Beliefs and Preferences during the Lifecycle

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Netspar

Industry paper 2025-17

Colophon

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Netspar Industry Paper 2025-17, August 2025

Acknowledgements
We wish to thank Joost Leenen, Marike Knoef, and seminar participants at the Research in Behavioral Finance Conference and the Netspar After-lunch Webinar for useful comments. We gratefully acknowledge financial support from Netspar.

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Summary

Life-cycle decisions ideally align with the individual characteristics of pension plan members. However, our understanding of people's preferences and beliefs in decision-making across the life cycle remains limited. To address this gap, we conducted a survey among a representative sample of the Dutch population and quantified preferences and beliefs using multiple elicitation methods across multiple life-cycle and pension domains. We elicit individual risk, time, and loss preferences, as well as probability weighting, for varying amounts, across five domains: pension, investment, work, health, and lotteries. We collect individual beliefs on a range of future outcomes, including expected final salary, retirement age, age of death, bequest motives, returns on invested pension, pension income, inflation, and stock market returns.

The following highlights the takeaways from our paper:

- *Preferences vary by domain* — Risk preferences (how much risk someone is willing to take) and time preferences (how patient someone is) vary across domains, taking into account socio-demographic differences between individuals. Regarding financial decisions, Dutch individuals are most risk-averse in the pension domain (pension income) and most patient in the health domain (healthcare costs). While individuals are loss-averse and distort probabilities, these constructs do not vary significantly across domains.
- *Limited sensitivity to stakes* — Preferences are generally stable across different monetary magnitudes, with key exceptions: larger stakes lead to higher risk aversion in lotteries and more patience in pension and investment contexts.
- *Widespread belief heterogeneity* — Individuals hold diverse beliefs about future outcomes, although median beliefs align closely with objective data on income, retirement, inflation, and returns.
- *Interrelated preferences and beliefs* — Risk aversion is positively correlated with impatience and loss aversion, and negatively with income expectations, revealing belief–preference patterns potentially relevant for life-cycle decisions.
- *Demographic differences matter* — Preferences and beliefs show substantial heterogeneity: risk aversion varies with age, time preferences vary with income, loss aversion varies with education, and probability weighting varies with both age and education.

Policy relevance — Given the heterogeneity in preferences and beliefs among pension members, a one-size-fits-all pension plan is unlikely to serve everyone optimally, such that (semi-)personalized pension products can potentially better align with individual needs. The heterogeneity in beliefs, and sometimes misaligned expectations, such as those

regarding retirement income or investment return, highlight the need for clear and tailored communication that inform pension plan members to make better decisions; increasing (pension) literacy may help as well. Furthermore, the domain dependence of risk and time preferences indicates that default (investment) options should not be based on preferences elicited from other contexts, such as the standard academic lottery domain. Finally, demographic patterns, such as younger individuals exhibiting lower risk aversion, point to the value of developing targeted pension plans that are tailored to age, income, and other relevant factors, in support of more effective pension planning and decision-making across diverse groups.

Samenvatting

Levensloopbeleggingen komen idealiter overeen met de karakteristieken van individuele pensioenfondsdeelnemers. Maar tot op heden ontbreekt een gedetailleerde analyse van de voorkeuren en verwachtingen van individuen met betrekking tot pensioen- en levensloopkeuzes. Wij dragen bij aan deze literatuur door het uitvoeren van een enquête onder een representatieve groep Nederlanders, van wie wij de voorkeuren en verwachtingen meten door middel van verschillende methoden over verschillende domeinen die relevant zijn voor levensloopkeuzes. Wij meten risico en tijdsvoorkeuren, verliesaversie en kansweging voor verschillende bedragen over vijf domeinen: pensioen, beleggingen, werk, gezondheid en loterijen (gebruikelijke standaard in de wetenschap). De verwachtingen die wij uitvragen, gaan over verschillende toekomstige uitkomsten als laatst verdiende inkomen, pensioenleeftijd, levensverwachting, erfenismotief, rendement op pensioenvermogen, pensioeninkomen, inflatie en rendement op de beurs.

De volgende resultaten zijn de belangrijkste uitkomsten van ons onderzoek:

- *Voorkeuren variëren per domein* — Risicovoorkeuren (hoeveel risico iemand wil nemen) en tijdsvoorkeuren (hoe geduldig iemand is) variëren tussen de domeinen, waarbij rekening wordt gehouden met verschillen in sociaal-demografische gegevens tussen individuen. Rondom financiële keuzes, zijn Nederlanders het meest risicoavers in het pensioendomein (pensioeninkomen) en het meest geduldig in het gezondheidsdomein (tegemoetkoming zorgkosten). Hoewel individuen verliesavers zijn en kansen wegen, varieert de omvang hiervan niet per domein.
- *Beperkt effect van grootte van de bedragen* — Voorkeuren zijn over het algemeen onafhankelijk van de grootte van de bedragen, met enkele uitzonderingen: grotere bedragen leiden tot hogere risicoaversie bij loterijen en meer geduld bij het pensioen- en investeringsdomein.
- *Grote heterogeniteit bij verwachtingen* — Percepties over toekomstige uitkomsten zijn sterk heterogeen, maar de mediane percepties sluiten vaak goed aan bij objectieve waarden van laatst verdiende inkomen, pensioeninkomen, inflatie en rendementen.
- *Correlaties tussen voorkeuren en verwachtingen* — Risicoaversie is positief gecorreleerd met ongeduldigheid en verliesaversie, en negatief met inkomensverwachtingen. Dit toont aan dat er correlaties zijn tussen voorkeuren en verwachtingen, mogelijk van belang voor levensloop keuzes.
- *Demografische verschillen zijn van belang* — Voorkeuren en verwachtingen zijn heterogeen: risicoaversie varieert met leeftijd, tijdsvoorkeuren variëren met inkomen, verliesaversie met opleidingsniveau en kansenweging met zowel leeftijd als opleidingsniveau.

Beleidsimplicaties — Gegeven de heterogeniteit in voorkeuren en verwachtingen onder pensioendeelnemers, is het onwaarschijnlijk dat één standaard pensioenproduct voor iedereen optimaal is. (Semi)gepersonaliseerde pensioenproducten en maatwerk kunnen daarom helpen om beter aan te sluiten bij individuele behoeftes. De heterogeniteit in verwachtingen (die soms irreëel zijn) laat zien dat er potentieel is voor betere pensioencommunicatie, zodat deelnemers betere keuzes kunnen maken; (pensioen) geletterdheid verhogen zou ook kunnen helpen. Bovendien laat de domeinafhankelijkheid zien dat bij het uitvragen van risico- en tijdsvoorkeuren hiervoor de juiste context dient te worden gebruikt en niet simpelweg de loterijencontext die standaard is in academische literatuur. Tot slot wijzen demografische patronen, bijvoorbeeld dat jongeren risicotoleranter zijn, op de waarde van het ontwikkelen van gepersonaliseerde pensioenproducten die zijn afgestemd op leeftijd, inkomen en andere relevante factoren. Dit kan bijdragen aan effectievere pensioenplanning- en keuzes.

1. Introduction

Pension capital is a major component of savings for many individuals worldwide.[1] The world-wide shift from defined benefit (DB) to defined contribution (DC) pension plans challenges pension plan members, as they have been given greater responsibility to manage their pensions, such that it best suits their situation. Optimal investments in the life cycle depend crucially on preferences and beliefs. Therefore, to determine what is optimal in terms of personalized investment advice, it is important to understand preferences, beliefs, and their interactions at the individual level. For example, in The Netherlands, elicitation of individual risk preferences plays an important role in life-cycle planning and pension provision. Thus far, much of the Dutch pension industry has focused on risk preference elicitation. Ideally, life-cycle planning is not only optimized over risk preferences, but also considers other individual characteristics, such as time preferences, loss aversion, and beliefs.[2] However, we currently lack a holistic overview of the preferences and beliefs of individuals across multiple components of the life cycle. We fill this gap by measuring multiple types of preferences and beliefs within a representative sample of the Dutch population. Via the LISS panel in The Netherlands, we field a survey that measures four types of preferences, across multiple life-cycle domains, and eight types of beliefs. As to preferences, we elicit risk preferences, time preference, loss aversion, and probability weighting per individual. Since life-cycle planning covers multiple domains, we measure each of these preferences in five domains: the pension domain, the investment domain, the work domain, the health domain, and the lottery domain. The fifth and last domain does not feature prominently in life-cycle planning, but is typically used in the literature (Wakker and Deneffe, 1996; Holt and Laury, 2002; Andersen et al., 2008; G¨achter et al., 2022), so we use it as a benchmark. Additionally, we measure preferences using small domain-independent amounts and larger domain-dependent amounts. Regarding beliefs, we elicit individual distributions of expectations on last salary, retirement age, age of death, bequest motive, return on invested pension, pension income, inflation, and stock returns.

1 OECD (2023), Pensions at a Glance 2023: OECD and G20 Indicators, OECD Publishing, Paris, https: //doi.org/10.1787/678055dd-en.

2 It is difficult to determine what is optimal. One could potentially rely on a classic distinction in decision-making theory: normative versus descriptive approaches. Normative decision theory focuses on how individuals should make decisions if they were fully rational. In this view, optimality is defined by strict rationality, which often leads to a paternalistic approach—where policymakers intervene to guide individuals toward the "right" decisions. Descriptive decision theory, on the other hand, examines how people actually behave, including patterns such as loss aversion, present bias, and belief-driven decisions. This approach takes real-world behavior seriously, even when it deviates from strict rationality. If you believe that rational behavior defines what is best, then a paternalistic approach makes sense. But if you believe that people's actual preferences and beliefs reflect what truly matters, then policy should respect and work with those choices, rather than override them.

Although much research has been done to elicit each of these preferences and beliefs in isolation, surprisingly little work has been done on a holistic measurement of preferences and beliefs at the individual level across multiple life-cycle domains. A holistic overview of preferences and beliefs at the individual level is important since life-cycle planning is a multifaceted issue. Life-cycle planning typically concerns risky decision-making over long horizons and calls for not only a measurement of risk preferences but also of time preferences.[3] Additionally, alternative explanations for risk preferences are loss aversion and probability weighting (O'Donoghue and Somerville, 2018), so studying the relations between these constructs is important. Given the pivotal role of risk preference elicitation in the Dutch pension industry, we want to understand the relationships between risk preferences and time preferences, loss aversion, and probability weighting.

Usually, the amounts to decide upon are large in a pension context, especially compared to the literature that typically works with smaller (incentivized) amounts in a lottery context with populations of students. Holt and Laury (2002) and Thaler (1981) show that the amounts at stake correlate with measured risk and time preferences such that investigating the influence of size effects on loss aversion and probability weighting also becomes relevant. O'Donoghue and Somerville (2018) and Van Rooij et al. (2007) find that risk preferences are domain-dependent and highest in the pension domain. However, little is known about the domain dependence of time preferences, loss aversion, and probability weighting.

Besides preferences, beliefs play an important role as well in life-cycle decision-making. A young individual typically does not know how much he or she will earn towards the end of his or her career, let alone what one's personal pension income will be during the retirement phase. Still, the individual will have certain or uncertain beliefs about this and may want to act accordingly. Additionally, he or she typically will not know his or her personal retirement age or age of death. However, it might well be that one's beliefs influence personal preferences, or vice versa. For example, if you have a preference for a particular football team, then you might well believe that your football time is likely to win the next match. Likewise, one can wonder: if an individual expects a higher salary or a more stable income, would that individual be willing to take more investment risk? Or, if an individual is more risk-averse, could this relate to the expectation that his or her future income will be less risky? As such relations are crucial to optimizing the life cycle investments, we study individual preferences, beliefs, and their interactions.

To measure preferences and beliefs, we apply multiple elicitation methods. To measure risk preferences, we use the seminal choice-sequence (CS) method of Barsky et al. (1997), which yields a quantitative interval for the coefficient of relative risk aversion: individuals choose sequentially between a risky option (with fifty-fifty bets) and a risk-free option.

3 Additionally, to avoid biased time preferences, one ideally measures risk preferences (Andreoni and Sprenger, 2012)

To measure time preferences, we use a quantitative method based on the approaches of Kureishi et al. (2021) and Andersen et al. (2008) to elicit intervals for discount rates: individuals choose between an early payoff and a later payoff. To measure loss aversion, we use the simple quantitative method of G¨achter et al. (2022): individuals choose between a constant payoff and a payoff with uncertainty in terms of losses and gains. To measure probability weighting, we use the quantitative probability equivalence method of Wakker and Deneffe (1996): individuals state the probability which would make them indifferent between a risky payoff and a guaranteed payoff. To elicit beliefs, we use the quantitative scenario-based design proposed by Altig et al. (2022), which has recently been shown to be the preferred method for eliciting belief distributions (Boctor et al., 2024). An advantage of belief distributions is that they yield both point estimates (e.g., in the form of an expected value) and uncertainty (e.g., in the form of a standard deviation) about the individually measured variable.

Our main observations for a representative sample in The Netherlands can be summarized as follows. First, we find that risk preferences, time preferences, loss aversion, and probability weighting are largely insensitive to the amounts at stake across all domains. However, our results should be carefully interpreted per domain. In the lottery domain, we confirm the findings of Holt and Laury (2002) that individuals are more risk-averse for larger amounts; this is potentially related to the effect of probability weighting. In the investment and pension domain, we confirm the findings of Thaler (1981) that individuals are more patient regarding larger amounts.

Second, we find that risk and time preferences are domain-dependent, whereas loss aversion and probability weighting appear to be uniformly present across all domains. Risk aversion is the highest in the pension domain, in line with Van Rooij et al. (2007), and differs significantly from risk aversion in the standard lottery context. Interestingly, time preferences are significantly sensitive to the domain. Individuals are the most impatient in the lottery context and the most patient in the health domain. We observe that individuals are loss-averse, in line with the general observation (Tversky and Kahneman, 1992; Kahneman and Tversky, 1979), but we find that this loss aversion does not vary significantly across domains. Similarly, we find that individuals distort probabilities, in line with the general observation (Tversky and Kahneman, 1992; Kahneman and Tversky, 1979), but we find that this probability weighting does not vary significantly across domains.

Third, we find that beliefs differ greatly within the population, i.e., there is a large degree of belief heterogeneity. However, the median beliefs are remarkably close to the objective statistics. This is the case for income both during working life and during retirement, and also for stock market returns and inflation. Going one step further and analyzing the correlations between our preferences and belief estimates, we find that risk aversion correlates positively with impatience and loss aversion and negatively with probability weighting. With respect to beliefs, we find that risk aversion correlates negatively with final pay and pension income. This intuitively suggests that individuals with higher risk aversion expect to take less risk in their career; they therefore earn lower expected salaries. Time preferences show dependencies with the other estimates that are similar to the risk aversion results discussed above, except that they also correlate with expected retirement age and wealth left behind. Impatient individuals expect to retire earlier and leave less wealth behind.

Fourth, we find that risk aversion correlates positively with expected riskiness of final salary.[4] This seems to provide more support for our earlier intuition that individuals with lower risk aversion are willing to take more risks during their career. Moreover, uncertainty about retirement age positively correlates with uncertainty about final pay. This shows that individuals who are less certain about their final pay may choose their retirement age strategically.

Finally, we find several strong differences regarding the preferences in the pension domain when separating our sample on personal characteristics. Younger respondents demonstrate significantly lower risk aversion and are subject to stronger probability weighting. Respondents with higher income are substantially more patient, and highly educated respondents have lower loss aversion but stronger probability weighting.

This paper is structured as follows. Section 2 describes the methods to elicit preferences and beliefs. Section 3 describes our sample, presents the estimated preferences across domains, and presents the aggregated beliefs as well as the correlations between beliefs and preferences. Section 4 discusses how preferences and beliefs relate to personal characteristics, such as socio-economic variables. Section 5 contains our conclusions.

4 The dispersion/volatility of the belief distribution that we elicit using the method of Altig et al., 2022.

2. Methodology

We adopt an experimental approach in an online survey to elicit preferences and beliefs. The goal of the survey is to better understand decision-making over the lifecycle.

We quantitatively elicit per individual (i.e., "within-subjects design") four types of preferences: risk aversion, patience, loss aversion, and probability weighting. We measure preferences in five domains by changing the context of the choice tasks: lottery, investment, pension, work, and health. The lottery domain does not feature prominently in a life-cycle context, but since the literature on preferences typically uses a form of lottery context (Wakker and Deneffe, 1996; Holt and Laury, 2002; Andersen et al., 2008; G¨achter et al., 2022), we use it as a benchmark for the other domains. Each individual is allocated to one of the five domains (i.e., "between-subjects design"). Additionally, half of the sample participants receive choice tasks with domain-dependent amounts at stake, while the other half of the sample receive choice tasks with identical fixed amounts at stake across domains. The domain-dependent amounts are mostly based on the individual's personal finances.

To elicit beliefs, we use the quantitative scenario-based design proposed by Altig et al. (2022), which has recently been shown to be the preferred method for eliciting belief distributions (Boctor et al., 2024). An advantage of belief distributions is that they yield point estimates (e.g., in the form of an expected value) and uncertainty (e.g., in the form of a standard deviation) about the individually measured variable. We measure beliefs on both macro- and micro-objects, such as the inflation rate, stock market returns, returns on pension wealth, income during the accrual and retirement phases, bequest motives, retirement age, and life expectancy. Each individual is allocated to two of these belief domains.

Overall, to control for order effects, we randomize the order of presentation of the preference and belief parts. Within the preferences and beliefs parts, we randomize the order of the questions.[5] Recently, Pedroni et al. (2017) and Frey et al. (2017) found the so-called risk elicitation puzzle to exist, i.e., the elicitation method influences the elicited preferences. To reduce any of those confounding effects, we use the same elicitation methods across individuals.

5 We also elicit attitudes in the survey, building on the qualitative approach of Duraj et al. (2024).
Using open questions, we ask participants to provide their main three reasons for decisions regarding (sustainable) investing, pension age, pension accrual, and pension decumulation. Each individual is allocated to one of these decision-making domains. These results are outside the scope of the current paper, so they are reported here.

Preference elicitation methods

For the preference elicitation part, the instructions state that there is no inflation and that all amounts are after tax. We let participants imagine that they are single households and that they only need to fulfill their own needs. To enhance interpretability, we elicit and estimate preferences in isolation in each choice task. This also implies, for example, that we abstain from simultaneous measurement of risk preferences and risk capacity.

Since we measure preferences in five domains for two versions with different amounts at stake, i.e., a total of ten different configurations of each choice task, we choose to elaborate on the methodology for each preference measure for the pension domain with the fixed domain- independent amount of €1000. The choice tasks for the other domains are similar to the pension domain and can be found in the Appendix.

Goossens and Knoef (2022) have also measured risk preferences, time preferences, loss aversion, and probability weighting in the LISS panel in 2020 in a pension-related context. They simultaneously measured risk preferences, time preferences, and probability with the Convex Time Budgets method (Andreoni and Sprenger, 2012); they measured loss aversion with a similar approach (G¨achter et al., 2022) as in the current paper.[6]

Risk preferences

To quantify risk preferences, we use the measure of constant relative risk aversion (CRRA) based on the following power utility function

$$U(x) = \frac{x^{1-\gamma}}{1-\gamma}. \tag{1}$$

Here γ is the coefficient of relative risk aversion: $\gamma = 0$ implies risk-neutral behavior, $\gamma > 0$ implies risk-averse behavior, and $\gamma < 0$ implies risk-seeking behavior.[7] The power utility function is one of the standard workhorse models in finance and economics and is commonly assumed in the literature on measurement of risk preferences (Barsky et al., 1997; Holt and Laury, 2002; Eckel and Grossman, 2002; Eckel and Grossman, 2008; Crosetto and Filippin, 2016; O'Donoghue and Somerville, 2018). According to Wakker (2008), "the power family, also known as the family of constant relative risk aversion (CRRA), is the most widely used parametric family for fitting utility functions to data."

To elicit risk preferences, we use the choice sequence method. This is a procedure used to elicit intervals for the coefficient of relative risk aversion. An individual makes a series of sequential choices. The choices shown to the individual depend on his or her previous choices, so that the risk aversion parameter is narrowed down to a specific interval. The most widely known implementation has been provided by Barsky et al. (1997).

6 See Goossens and Knoef (2022) for the results on those estimated preferences.

7 In the case where $\gamma = 1$, we use $\ln(x)$.

This method quantitatively elicits risk preferences in intervals, which are based on the coefficients of relative risk aversion γ. The intervals yield a natural individual-level measure of risk preferences. The choice sequence method is a commonly used elicitation method in the Dutch pension industry and is commonly used in financial economics to measure risk preferences. Among others, the choice sequence method has been used to measure risk preferences of CEOs (Graham et al., 2013), pension members (Alserda et al., 2019), retail investors (van Rooij et al., 2011), and households (Barsky et al., 1997).

At each choice, an individual is asked to choose between two pensions: a risky (R) pension and a non-risky (N) pension. The risky pension is defined as a fifty-fifty gamble between a high and low outcome. Subsequent choice tasks differ in the level of risk of the risky pension. This variation is obtained through manipulations of the low outcome of each gamble, while keeping the probability of the two outcomes fixed at 50% (i.e., similar as a coin toss for heads and tails, which is also explained to the participants). We use a format with a fixed probability and varying payoffs, as in, for example, Binswanger (1980), Barsky et al. (1997), Eckel and Grossman (2002), Eckel and Grossman (2008), and Tanaka et al. (2010). By keeping probabilities fixed, the potential effects from probability weighting are held constant (Quiggin, 1982). The use of 50-50 gambles also makes the procedure transparent and particularly easy to understand, which is essential to limit noisy behavior (Dave et al., 2010).

For each individual, the series of questions starts with the following question: *Suppose you are retired and have to make a choice for your pension. The amount involved is the sum of your state pension (AOW) and your employer's pension. You can choose between two pensions. Which monthly pension income would you choose?*

a. *100% chance that you will receive a monthly income of €1000 from your retirement date to the end of your life.*
b. *50% chance that you will receive a monthly income of €2000 from retirement for the rest of your life and 50% chance that you will receive a monthly income of €667 from your retirement date to the end of your life.*

The wording is chosen deliberately to match the situation of the Dutch participants in the LISS panel. After all, Dutch individuals are used to this specific wording, as pension plan members receive annual letters stating their monthly pension payouts at retirement to the end of their life. Additionally, this type of wording is commonly used in the risk preference elicitation methods in the Dutch pension industry.

If the individual chose the non-risky pension A, then he or she is confronted with less risky lotteries in the follow-up questions. If the individual chose risky pension B, then he or she is confronted with riskier lotteries in the follow-up questions. Each follow-up question is conditional on the previous answer, see Table 1, Panel A for an overview. After the first question, the individual makes two more choices such that three questions in total are answered. Thus, the questions separate respondents into 8 (= 2^3) distinct risk preference categories.

Table 1: **Choice sequence method, based on Barsky et al. (1997)**. Individuals choose a sequence of three pensions. This table reports the pension choices together with the implied CRRA ranges. Each question is a choice between a non-risky (N) and a risky (R) pension; each risky pension has a high and a low outcome, both with 50% chance of occurrence. The implied CRRA range is based on the power utility function $U(x)=\frac{x^{1-\gamma}}{1-\gamma}$. Each range is calculated by equalizing the gamble to its neighboring pension, plus computing the value of γ that makes the individual indifferent in utility between each adjacent gamble.

		Risky (R) pension		Non-risky (N) pension	Implied CRRA range	
Sequence		High	Low		Min.	Max.
Panel A: Questions						
Question 1		2000	667	1000		
Question 2	N	2000	800	1000	2.0289	$+\infty$
Question 3	R	2000	500	1000	$-\infty$	2.0289
Question 4	NN	2000	900	1000	3.7635	$+\infty$
Question 5	NR	2000	750	1000	$-\infty$	3.7635
Question 6	RN	2000	600	1000	1	$+\infty$
Question 7	RR	2000	333	1000	$-\infty$	1
Panel B: Risk preferences categories						
Pension 1	NNN	7.5272				$+\infty$
Pension 2	NNR	3.7635				7.5272
Pension 3	NRN	2.915				3.7635
Pension 4	NRR	2.0289				2.915
Pension 5	RNN	1.511				2.0289
Pension 6	RNR	1				1.511
Pension 7	RRN	0.4689				1
Pension 8	RRR	$-\infty$				0.4689

The third and final pension choice (Table 1, Panel B) is used as a measure of the individual's risk preference. More specifically, for each of the eight pension payouts we compute the interval of the coefficient of relative risk aversion γ by equalizing each pension to its neighboring pension and computing the value of γ that makes the individual indifferent in terms of power utility between both pensions. In our analysis, we take the average value of the implied CRRA range as an estimate of the individual's risk preferences. At the extremes, only one value can be meaningfully computed, the other being $\gamma \rightarrow \pm\infty$. We assigned for these cases the only computable boundary of γ.

Our approach remains deliberately close to the original setup of Barsky et al. (1997), but we expand it in two ways. First, in the original method, individuals answer two questions in total, which allows us to separate the respondents into four distinct risk preference categories. Our approach is less rough as individuals answer three questions, which allows us to separate respondents into eight unique distinct risk preference categories. Second, the original method uses the explicit wording of (family) income every year for remaining life, which could increase or decrease with a particular fraction based on the 50-50 gambles. We use explicit low and high monthly monetary pension income from the retirement date to the end of life.

Time preferences

To quantify time preferences, at time t, we use a discount function $D(k)$ that discounts future instantaneous utility $U(x_{t+k})$,

$$U(x_t, \dots x_T) = \sum_{k=0}^{T-t} D(k) U(x_{t+k}). \qquad (2)$$

We proxy the discount function $D(.)$ by an individual's annual discount rate ρ. $\rho = 0$ implies that the individual values the present and future identically, i.e., no discounting; $\rho > 0$ implies that the individual displays impatience by discounting future consumption relative to today's consumption; and $\rho < 0$ implies that the individual is willing to pay interest to receive future consumption. Hence, we adopt the convention that an increase in ρ implies that an individual becomes more impatient, as he or she discounts future consumption more.[8]

To measure time preferences, we elicit monetary discount rates, based on the approaches by Andersen et al. (2008) and Kureishi et al. (2021). The method quantitatively elicits time preferences in intervals, based on the annual subjective discount rates. Elicitation is done by the common approach of a money-earlier-or-later (MEL) task (Ericson and Laibson, 2019). Participants are asked whether they would wish to receive a guaranteed lump-sum of €1000 in one month (Option A) or a guaranteed lump-sum in 13 months (Option B), all from the perspective of the assumed retirement date. A participant is presented with a list of decisions where the latter option ranges between €950 and €1400, i.e., annual rates of return from -5% to 40%. From the answers to these questions, we calculate an annual subjective discount rate ρ (i.e., internal rate of return) for each individual. Participants who switch more than once between the lump-sum options are left out of the analysis, which is common practice in the field as their answers are non-monotonic (Andreoni, Kuhn, et al., 2015).

8 Note that, under expected utility, concavity of the power utility function in (1), denoted by the utility curvature parameter γ, captures classical risk aversion, giving rise to a preference for more equally- distributed payouts over states of nature. However, under discounted utility as in (2), concavity of the instantaneous power utility function, denoted by the utility curvature parameter α, captures resistance to intertemporal substitution.

The question reads as follows:

Imagine that you are retired. You receive part of your pension through a lump sum payment. You can choose to receive this lump sum earlier or later.

- *Option A: If you choose to receive your lump sum at the earlier date, you are guaranteed to receive €1000 in 1 month.*
- *Option B: If you choose to receive your lump sum at the later date, you will receive a guaranteed different amount with interest in 13 months.*

Indicate per row whether you would choose Option A or B.

	Option A Lump sum in 1 month (€)	Option B Lump sum in 13 months (€)	Annual discount rate ρ
1.	1000	950	-5%
2.	1000	1000	0%
3.	1000	1020	2%
4.	1000	1040	4%
5.	1000	1060	6%
6.	1000	1100	10%
7.	1000	1200	20%
8.	1000	1400	40%

Given the potential future opportunity for Dutch pension plan members to take a lump-sum, we have chosen to elicit discount rates within this context. The delay till retirement date plus one month avoids effects of present bias.

Individuals who chose option A for all eight decisions show themselves to be very impatient as they then have an annual subjective discount rate of more than 40%, i.e., they would need a risk-free return of at least 40% to make them indifferent regarding a lumpsum in one month or a lumpsum in thirteen months. Instead, if they chose option B for all eight decisions, then show themselves to be very patient as they has an annual subjective discount rate of less than -5%, which means that they would be willing to pay interest to receive future consumption. In general, the choice task separates the respondents into eight distinct time preference categories. We use the exact same time preference categories as Kureishi et al. (2021), while deliberately setting the amounts higher to align them with those used in the other elicitation tasks.

More specifically, each of the eight decisions yields an interval for the subjective annual discount rate ρ by equalizing the amounts of options A and B. In our analysis, we take the average value of the neighboring implied subjective annual discount rates as an estimate of the individual's time preferences. Only one value can be meaningfully computed for intervals at the extremes, the other being $\rho \to \pm\infty$. We assigned for these cases the only computable boundary of ρ.

Monetary discounting is one of the main tools for eliciting time preferences (Dohmen et al., 2010; Meier and Sprenger, 2015; Kureishi et al., 2021). Hypothetical questions such as the one we use are experimentally validated (Ericson and Laibson, 2019). Frederick et al. (2002) and Cohen et al. (2020) provide survey studies for measuring time preferences.

Loss aversion

To quantify loss aversion, we use a piecewise-linear formulation of the value function of cumulative prospect theory (Tversky and Kahneman, 1992). This implies that losses are penalized by a factor λ relative to gains.[9] An individual is indifferent between a gain (G) and a loss (L) if

$$v(G) = \lambda v(L) \tag{3}$$

where $v(x)$ denotes the value of the outcome x (either a gain G or a loss L). λ denotes the coefficient of loss aversion: $\lambda = 0$ implies loss-neutral behavior, $\lambda > 0$ implies loss-averse behavior, and $\lambda < 0$ implies loss-seeking behavior. We assume that $v(x)$ is linear ($v(x) = x$) for small distortions of size ε around point x. This gives us a very simple measure of loss aversion $\lambda = G/L$.

To measure loss aversion, we use a simple choice task of G¨achter et al. (2022). This task elicits intervals for the loss aversion parameter of an individual. All individuals decides six times whether they wish a constant (certain) pension or a pension with a certain risk. The constant (certain) pension yields €1000 pension per month from the individual's retirement date onward until the end of life. The risky pension has a 50% chance to incur a loss and a 50% chance to receive a gain. For each pension, the gain is fixed at €60, and only the losses are varied, ranging between -€20 and -€70. From the answers to this question, we can easily calculate the individual's loss aversion parameter λ by the ratio of gain over loss. Participants who switch more than once between options A and B are left out of the analysis, which is common practice when using multiple price list (MPL) tasks as their answers are non-monotonic (Andreoni, Kuhn, et al., 2015).

9 We focus on loss aversion in isolation and do not consider the s-shape of the value function, as is done more frequently in the literature; see, for instance, Barberis and Huang, 2001. The argument is that for gains and losses the effect of λ dominates such that, for ease of computation, the s-shape of the value function is omitted.

The question reads as follows:

Suppose you are retired. You have to choose between two pensions:

- *Option A: You will receive a monthly pension of €1000 from your retirement date onward for the rest of your life.*
- *Option B: You will receive a pension with a certain risk.*

The table below shows the different payouts for the pension with risk. The payouts differ in how much you can lose. Regarding the first payout, there is a 50% chance that you will receive €20 less per month from your retirement date onward to the end of your life and 50% chance that you will get €60 more per month from your retirement date onward to the end of your life, all compared to Option A. For each payout, indicate which pension you prefer:
A or B.

	Option B		Loss aversion parameter
	50% chance of a loss (€)	50% chance of a gain (€)	λ
1.	-20	+60	3.00
2.	-30	+60	2.00
3.	-40	+60	1.50
4.	-50	+60	1.20
5.	-60	+60	1.00
6.	-70	+60	0.86

Individuals who chose option A for all six decisions show themselves to be the most loss averse as they do not want to risk losing €20 with 0.5 probability. That is, they have a loss aversion parameter λ greater than or equal to 3. If they chose option B for all six decisions, then they are the least loss averse as they are willing to accept the risk of losing €70 with 0.5 probability. That is, they have a loss aversion parameter λ smaller than or equal to 0.86. The choice task separates individuals into six distinct loss aversion categories. In our analysis, we take the average value of the neighboring implied loss aversion parameters as an estimate of the individual's loss aversion. Only one value can be meaningfully computed for intervals at the extremes, the other being $\lambda \rightarrow \pm\infty$. We assigned for these cases the only computable boundary of λ

We use 50-50 gambles as they are easy to use (Ga¨chter et al., 2022). Note that the gains (G) and losses (L) are deliberately small compared to the amount of €1000 so as to minimize the effects of risk aversion. Since we cannot completely rule out that risk aversion is at stake, the choice task provides a conservative measure of loss aversion (Ga¨chter et al., 2022). We use the exact same six loss aversion categories as Ga¨chter et al. (2022), although we deliberately set the amount at higher values to align them with those used in the other elicitation tasks.

Probability weighting (M)

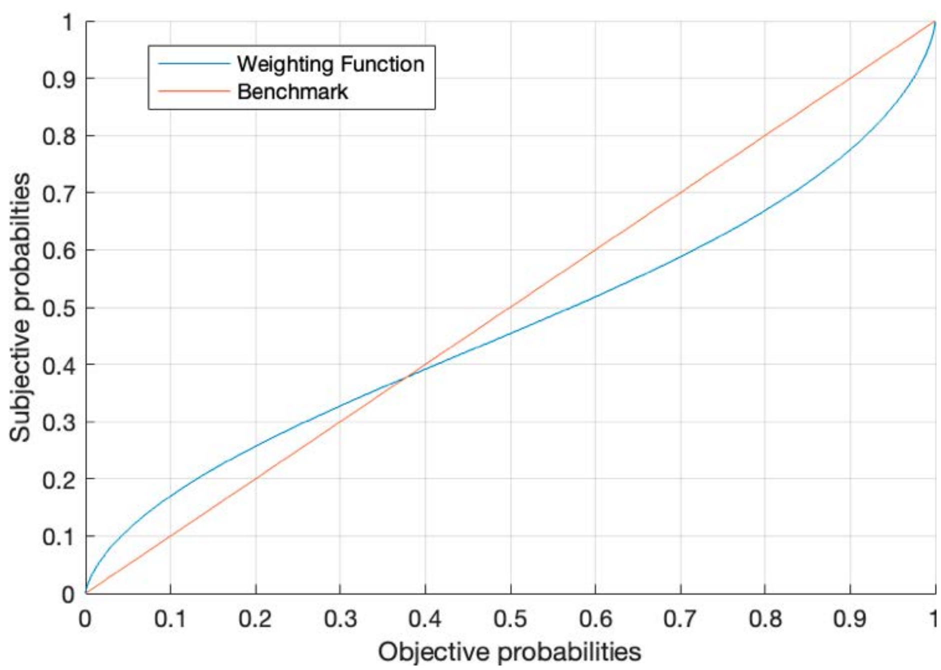
Probability weighting is a behavioral bias that causes individuals to adapt probabilities when using them for decision-making. To quantify probability weighting, we assume participants to possess probability weighting as in Tversky and Kahneman (1992). Their seminal work considers the following functional form for the probability weighting function,

$$w(p) = \frac{p^{\delta}}{(p^{\delta} + (1-p)^{\delta})^{1/\delta}}. \tag{4}$$

Tversky and Kahneman's (1992) original estimate of δ is 0.69.[10] The biases that this implies are best understood graphically, which is shown in Figure 1.

This figure shows that for certain objective probabilities, the weights people tend to use are heavily biased. Low probabilities tend to be overweighted, and high probabilities tend to be underweighted. This is the case for all values of $\delta < 1$. When $\delta = 1$ there is no weighting, i.e., the two lines in Figure 1 coincide, and for $\delta > 1$ the biases reverse such that low probabilities get underweighted and high probabilities get overweighted.

Figure 1: Probability weighting as in Tversky and Kahneman (1992).



10 Their original setup differentiates between gains and losses. The δ for gains equals 0.69 and for losses 0.61. Given that both values have relatively similar implications for behavior, the literature typically does not assume two different probability weighting functions for gains and losses.

We elicit probability weighting (δ) using the probability equivalence method (Wakker and Deneffe, 1996). The participant is given a list of choices and at every decision can choose between a risky lottery and a lottery that pays a guaranteed amount. The risky payoff gives a high amount with probability p1 and zero otherwise. The novelty of this approach is that at each decision the participant is asked to provide a probability, p1, for which he or she is indifferent between the risky lottery and the lottery with the guaranteed payoff. We use the exact same five decisions as the probability equivalent of Wakker and Deneffe (1996), while deliberately setting the amounts at higher values to align them with those used in the other elicitation tasks.

The question reads as follows:

Suppose you are retired. You have to choose between two pensions:

- *Option A: You will receive either €2000 or €0 pension per month from your retirement date onward for the rest of your life.*
- *Option B: You receive a pension with some guaranteed amount from your retirement date onward for the rest of your life.*

For which probability between 0% and 100% is the monthly payoff of option A equally desirable for you as the monthly payoff of option B?

For your first choice below, you have a chance of x% to receive a monthly income of €2000 and of €0 otherwise (Option A), or you receive a guaranteed monthly pension income of €250 (Option B). Both pensions are paid from your retirement date onward for the rest of your life.

			Option A			**Option B**
	chance	Income	chance	Income	Both options are equally desirable for a probability of p%	Guaranteed Income
1.	p_1	2000	100-p_1	0	[0%-100%]	250
2.	p_2	2000	100-p_2	0	[0%-100%]	500
3.	p_3	2000	100-p_3	0	[0%-100%]	750
4.	p_4	2000	100-p_4	0	[0%-100%]	1250
5.	p_5	2000	100-p_5	0	[0%-100%]	1750

Assuming risk neutrality, an individual without probability weighting would give the following five answers: 12.5%, 25%, 37,5%, 62,5%, and 87.5%. Answers that differ from these responses therefore suggest a degree of probability weighting. These answers are subsequently used to determine the level of probability weighting (δ) for each individual following the probability equivalence method.

Contrary to other approaches, this method yields an equality between two utilities per decision. This implies that at each decision we can solve the equality for δ. For the first decision this equality reduces to

$$\frac{w(p,\delta)}{w(p,\delta)-w(1-p,\delta)}=\frac{u(250)}{u(2000)} \tag{5}$$

where p denotes the probability entered by the participant and $w(p, \delta)$ denotes the probability weighting function (4). The other decisions differ in terms of guaranteed income ($u(250)$ in (5)) and the response of the individual (p in (5)). We minimize the mean squared error of the five decisions combined to find the optimal δ. Similar to the methods above, we adopt a non-monotonicity constraint such that we drop respondents where the probabilities decrease when moving to the next decision (with a larger guaranteed outcome).

B. Belief elicitation methods

The optimal investments for an individual during the lifecycle also depend on various beliefs. It is thus worthwhile to measure these beliefs and potentially relate them to preferences. To obtain a belief measure we adopt the method of Altig et al. (2022). This method gives two questions. For beliefs about the return obtained on the pension wealth of the respondent, the first question reads as follows,

When you accumulate pension wealth, this wealth is invested. Such an investment normally consists of 60% risky investments and 40% risk-free investments. A return is the change of value of these investments. What return do you expect on average for your pension wealth over the next 12 months in each of the three scenarios below? If you predict a gain please state a positive number. If you expect a loss, then state a negative number. If you don't expect a gain or a loss, then state this as zero.

*Scenario 1: A **low** return would be about:*
*Scenario 2: An **average** return would be about:*
*Scenario 3: A **high** return would be about:*

After answering each of these scenarios, participants read the following statement.
It is of course difficult to predict what the future return on your investment will be. We therefore want to ask you how likely you think that each of your predictions will be realized?

This is followed by the second question,

*How likely do you think the **low**, **average** and **high** scenarios are? You need to divide a total of 100 percent over the three returns that you provided. These percentages indicate the likelihood you give to each return being realized. Giving a scenario more points relative to another indicates that you think this scenario is more likely to be realized.*

*The likelihood of the **low** return is:*
*The likelihood of the **average** return is:*
*The likelihood of the **high** return is:*
Total:

One advantage of this approach is that respondents not only provide an expectation, but that their responses are actually more detailed as they provide information about their belief distribution for, in this case, the return on their pension wealth.

We adopt this method for a list of elements that are important for investments during the lifecycle and that contain some uncertainty, such as annual return on pension investments, annual return on the stock market, annual inflation, labor income, life expectancy, retirement age, and value of bequest left at time of death.

3. Preferences and beliefs

A. Sample

We conducted our survey using a representative sample of Dutch households through the Longitudinal Internet Study in the Social Sciences (LISS) panel in the Netherlands. The LISS panel is widely regarded as one of the most comprehensive, reliable, and representative datasets in household finance research (Noussair et al., 2013; Dimmock et al., 2015; Parise and Peijnenburg, 2019). Administered by CentERdata, a non-profit research institute at Tilburg University, the LISS panel is based on a probability-address sampling method. Households are randomly selected from the Dutch population register, thereby avoiding self-selection bias. To ensure inclusiveness, households without access to a computer or the Internet are provided with the necessary equipment and connectivity at no cost. Participants in the LISS panel complete online questionnaires on a variety of topics, with incentives provided for their participation, all on a monthly basis. This setup ensures high engagement and data reliability, making it an invaluable resource for academic, social, and policy-related research.

We invited a total of 2,415 LISS panel household members between the ages of 18 and 70 in August and September 2024. We chose 70 years as an upper cutoff age to minimize potential effects of mortality risk in our chosen tasks. A total of 1,330 panel members responded, leading to a response rate of about 55%. The overall completion rate was 51.1%, yielding N = 1,233 respondents. Note that the number of respondents differs per question, for two reasons. First, we apply a between-subjects design, such that an individual responds to a particular subset of the full set of questions. Second, for time preferences, loss aversion, and probability weighting, we leave non-monotonic responses out of the analysis.

Table 2 reports information about socio-economic variables, which is known by the LISS panel for all individuals that responded. 52% of our sample is male. The average age is 51 years. 70% of our sample has a partner, and 65% has at least one child. The individual monthly after-tax income is €2,326. We omit two individuals, who have a reported income of more than 1000 billion euros. We categorize education levels using the definitions of Statistics Netherlands (CBS). 19% have a low-level education (Dutch: "basisonderwijs" and "VMBO"), 36% have a medium-level education (Dutch: "havo/vwo" and "mbo"), and 45% have a high-level education (Dutch: "hbo" and "universiteit").

Table 2: **Summary statistics of aggregate sample**. This table presents summary statistics for the participants that we observed. *Male*, *Partner*, and *Education* are dummy variables. Using the categories employed by Statistics Netherlands (CBS), *Education low* comprises "basisonderwijs" and "VMBO", *Education medium* comprises "havo/vwo" and "mbo", and *Education high* comprises "hbo" and "universiteit". *Age* is in years, *Children* is the number of children of a participant, and *Income* is the individual monthly after-tax income, expressed in Euros.

	Mean	St. Dev.	N
Male	0.52	0.50	1330
Age	51	17	1330
Partner	0.70	0.46	1330
Children	0.65	1.07	1330
Income	2326	3124	1268
Education low	0.19	0.39	1323
Education medium	0.36	0.48	1323
Education high	0.45	0.50	1323

LISS ensures that the study is clear to its panel members and ensures consent. The median time to complete the online survey is about 14 minutes (*N* = 1233). Using a 5-point Likert scale ('1 = definitely not' to '5 = definitely yes'), participants at the end of the survey answer the two questions, "Did you find it difficult to answer the questions?" and "Did you find the questions clear?". We average the scores of those answers per individual and take the population median, which yields 3.0 out of 5.0. This indicates that it was rather clear to the participants what was expected from them and that they understood their tasks rather well.

B. Preferences

This section addresses two main questions. First, are preferences independent of the size at stake? For example, Holt and Laury (2002) find that individuals show a higher level of risk aversion when payoffs increase. Second, are preferences domain-dependent? For example, Van Rooij et al. (2007) find that individuals are most risk-averse in the pension domain. These two questions are relevant for the pension industry as no holistic research has been conducted to date on the implications of stake sizes in the elicitation methods and of differences in decision-making domains for life-cycle consumption and investment decisions.

Are preferences independent of the size at stake?

We want to better understand whether the amounts at stake influence the measured preferences. On the one hand, half of the sample received a survey question with a standard domain-independent amount of €1000. That is, the risk preference elicitation method has a risk-free amount of €1000, the time preference elicitation method has a lumpsum amount of €1000, the loss aversion elicitation method has a certain amount of

€1000, and the probability weighting elicitation method has an expected amount of €1000. We call this the 'standard' amount at stake. The other half of the sample received a survey with personal domain-dependent amounts at stake. That is, each elicitation method has amounts at stake which are scaled versions of the standard domain-independent amounts, in which the scaling factor is determined by the individual's personal finances. We refer to these amounts as the 'domain-dependent' amounts.

For each individual we estimate that person's risk and time preferences, loss aversion, and probability weighting. We aggregate the results per domain, Table 3 showing the results. For each pref- erence measure, we show the mean, standard deviation, and number of observations across domains and sizes at stake. We test for significant differences in the estimated preferences between the amounts at stake using an unpaired t-test that assumes unequal variances; we show the corresponding *p*-values. Results are robust to a Wilcoxon ranksum test (equivalent to a Mann-Whitney U-test). For readability, values in **bold** are significant at minimally the 10% significance level.

Table 3: **Preferences across sizes at stake**. This table presents summary statistics of the estimated preferences per domain for the domain-dependent and standard amounts at stake. We test for significant differences in the estimated preferences between the amounts at stake using an unpaired t-test assuming unequal variances; we show the corresponding *p*-values. Results are robust to a Wilcoxon ranksum test (equivalent to a Mann-Whitney U-test). For readability, values in **bold** are significant at minimally the 10% significance level.

	Lottery			Investment			Pension			Work			Health		
	Mean	St. Dev.	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	*N*
Risk preferences Domain	3.02	2.72	134	3.02	2.51	155	5.02	2.56	136	4.48	2.66	129	3.86	2.99	105
Standard	3.76	2.87	136	3.51	2.78	115	4.52	2.47	104	4.18	2.52	130	4.61	2.73	130
p-value	0.03			0.13			0.12			0.35			0.05		
Time preferences Domain	15.29	13.94	124	9.48	12.90	145	9.09	12.15	131	11.06	14.65	121	9.01	12.14	96
Standard	13.58	13.66	127	12.66	14.09	107	13.06	14.24	96	11.20	13.09	121	8.45	10.77	119
p-value	0.33			0.06			0.02			0.94			0.72		
Loss aversion Domain	1.80	1.03	84	1.68	0.97	88	1.58	0.92	74	1.61	0.98	84	1.61	0.96	65
Standard	1.72	0.98	79	1.63	0.99	72	1.65	0.96	62	1.49	0.89	74	1.62	0.98	82
p-value	0.61			0.74			0.69			0.42			0.96		
Probability Weighting Domain	0.76	0.33	91	0.82	0.42	107	0.77	0.37	98	0.77	0.35	87	0.84	0.34	73
Standard	0.88	0.44	94	0.81	0.36	81	0.83	0.36	65	0.86	0.40	87	0.77	0.35	86
p-value	0.04			0.94			0.33			0.11			0.18		

Our main observation is that preferences, within all domains, do not differ significantly across the standard amount of €1000 and the personal domain-dependent amount. Stated differently, risk and time preferences, loss aversion, and probability weighting are independent of the amounts at stake.

There are three exceptions to this. First, risk preferences in the lottery and health domains differ significantly, in statistical terms, between the domain-dependent amount and the standard amount of €1000. For the lottery domain, γ equals 3.76 for the standard amount and 3.02 for the domain-dependent amount. For the health domain, γ equals 4.61 for the standard amount and 3.86 for the domain-dependent amount. Hence, for both the lottery and health domains, risk aversion is higher for the standard amounts at stake compared to the domain-dependent amounts at stake. This effect is economically also significant, as the domain-dependent amounts equal €100 and €385 in the lottery and health domains, respectively. Thus, the standard amounts at stake in the two domains are lower than the domain-dependent amounts at stake. Our findings exactly capture the seminal finding of Holt and Laury (2002) in a similar lottery context, namely that risk aversion is higher when the amounts at stake increase. We find that this effect also extends to the health domain.

Second, time preferences in the investment and pension domains differ significantly, in statistical terms, between the domain-dependent amount and the standard amount of €1000. Regarding the investment domain, the subjective annual discount rate is 12.66% for the standard amount and 9.48% for the domain-dependent amount. Regarding the pension domain, the subjective annual discount rate is 13.06% for the standard amount and 9.09% for the domain-dependent amount. Hence, participants are more impatient — as they discount the future more — for the standard amounts at stake, compared to the domain-dependent amounts, in the investment and pension domains. This effect is economically also significant, as the difference in subjective discount rates is 3 to 4 percentage points. For the investment domain, the domain-dependent amount is €6,750, which is based on the investment holdings of the Dutch population. For the pension domain, the domain-dependent amount equals 70% of personal monthly income, which is typically taken as ambition for the replacement rate. Thus, the domain-dependent amounts at stake in the investment and pension domains are generally higher than the standard amounts at stake. We find that larger amounts at stake lead to greater patience. This is in line with the finding of Thaler (1981) in a lottery context, where we do not find significant differences.

Third, probability weighting in the lottery domain differs significantly, in statistical terms, between the domain-dependent amount and the standard amount of €1000. The parameter of probability weighting (δ) is 0.76 for the domain-dependent amount and 0.88 for the standard amount. To interpret these differences, objective probabilities of 1%, 5%, and 10% translate to 1.72%, 6.95%, and 12.56% when δ = 0.88 and to 2.93%, 9.45%, and 15.39% when

δ = 0.76, which shows that the differences are also economically significant. Participants are thus overweighting small probabilities more for the lottery domain, whereas no significant differences are observed for the other domains. This is important since the lottery domain is often used as a standard domain for eliciting risk preferences and does not seem to provide the same results as the other domains.

It is important to note that our findings are not driven by differences in personal characteristics of the underlying populations in our between-subjects design. Table 8 in the Appendix shows that the populations for all domains, between the domain-dependent and standard treatments, do not statistically differ in terms of gender, age, and income composition.

Are preferences domain-dependent?

Given our main observation that preferences do not differ significantly between the standard amount of €1000 and the personal domain-dependent amount, we feel comfortable in aggregating the estimated preferences across the standard and domain-dependent amounts. This enhances the tractability and interpretability of our consecutive analysis.

These aggregated estimated preferences are shown in Table 4. For each preference measure, we show the mean, standard deviation, and number of observations per domain. To test for domain dependence of preferences, we test whether the preferences in the investment, pension, work, and health domains are significantly different from the lottery domain. Thus, we take the lottery domain as the benchmark, which is the typical domain or context in the academic literature (Wakker and Deneffe, 1996; Holt and Laury, 2002; Andersen et al., 2008; Ga¨chter et al., 2022). We use an unpaired t-test assuming unequal variances; we show the corresponding p-values. Results are robust to a Wilcoxon ranksum test (equivalent to a Mann-Whitney U-test). For readability, values in **bold** are minimally significant at the 10% significance level.

Our main observation is that risk and time preferences are domain-dependent, whereas loss aversion and probability weighting seem more uniform over all domains. Regarding risk preferences, the estimated coefficient of relative risk aversion, γ, varies between 3.23 in the investment domain and 4.80 in the pension domain. This implies that individuals are most risk-averse in the pension domain, consistent with Van Rooij et al. (2007), and least risk-averse in the investment domain. Risk preferences in the pension, work, and health domains are significantly different, in statistical terms, from risk preferences in the lottery domain. In terms of magnitude, the difference between the average estimated coefficient of relative risk aversion, γ, in the pension and lottery domains is 1.41, which is sizeable.

Table 4: **Preferences across domains**. This table presents summary statistics of the estimated preferences across domains, aggregated over the domain-dependent and standard amounts at stake. We test for significant differences in the estimated preferences with regard to the lottery domain using an unpaired t-test that assumes unequal variances; we show the corresponding *p*-values. Results are robust to a Wilcoxon ranksum test (equivalent to a Mann-Whitney U-test). For readability, values in **bold** are significant minimally at the 10% significance level.

	Risk preferences			**Time preferences**			**Loss aversion**			**Probability Weighting**		
	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N
Lottery	3.39	2.82	270	14.42	13.79	251	1.76	1.01	163	0.76	0.29	185
Investment	3.23	2.63	270	10.83	13.48	252	1.66	0.98	160	0.76	0.30	188
p-value	0.48			**0.00**			0.38			0.99		
Pension	4.80	2.53	240	10.77	13.19	227	1.61	0.94	136	0.75	0.30	163
p-value	**0.00**			**0.00**			0.20			0.93		
Work	4.33	2.59	259	11.13	13.86	242	1.56	0.94	158	0.76	0.30	174
p-value	**0.00**			**0.01**			**0.06**			0.78		
Health	4.28	2.87	235	8.70	11.38	215	1.62	0.97	147	0.77	0.28	159
p-value	**0.00**			**0.00**			0.21			0.73		

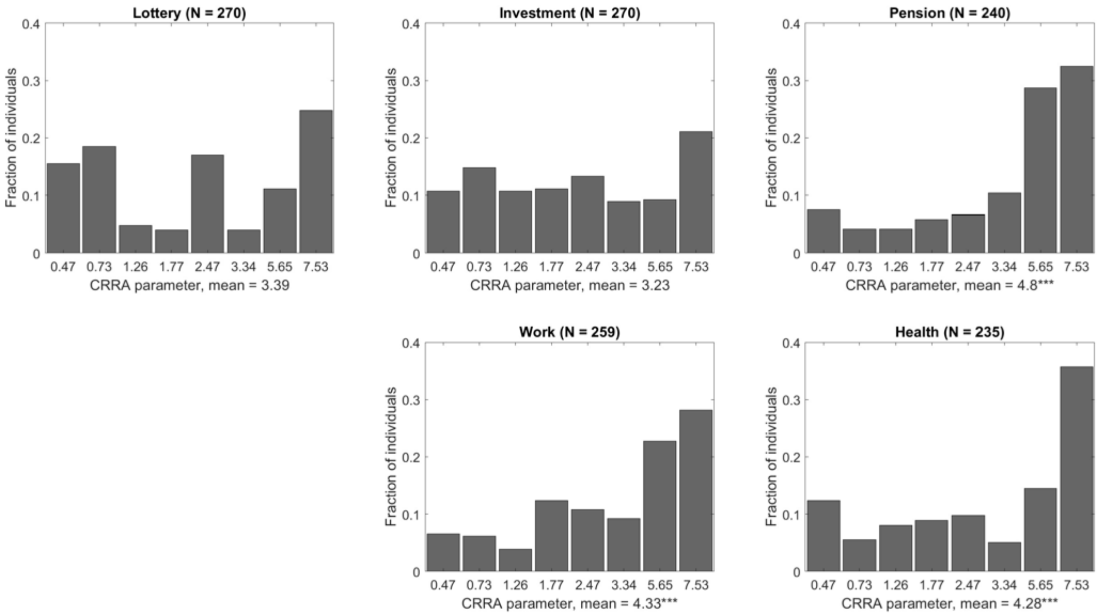
Differences in γ between the work and lottery domains and the health and lottery domains are 0.94 and 0.89, respectively. Risk preferences in the investment and lottery domains are statistically indistinguishable.

Figure 2 shows the observed distributions of the coefficient of relative risk aversion, γ, per domain. One can clearly observe that a larger share of individuals cluster at higher levels of γ in the pension, work, and health domains, compared to the lottery and investment domains.

Regarding time preferences, the estimated subjective annual discount rate, ρ, varies be- tween 8.7% in the health domain and 14.42% in the lottery domain. Stated differently, individuals discount the future most in the lottery domain and least in the health domain. This means that individuals are the most patient in the health domain and the least patient in the lottery domain. Time preferences in the investment, pension, work, and health domains are significantly different, in statistical terms, from time preferences in the lottery domain. In terms of magnitude, the difference between the average estimated subjective annual discount rate, ρ, in the health and lottery domains is 5.72 percentage points, which is sizeable. The difference in ρ between the pension and lottery domains is about 4 percentage points, which is sizeable as well. Overall, time preferences in the lottery domain are quite different from time preferences in other domains.

Figure 3 in the Appendix shows the observed distributions of the subjective annual discount rate, ρ, per domain. In general, the level of our estimated subjective annual discount rates is in line with what is commonly found in the literature (Frederick et al., 2002; Kureishi et al., 2021).

Figure 2: **Risk preferences across domains**. This figure displays the observed distributions of risk preferences by domain. On the horizontal axis the CRRA parameter value γ from $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$, and on the vertical axis the fraction of individuals. *,**,*** indicate whether the mean CRRA parameter is significantly different from the lottery domain at the 10%, 5%, and 1% significance level, respectively.



Regarding loss aversion, the estimated loss aversion parameter, λ, varies between 1.56 in the work domain and 1.76 in the lottery domain. The level of these estimates is in line with what is commonly found in the literature (Tversky and Kahneman, 1992; Ga¨chter et al., 2022). Loss aversion is similar across the domains. An exception is the work domain compared to the lottery domain, which are slightly different in statistical terms. Individuals tend to be more loss-averse in the lottery domain than the work domain, but the difference is not significant. Figure 4 in the Appendix shows the observed distributions of the loss aversion parameter, λ, per domain. We observe a large fraction of the population at the boundary of our loss aversion parameter measure, which might be an indication that the design range of our loss aversion measure could have been wider.

Regarding probability weighting, the estimated probability weighting parameter, δ, equals about 0.76 and is rather uniform across the domains. This indicates that probability weighting is not a phenomenon that only exists in a specific domain, but that it is a feature that impacts decision-making in any domain similarly. The estimates are also relatively close to the frequently assumed 0.69, which is found in the experiments of Tversky and Kahneman (1992). Figure 5 in the Appendix shows the observed distribution of the probability weighting parameter, δ, per domain. The graphs show dispersion over de delta values, but also an accumulation at the value of delta equal to one. That is because we do not analyze alternative forms of probability weighting in depth and therefore choose to truncate deltas in excess of one. After all, delta values in excess of one indicate an S-shaped probability weighting instead of the common inverse-S-shape. Such functional forms are beyond the scope of our research. Due to the truncation, the graphs may, however, suggest many individuals being without probability weighting, although many of them actually obey some alternative sort of probability weighting.

It is important to note that our findings are not driven by differences in personal characteristics of the underlying populations in our between-subjects design. Table 9 in the Appendix shows that the populations of the investment, pension, work, and health domains do not statistically differ from the population of the lottery domain in terms of gender, age, and income composition. An exception is the age composition of the population in the health domain compared to that of the lottery domain. However, we feel comfortable that this does not drive our results in the health domain to any significant extent.

C. Beliefs

This section gives insights into an important aspect of personal life-cycle investing, namely beliefs. Models of optimal life-cycle investing typically set beliefs at a level equal to objective statistics. However, this may be very different from the subjective beliefs of individuals. Moreover, subjective beliefs may also differ greatly from one individual to another, thus yielding heterogeneity. In this section, we attempt to provide insights into these subjective beliefs and the extent to which belief heterogeneity exists.

Given that we have both belief data and preference estimates, we can analyze the depen- dencies between preferences and beliefs. If there are preference-induced beliefs (a person gives higher weight to certain events because of a higher preference for those events), this will lead to suboptimal investments in optimal life-cycle strategies (and possibly high discrepancies. We therefore also study the correlations between the preference and belief estimates.

Aggregate results

We use the method developed by Altig et al. (2022) to obtain belief distributions per individual. These distributions consist of three scenarios: the bad scenario, the average scenario, and the good scenario. Using the probabilities that these scenarios occur and the outcome in each of these scenarios, we can compute expectations per individual. Table 5 shows the characteristics of the expectations over all individuals for (net) final salary, retirement age, age of death, bequest wealth at time of death, return on pension wealth over the next 12 months, (net) pension income including state benefits (AOW), the inflation rate over the next 12 months, and the return on the stock market over the next 12 months. Graphical overviews of these distributions are given in Figures 6 and 7 in the Appendix.

Table 5: **Summary statistics of beliefs**. This table presents summary statistics of the measured beliefs. All data are winsorized at the 5% level at the bottom and top of the distribution.

	Median	Mean	St. Dev.	Min.	Max.	*N*
Expected (monthly after-tax) last salary	2826	2888	1677	0	6599	480
Expected retirement age	67	66	4	53	71	480
Expected age of death	80	75	20	11	88	158
Expected bequest amount	115000	186332	211497	0	718000	157
Expected (annual) pension portfolio return	5.31	12.82	15.37	0.00	50.00	614
Expected (monthly after-tax) pension income (includes state pension benefits)	1936	1933	1230	0	4480	616
Expected (annual) inflation rate	4.88	10.49	12.26	1.00	44.00	404
Expected (annual) market return	6.00	13.33	14.29	0.00	44.00	400

Overall, we observe that the median values are fairly close to the objective values. For instance, net median income for the 55-65 age group was about €3,000 per month,[11] which does not differ greatly from the median answer of the respondents regarding net income, which was €2,826. Furthermore, the ad-hoc assumption of receiving 70% of final salary as retirement income also seems to be rather accurately found in the responses, as the answers of respondents give a median conversion of 68.5%. Similarly, the age at which respondents expect to retire and their life expectancy are close to what we objectively assume.

The same holds for the return variables. Inflation expectations are relatively high when taking a historical benchmark, even though inflation in The Netherlands was very high prior to the survey, leading to a median expectation of 4.88% over the next 12 months. Respondents expect the stock market to yield an average return of 6% and expect their pension wealth to show a return of 5.31%. This implies that they would expect their pension investment portfolio to contain a fair proportion of stocks or other assets of similar risk.

Going one step further, beyond the median of the beliefs of all respondents, we observe a large heterogeneity among respondents. For instance, even though the median belief of both final pay and pension income are fairly close to the objective value, many respondents express beliefs that range quite far above and far below these values. This can be seen from the standard deviations in Table 5. The same holds for the other belief distributions, as we observe a similarly strong heterogeneity in the expected returns on the stock market, on inflation, and on the return on pension wealth. The retirement age is in absolute terms relatively homogeneous, although it should be noted that small changes in the retirement date can have a strong impact on the optimal life-cycle investment strategy. Finally, there

11 See Statistics Netherlands, www.cbs.nl.

is also much heterogeneity with regards to life expectancy.[12] For more details about the specific distribution, we refer to Figures 6 and 7 in the Appendix.[13]

Are preferences and beliefs correlated?

In our survey, we elicit several dimensions of preferences and obtain belief distributions about elements that play a key role in optimizing individual life-cycle investments. In the previous section, we saw that the population medians regarding expectations are relatively close to the objective values. However, we also observed strong heterogeneity among the population. When the deviations of the preference estimates and beliefs estimates from the median for certain individuals are highly correlated, their optimal investment strategies will be quite different from the median case. We therefore compute the correlations between each of these outputs of our survey. To do so we aggregate all domain-specific preferences to one preference dimension. Even though there are differences between dimensions, we expect the correlations of each preference dimension with other preferences or beliefs to be similar.[14] Table 6 below shows the correlation table where we take the expectation of the belief distribution per individual.

First, focusing on the first column, we discuss the relation of risk aversion to other preferences and beliefs. Our results support the finding that risk aversion correlates positively with impatience (Andersen et al., 2008). We also find positive correlations with loss aversion and probability weighting. That is, individuals with higher risk aversion are more likely to have higher loss aversion but lower probability weighting (δ closer to 1 gives less probability weighting). The magnitudes of the effects also reveal the importance of including these preference dimensions for optimal investments.

We also observe the relations of risk aversion to beliefs. Specifically, higher risk aversion is correlated with lower expected last pay. This implies that individuals with lower risk aversion tend to expect a higher final salary. This could be explained by individuals with lower risk aversion taking more risk during their career (including education) and thus expecting to end up with higher-paying jobs. Without speculating further on the causes of this relation, the result does show a strong relation that indicates relevance for life-cycle investing. The result for pension income is similar. Individuals with lower risk aversion expect higher pension income. These expectations are intuitively consistent, and the mechanism is potentially the same as for the expectations about final salary.

12 Part of this variation may be caused by the large deviations that might be due to misreading of the question and answering not the age of death but years until death. We did anticipate this potential misreading and emphasized the intent of our question, but it seems that some individuals nonetheless answered it differently.

13 While some responses in Table 5 — such as rather extremely high return expectations — are striking, they provide insight into the wide level of financial knowledge among respondents. The fact that the medians are close to widely accepted values supports our confidence in the main findings.

14 Note that correlations are invariant to differences in levels or scale.

Table 6: **Preference-belief expectation correlations**. This table presents correlations among and between preference estimates and belief expectations. Correlations are taken over individuals of whom we have both results. As not all participants answered all belief elicitation tasks, some combinations are missing. *RA* is the coefficient of risk aversion, *TD* is the coefficient of time discounting, *LA* is the coefficient of loss aversion, and *PW* is the coefficient of probability weighting. We test for significance of the correlations and show the *p*-values between brackets.

		Preferences						**Beliefs**				
	RA (n=1274)	TD (n=1187)	LA (n=764)	PW (n=869)	Last pay (n=480)	Ret. Age (n=480)	Life Exp. (n=158)	Bequest (n=157)	Pen. ret. (n=614)	Pen. Income (n=616)	Inflation (n=404)	Stock ret. (n=400)
RA	-											
TD	0.11*** (0.00)	-										
LA	0.14*** (0.00)	0.11*** (0.00)	-									
PW	0.07** (0.04)	0.06* (0.10)	0.06 (0.17)	-								
Last pay	-0.27*** (0.00)	-0.20*** (0.00)	0.02 (0.79)	0 (0.94)	-							
Ret. Age	-0.03 (0.51)	-0.14*** (0.00)	0.01 (0.93)	-0.08 (0.16)	0.14*** (0.00)	-						
Life Exp.	-0.03 (0.71)	0.08 (0.34)	0 (0.96)	-0.05 (0.63)	-	-	-					
Bequest	-0.06 (0.45)	-0.23*** (0.00)	0.03 (0.74)	0 (1.00)	-	-	0.07 (0.42)		-			
Pen. ret.	-0.02 (0.64)	-0.05 (0.25)	-0.06 (0.25)	0.05 (0.32)	-	-	-	-	-			
Pen. income	-0.11*** (0.01)	-0.19*** (0.00)	0 (0.94)	-0.03 (0.48)	-	-	-	-	-0.03 (0.53)	-		
Inflation	-0.015 (0.77)	-0.01 (0.84)	-0.04 (0.52)	0.09 (0.16)	-0.09 (0.32)	0 (0.98)	0.03 (0.81)	-0.20 (0.14)	0.34*** (0.00)	-0.10 (0.13)	-	
Stock ret.	0.04 (0.46)	-0.05 (0.31)	-0.14** (0.03)	-0.05 (0.41)	-0.04 (0.62)	0 (0.98)	-0.12 (0.37)	-0.15 (0.26)	0.54*** (0.00)	-0.05 (0.47)	0.38*** (0.00)	-

The second column presents the time preferences. The significance of the correlations is very similar to those of risk aversion. However, time preferences also seem to be correlated with expected retirement age and the size of the bequest at the time of death. The results show that impatient individuals expect to retire earlier and leave less wealth as bequest. Com- bining this insight with the notion that impatient individuals save less shows their optimal pension to be significantly lower. The optimal investment plan for impatient individuals is likely to be very different from patient ones.

Finally, some belief expectations are strongly correlated. For example, individuals who expect high stock returns also tend to expect high inflation and high pension returns. These patterns matter as even small differences in beliefs can significantly affect optimal life-cycle investment choices, as they typically concern decisions over a long horizon. Given that life- cycle models typically assume constant beliefs (Cocco et al., 2005), small deviations persist over time and can lead to substantial differences in optimal risk-taking and asset allocation.[15] In addition to the belief expectations, we also analyze the correlations of belief dispersions or uncertainty as measured by the standard deviation of the belief distribution. These are shown in Table 10 in the Appendix. We find that lower risk aversion correlates with higher uncertainty/risk in final pay. Individuals who are less risk-averse believe that their final salary is riskier. This is rather consistent. Individuals with lower risk aversion will take more risk during their career, such that they expect a higher final salary (as we saw in Table 6) even though they believe this to come with more risk. Moreover, the uncertainty of retirement age also correlates with uncertainty of final pay. This suggests that individuals who expect more uncertainty in their final pay may choose their retirement age strategically. Finally, similar to the earlier results, the beliefs of stock return, inflation, and return on pension wealth highly correlate. Individuals who believe stocks to be riskier also expect more variation in inflation and in pension returns.

15 An interesting subject for follow-up work would be to dive more into the details of the beliefs formation process and analyze whether there is a predictable change in beliefs over the life cycle.

4. Personal characteristics

The respondents to our survey are chosen as being representative for the Dutch population. This allows us to analyze the input of the respondents by personal characteristic. We analyze heterogeneity along the following dimensions: gender, age, marital status, children, income, education, retirement, and level of risk aversion. The subgroups are divided as follows: males versus females, above median age versus below, partner versus no partner, children versus no children, above median income versus below, high education versus low and medium ed- ucation, retired versus not retired, and, above median risk aversion (pension domain) versus below median risk aversion (pension domain). Table 7 shows the preference parameters for the pension dimension for the different sample splits.

We find that older individuals display higher risk aversion, in line with the empirical evidence (Schildberg-Ho¨risch, 2018).[16] Also, older individuals display weaker probability weighting in the pension domain. In any case, the difference in the level of the risk preferences is fairly high even though the dispersion for both age groups is similar. On the other hand, the probability weighting of younger individuals for the pension domain is stronger than that of older individuals. As the pension domain entails payoffs that are far into the future for younger individuals, there are many scenarios with low probabilities due to the many alternative events that can occur in the meantime. Having a larger degree of probability weighting will thus cause stronger overweighting of these distant scenarios, in turn causing biased future expectations.[17]

Separating our respondents by income shows that individuals with a higher income have a lower time discounting preference, i.e. they are more patient. Individuals with more education show a smaller degree of loss aversion but are more strongly subject to probability weighting. This is surprising as individuals with higher education are commonly assumed to be less biased. In this case we observe that probability weighting is especially strong for such individuals, even though this does not translate into differences based on income. As education is often a differentiation criterion for customized optimal portfolio theory (Cocco et al., 2005), it is important to take the difference of the degree of probability weighting into account.

When we separate individuals with high risk aversion in the pension domain from those with low risk aversion, we clearly see differences in the loss aversion of these two groups.

16 As our data involve a one-time cross-sectional survey, we cannot differentiate whether this age effect stems from a cohort effect or shows an age dependency. Furthermore, human capital (which could be proxied by background income) and risk capacity may play a role as well. Testing for these effects is outside the scope of the paper.

17 Our results indicate the presence of a maturity dependence when eliciting probability weighting pref- erences. Pension decisions being more distant for young individuals may be influenced by this. A proper analysis of this potential mechanism is left to future research.

Table 7: **Preferences in the pension domain across personal characteristics**. This table presents summary statistics of the estimated pension-domain preferences across socio-demographic variables. We test for significant differences in the estimated preferences within different personal characteristics using an unpaired *t*-test assuming unequal variances; we show the corresponding *p*-values. For readability, values in **bold** are minimally significant at the 10% significance level.

	Risk preferences			Time preferences			Loss aversion			Probability Weighting		
	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N
Gender												
Male	4.99	2.55	132	9.62	12.00	124	1.64	0.97	74	0.77	0.29	89
Female	4.57	2.49	108	12.15	14.44	103	1.59	0.91	62	0.73	0.31	74
p-value	0.19			0.16			0.74			0.43		
Age												
High	5.28	2.49	114	11.37	14.47	108	1.65	0.99	68	0.80	0.28	82
Low	4.38	2.50	126	10.22	11.94	119	1.58	0.89	68	0.71	0.32	81
p-value	**0.01**			0.52			0.64			**0.04**		
Partner												
Yes	4.75	2.51	154	11.50	13.56	145	1.60	0.92	94	0.75	0.30	110
No	4.90	2.57	86	9.47	12.49	82	1.65	0.99	42	0.76	0.30	53
p-value	0.65			0.25			0.80			0.86		
Children												
Yes	4.52	2.55	75	9.62	11.69	67	1.66	0.91	44	0.76	0.30	47
No	4.93	2.51	165	11.25	13.77	160	1.59	0.96	92	0.75	0.30	116
p-value	0.24			0.37			0.71			0.79		
Income												
High	4.65	2.40	124	8.98	11.07	118	1.49	0.84	60	0.73	0.31	83
Low	4.99	2.68	105	12.64	14.91	98	1.67	0.99	67	0.78	0.29	73
p-value	0.32			0.05			0.27			0.27		
Education												
High	4.77	2.40	103	10.90	12.74	99	1.43	0.84	49	0.69	0.31	72
Low	4.83	2.63	137	10.66	13.58	128	1.72	0.98	87	0.80	0.29	91
p-value	0.85			0.89			**0.08**			**0.01**		
Retired												
Yes	5.64	2.28	65	9.99	13.88	63	1.59	0.99	41	0.76	0.30	47
No	4.49	2.55	175	11.07	12.95	164	1.63	0.92	95	0.75	0.30	116
p-value	**0.00**			0.60			0.84			0.80		
Risk averse												
High				12.73	16.23	74	1.86	1.04	54	0.80	0.29	58
Low				9.82	11.37	153	1.46	0.83	82	0.73	0.30	105
p-value				0.17			**0.02**			0.13		

The high risk aversion individuals also have significantly higher loss aversion. These results suggest that loss aversion is an important risk dimension to account for when determining the risk attitude of an individual. After all, strictly eliciting risk aversion would lead to a downward bias as this foregoes the additional aversion to risk that is due to loss aversion.

In addition to the differences in preferences for all characteristics in Table 7, we also document the impact of personal characteristics on beliefs (see Tables 11 and 12 in the Appendix). We observe that education is the most robust predictor of belief heterogeneity. Individuals with higher education expect lower inflation, lower stock market returns, lower returns on pension wealth, and higher pension income. The results suggest that individuals with higher education on average have a higher expectation of return variables and are more likely to have higher pension savings and thus higher pension income. Furthermore, pension income, final salary, and bequest amount vary most strongly over personal characteristics. These differences are sizable, which we see, for instance, in the difference in expected average monthly pension income of male persons (€2,231) and of female persons (€1,608). These differences are, more naturally, also large in the dimension of education and income. The differences for final salary are similar to those of pension income. Expected retirement age is on average lower for older and low income individuals. A final striking observation is average life expectancy. This is substantially higher for individuals with children (80 years) than for those without children (74 years).

5. Conclusion

Pension plans are increasingly being tailored to the individual. To achieve this, one needs to know the beliefs and preferences of the individual person. Interaction effects between beliefs and preferences may cause strong deviations from pension plans that are otherwise optimal. In this paper, we therefore address the task of providing a holistic view of optimal life-cycle investing and elicit both preferences and beliefs. Given that financial decisions over the life cycle involve multiple domains, and that recent results highlight differences between domains on risk preferences, we conduct our analysis in five domains: lottery, investments, pension, work, and health.

We find strong heterogeneity of risk and time preference among the respondents, although we also find strong evidence of domain dependence. Loss aversion and probability weighting are significantly present in all domains without showing significant differences between them. In the pension domain, we find that individuals are more risk-averse and patient relative to the lottery domain. We hereby show the relevance of using the pension domain rather than the general benchmark lottery domain when pension providers elicit risk preference from their members for optimization of their pension plans.

Finally, we show the importance of interactions between preferences and beliefs and which personal characteristics explain most of the heterogeneity among respondents. We find that risk aversion strongly correlates with expected final income, retirement income, and the expected riskiness of final income. These results imply strong interaction between risk aversion and beliefs about human capital, which are both key for determining the optimal life-cycle investment plan. Concerning the role of personal characteristics on the heterogeneity of preferences, we find that risk aversion varies with age, time preferences with income, loss aversion with education, and probability weighting with both age and education.

Future research could build on these findings by exploring several paths. Longitudinal studies are required to distinguish whether differences that are observed in preferences and beliefs arise from aging or represent cohort effects, shaped by generational experiences. Additionally, investigating how individuals form and update their beliefs over time, particularly in response to economic shifts or policy changes, would deepen our understanding of decision-making dynamics in the life-cycle context. Incorporating measures of financial literacy and cognitive ability could further clarify the sources of heterogeneity, shedding light on the role of knowledge and comprehension in shaping preferences and beliefs. Another direction involves segmentation: identifying clusters of individuals with similar preference-belief profiles to enable more targeted and effective pension products. Finally, experimental studies can test whether information interventions can shift unrealistic beliefs or “misaligned” preferences towards more optimal life-cycle planning behavior.

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Appendix

Table 8: **Socio-demographic variables across sizes at stake.** This table presents summary statistics of socio-demographic variables (male, age, and income) per domain for the domain-dependent and standard amounts at stake. We test for significant differences in the socio-demographic data between the amounts at stake using an unpaired *t*-test assuming unequal variances; we show the corresponding *p*-values. We exclude individuals with more than €1000 billion after-tax monthly individual income. For readability, values in **bold** are significant at minimally the 10% significance level.

	Male			**Age**			**Income**		
	Mean	St. Dev.	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	*N*
Lottery Domain	0.52	0.50	134	54	16	134	2301	1288	134
Standard	0.50	0.50	136	52	17	136	2122	1322	136
p-value	0.71			0.31			0.27		
Investment Domain	0.50	0.50	155	51	17	155	2708	8319	155
Standard	0.55	0.50	115	51	17	115	2230	1147	115
p-value	0.47			0.97			0.55		
Pension Domain	0.55	0.50	136	50	17	136	2281	1258	130
Standard	0.55	0.50	104	52	17	104	2408	1693	97
p-value	0.96			0.50			0.52		
Work Domain	0.43	0.50	129	51	17	129	2461	2359	129
Standard	0.53	0.50	130	50	16	130	2163	1217	130
p-value	0.12			0.55			0.21		
Health Domain	0.54	0.50	105	51	16	105	2308	1413	105
Standard	0.55	0.50	130	49	17	130	2266	1127	130
p-value	0.96			0.20			0.81		

Figure 3: **Time preferences across domains**. This figure displays the observed distributions of time preferences by domain, with the annual subjective discount rate on the horizontal axis, and the fraction of individuals on the vertical axis. $*, **, ***$ indicate whether the mean annual discount rate is significantly different from the lottery domain at the 10%, 5%, and 1% significance level, respectively.

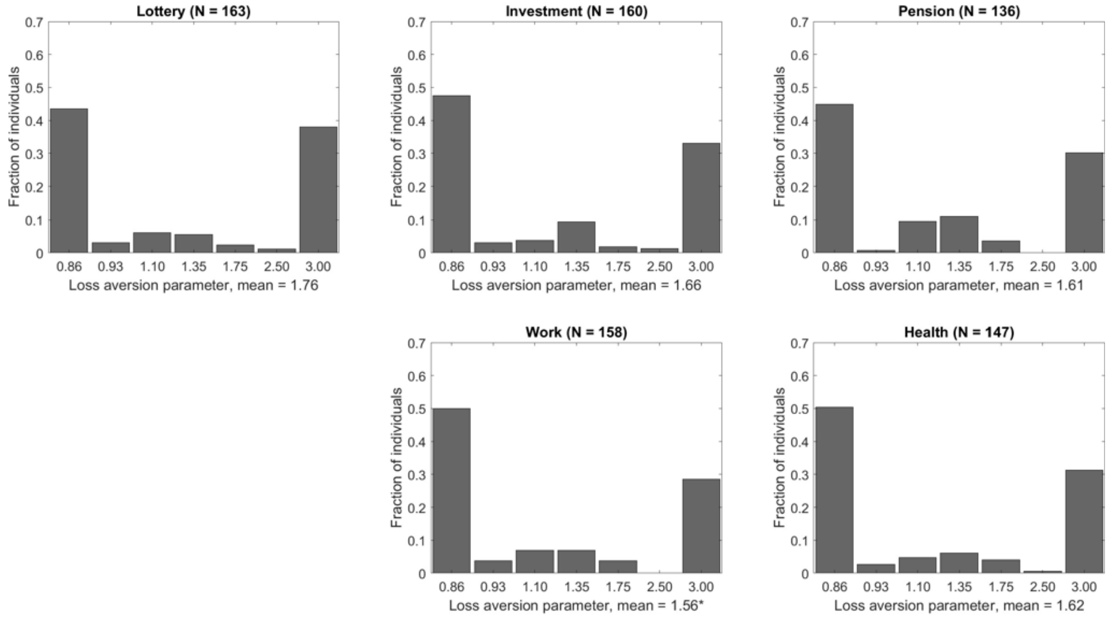

Figure 4: **Loss aversion across domains**. This figure displays the observed distributions of loss aversion by domain, with on the horizontal axis the loss aversion parameter value λ by applying cumulative prospect theory (Tversky and Kahneman, 1992), and on the vertical axis the fraction of individuals.. $*, **, ***$ indicate whether the mean loss aversion parameter is significantly different from the lottery domain at the 10%, 5%, and 1% significance level, respectively.

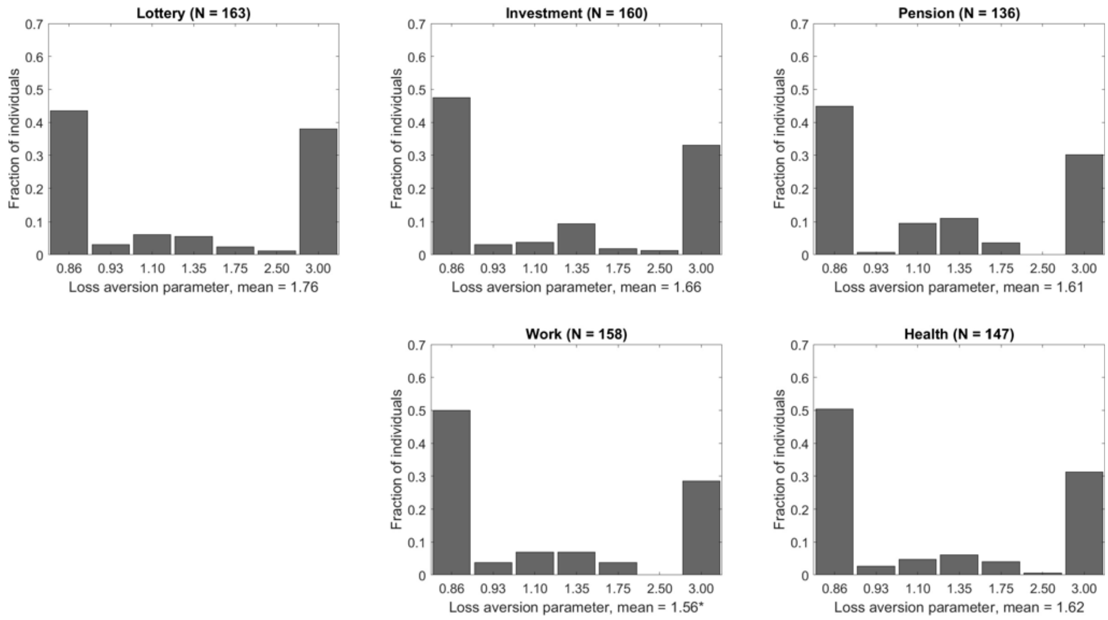

Figure 5: **Probability weighting across domains**. This figure displays on the horizontal axis the quantified probability weighting parameters of the probability weighting function of cumulative prospect theory (Tversky and Kahneman, 1992) when fitted on the survey questions, and on the vertical axis the fraction of individuals. ∗,∗∗ ,∗∗∗ indicate whether the mean probability weighting parameter is significantly different from the lottery domain at the 10%, 5%, and 1% significance level, respectively.

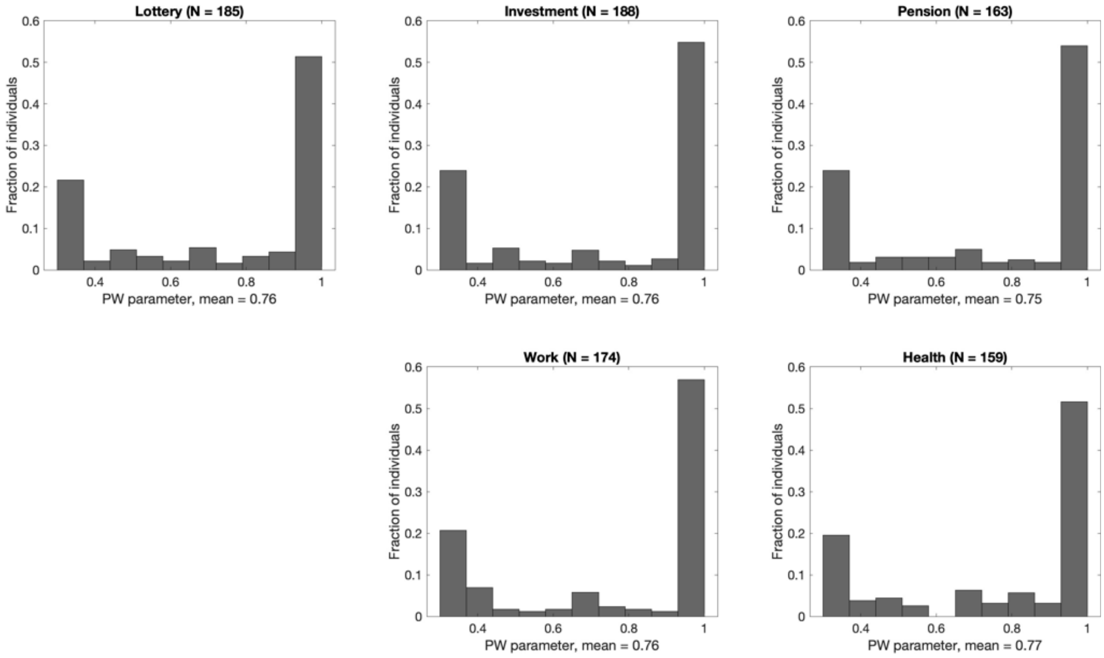

Table 9: **Socio-demographic variables across domains**. This table presents summary statistics of socio-demographic variables (male, age, and income) per domain, aggregated over the amounts at stake. We test for significant differences in the socio-demographic data with regard to the lottery domain using an unpaired *t*-test assuming unequal variances; we show the corresponding *p*-values. We exclude individuals with more than €1000 billion after-tax monthly individual income. For readability, values in bold are significant at minimally the 10% significance level.

	Male			**Age**			**Income**		
	Mean	St. Dev.	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	*N*
Lottery	0.51	0.50	270	53	16	270	2211	1306	270
Investment	0.52	0.50	270	51	17	270	2504	6337	270
p-value	0.80			0.20			0.46		
Pension	0.55	0.50	240	51	17	240	2335	1458	227
p-value	0.38			0.24			0.32		
Work	0.48	0.50	259	51	16	259	2312	1879	259
p-value	0.51			0.17			0.48		
Health	0.54	0.50	235	50	17	235	2284	1260	235
p-value	0.45			**0.04**			0.53		

Figure 6: **Pension belief distributions**. This figure is obtained by computing the expected value for a certain variable per individual using the method of Altig et al. (2022). The variables are (net) pension income, (net) final pay, (gross) bequest upon death, retirement age, and life expectancy. Each subfigure shows the distributions over all individuals. The red vertical lines indicate the median expectations. The number of participants that make up each subfigure are 616, 480, 157, 480, 158, respectively. The difference in the number of participants per question originates from the between-subjects design and the allocation of questions.

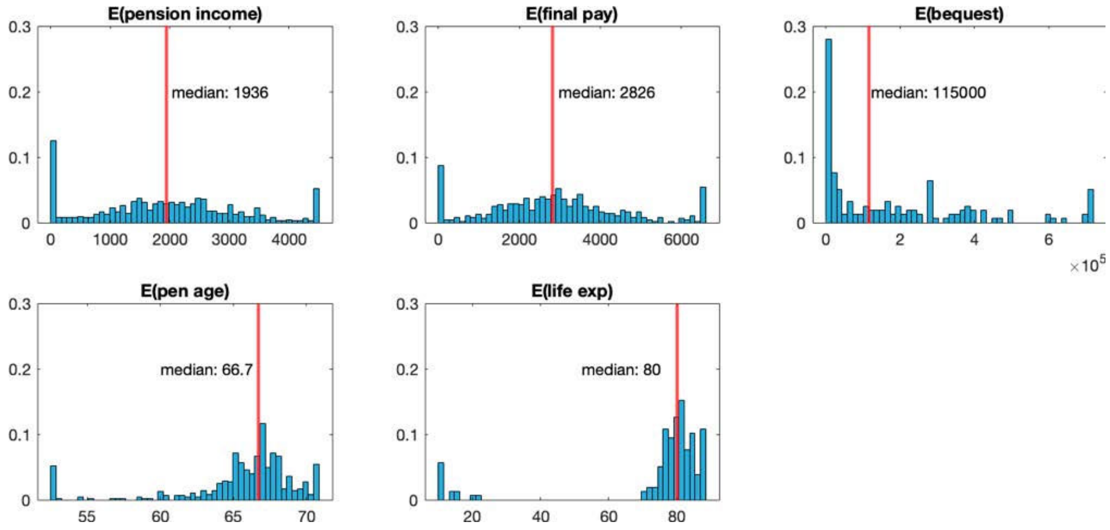

Figure 7: **Return belief distributions.** This figure is obtained by computing the expected value for a certain variable per individual using the method of Altig et al. (2022). The variables are inflation, return on pension wealth, and return on market equity index. Each subfigure shows the distributions over all individuals. The red vertical lines indicate the median expectations. The number of participants that make up each subfigure are 404, 614, 400, respectively.

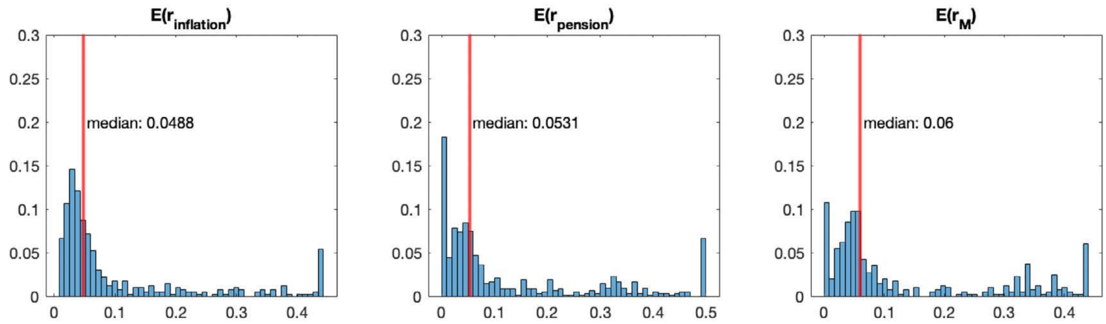

Table 10: **Preference-belief volatility correlations**. This table presents correlations among and between preference estimates and belief dispersions as measured by the volatility of the distribution. Correlations are taken over individuals, of which we have both results. As not all participants answered all belief elicitation tasks, some combinations are missing. *RA* is the coefficient of risk aversion, *TD* is the coefficient of time discounting, *LA* is the coefficient of loss aversion, and *PW* is the coefficient of probability weighting. We test for significance of the correlations. The *p*-values are shown between brackets.

	Preferences				Beliefs							
	RA (n=1274)	TD (n=1187)	LA (n=764)	PW (n=869)	Last pay (n=480)	Ret. Age (n=480)	Life Exp. (n=158)	Bequest (n=157)	Pen. ret. (n=614)	Pen. Income (n=616)	Inflation (n=404)	Stock ret. (n=400)
RA	-											
TD	0.11*** (0.00)	-										
LA	0.14*** (0.00)	0.11*** (0.00)	-									
PW	0.07** (0.04)	0.06* (0.10)	0.06 (0.17)	-								
Last pay	-0.25*** (0.00)	-0.10** (0.03)	-0.04 (0.55)	0 (0.97)	-							
Ret. Age	-0.08 (0.11)	0.01 (0.79)	0.03 (0.69)	0.01 (0.92)	0.30*** (0.00)	-						
Life Exp.	-0.03 (0.70)	-0.07 (0.40)	0.13 (0.18)	0.06 (0.55)	-	-	-					
Bequest	-0.05 (0.61)	-0.17* (0.07)	0 (0.97)	0.02 (0.89)	-	-	0.13 (0.16)	-				
Pen. ret.	-0.02 (0.62)	0 (0.96)	-0.10 (0.11)	0.05 (0.35)	-	-	-	-	-			
Pen. income	-0.12*** (0.01)	-0.04 (0.36)	-0.04 (0.53)	0.03 (0.56)	-	-	-	-	-0.10** (0.04)	-		
Inflation	-0.03 (0.62)	0.01 (0.80)	0.02 (0.80)	0.13** (0.04)	-0.04 (0.67)	0.15 (0.15)	-0.29** (0.04)	-0.28* (0.07)	0.27*** (0.00)	-0.04 (0.57)	-	
Stock ret.	-0.07 (0.17)	-0.05 (0.40)	-0.07 (0.31)	0 (0.98)	0.05 (0.59)	0.04 (0.71)	-0.13 (0.35)	-0.14 (0.36)	0.33*** (0.00)	0.05 (0.52)	0.35*** (0.00)	-

Table 11: **Beliefs across personal characteristics**. This table presents summary statistics of the beliefs across socio-demographic variables. We test for significant differences in the beliefs within different personal characteristics using an unpaired t-test assuming unequal variances; we show the corresponding *p*-values. For readability, values in **bold** are significant at minimally the 10% significance level.

	Inflation rate			Stock market return			Pension portfolio return			Pension income		
	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N
Gender												
Male	9.88	11.79	214	14.40	14.52	213	11.86	14.45	319	2231	1209	321
Female	11.18	12.76	190	12.12	13.96	187	13.85	16.27	295	1608	1170	295
p-value	0.29			0.11			0.11			**0.00**		
Age												
High	10.82	12.31	203	14.16	14.50	199	11.91	15.00	300	1860	1270	299
Low	10.16	12.23	201	12.52	14.06	201	13.68	15.69	314	2001	1188	317
p-value	0.59			0.25			0.15			0.16		
Partner												
Yes	10.93	12.51	287	13.48	14.24	284	13.34	15.55	444	1970	1243	445
No	9.41	11.59	117	12.98	14.45	116	11.45	14.85	170	1836	1194	171
p-value	0.25			0.75			0.16			0.22		
Children												
Yes	11.19	12.99	135	14.62	14.98	134	14.17	15.83	218	1872	1158	220
No	10.14	11.88	269	12.68	13.91	266	12.07	15.08	396	1967	1268	396
p-value	0.43			0.21			0.11			0.35		
Income												
High	9.46	11.48	185	12.04	13.32	183	13.63	15.54	291	2511	1089	292
Low	10.85	12.39	201	14.34	15.01	199	11.83	14.96	291	1408	1100	293
p-value	0.25			0.11			0.15			**0.00**		
Education												
High	7.72	9.52	180	11.70	12.95	177	11.56	14.18	261	2419	1199	262
Low	12.72	13.70	224	14.63	15.17	223	13.80	16.20	348	1561	1109	349
p-value	**0.00**			**0.04**			**0.07**			**0.00**		
Retired												
Yes	10.03	11.32	114	13.87	14.78	111	12.79	15.34	159	2092	1358	158
No	10.67	12.62	290	13.13	14.11	289	12.82	15.40	455	1878	1179	458
p-value	0.62			0.65			0.98			**0.08**		
Risk averse												
High	10.65	12.74	180	14.21	14.60	180	12.44	14.98	272	1828	1221	273
Low	10.43	11.98	220	12.67	14.02	219	13.06	15.62	339	2033	1229	338
p-value	0.86			0.29			0.62			**0.04**		

Table 12: **Beliefs across personal characteristics, continued**. This table presents summary statistics of the beliefs across socio-demographic variables. We test for significant differences in the beliefs within different personal characteristics using an unpaired t-test assuming unequal variances; we show the corresponding *p*-values. For readability, values in **bold** are significant at minimally the 10% significance level.

	Last salary			Retirement age			Life expectancy			Bequest motive		
	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.	N
Gender												
Male	3349	1666	244	66	4	245	75	19	92	233686	240774	91
Female	2412	1555	236	66	4	235	74	22	66	121042	140062	66
p-value	**0.00**			0.87			0.73			**0.00**		
Age												
High	2089	1374	157	65	4	158						
Low	3276	1676	323	66	4	322						
p-value	**0.00**			**0.00**								
Partner												
Yes	2796	1685	329	66	4	328	73	22	110	209424	220660	109
No	3089	1648	151	66	4	152	77	17	48	133896	180385	48
p-value	**0.07**			0.84			0.30			**0.03**		
Children												
Yes	2893	1615	193	66	4	193	80	4	10	319151	314924	10
No	2885	1721	287	66	4	287	74	21	148	177297	200974	147
p-value	0.96			0.75			**0.01**			0.19		
Income												
High	3615	1398	236	66	4	235	74	22	64	275146	232199	64
Low	2229	1622	224	65	5	225	75	19	88	131049	175055	87
p-value	**0.00**			**0.05**			0.65			**0.00**		
Education												
High	3484	1621	234	66	4	233	72	24	58	264016	237062	58
Low	2330	1529	244	65	4	245	76	18	100	140821	181255	99
p-value	**0.00**			0.13			0.29			**0.00**		
Risk averse												
High	10.65	12.74	180	14.21	4	204	72	23	78	178518	209929	78
Low	10.43	11.98	220	12.67	4	270	76	17	79	194048	214092	79
p-value	0.86			0.29			0.23			0.65		

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Network for Studies on
Pensions, Aging and Retirement

This is a publication of Netspar
August 2025

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