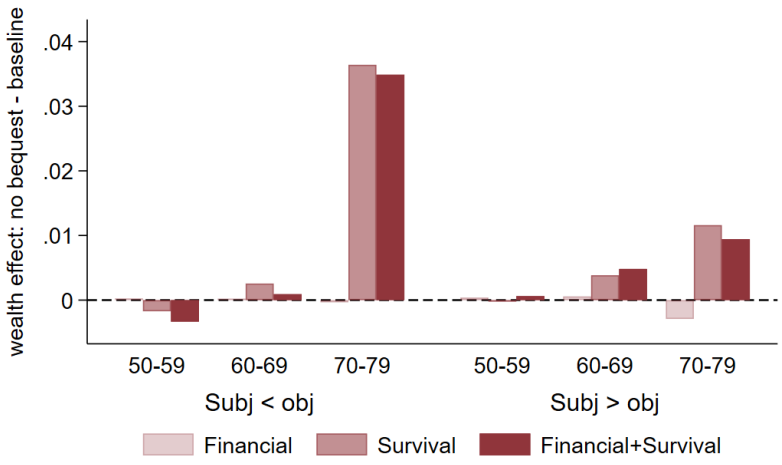


Figure H.2: Role of Bequest Motives: Market Exit

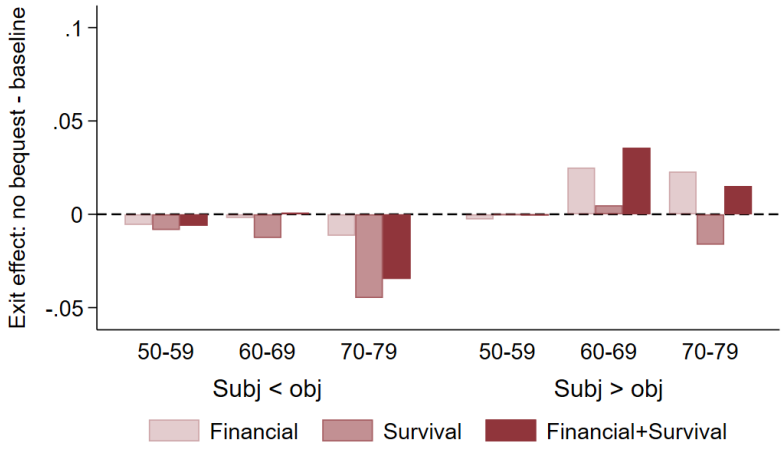


Figure H.3: Role of Bequest Motives: Risky Portfolio Share

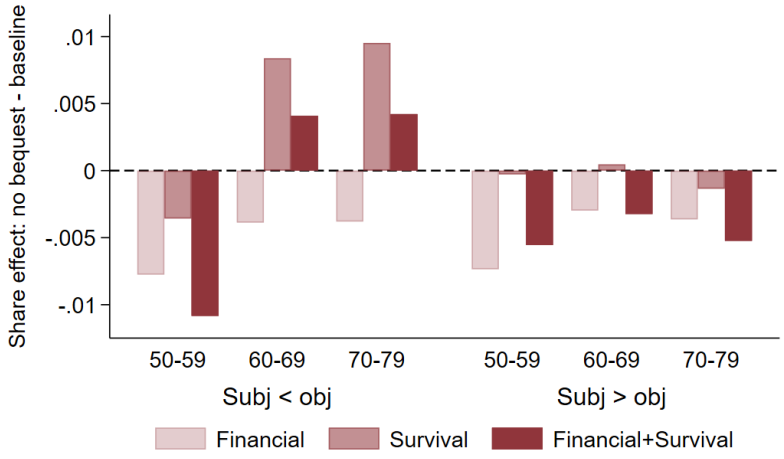


Figure H.4: Role of Long-Term-Care Risk: Wealth

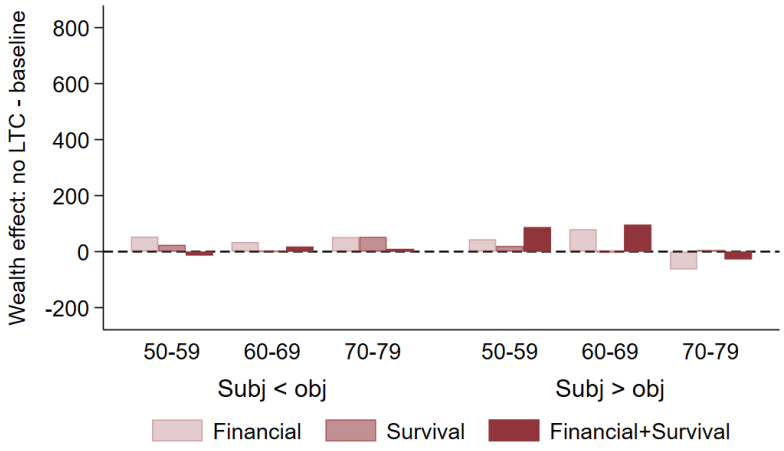


Figure H.5: Role of Long-Term-Care Risk: Wealth (IHS)

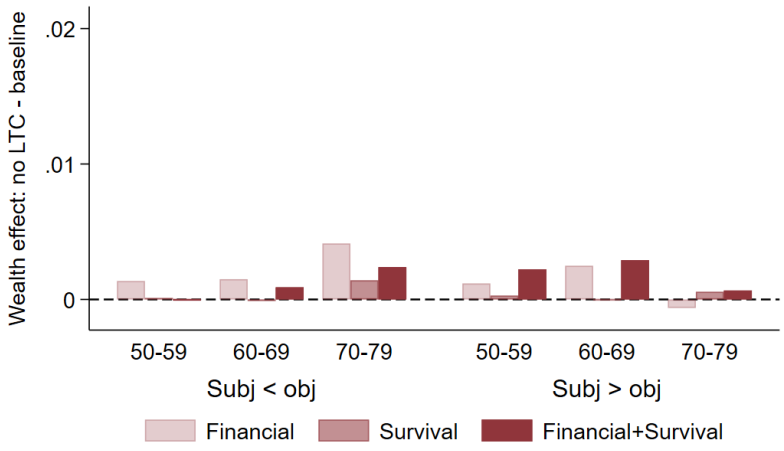


Figure H.6: Role of Long-Term-Care Risk: Market Exit

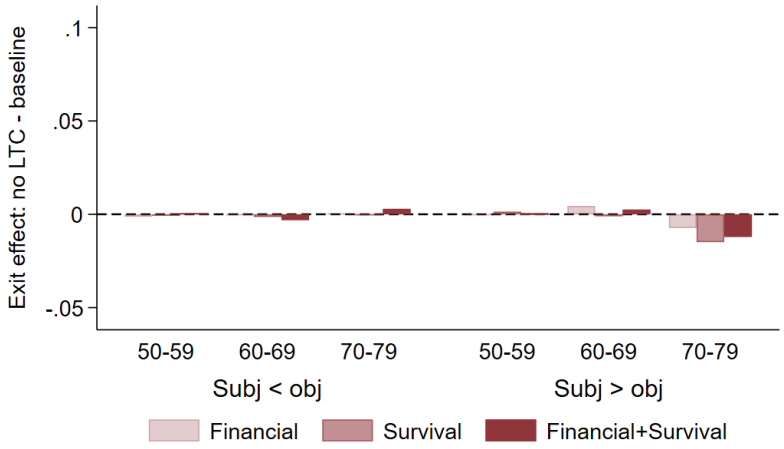


Figure H.7: Role of Long-Term-Care Risk: Risky Portfolio Share

